Development and testing of a multi-model ensemble prediction system for sub-monthly forecasts

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# Objectives

- Quantify the sub-monthly hindcast skill of the CFSv2 and selected other individual models over the U.S. in terms of: gridded fields of precipitation and temperature, as well as atmospheric indices such as the NAO and PNA; lead time and averaging range, including weekly averages in weeks 2–4; deterministic and probabilistic forecast skill metrics; and diagnostics of predictability.
- Develop the methodology and evaluate the benefit of including an additional 1–3 models in a multi-model ensemble, with focus over the U.S.
- Improve physical understanding of sub-monthly predictability over the U.S.
- Establish the applicability of MME methods developed for seasonal forecasts to the sub-monthly scale.
- (Implement a real-time S2S MME at CPC, built using the most skillful and models that are available to CPC in real time.)

# Forecast Lead Times



#### **Evaluation of Submonthly Precipitation Forecast Skill from Global Ensemble Prediction Systems**

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#### ABSTRACT

The prediction skill of precipitation at submonthly time scales during the boreal summer season is investigated based on hindcasts from three global ensemble prediction systems (EPSs). The results, analyzed for lead times up to 4 weeks, indicate encouraging correlation skill over some regions, particularly over the Maritime Continent and the equatorial Pacific and Atlantic Oceans. The hindcasts from all three models correspond to high prediction skill over the first week compared to the following three weeks. The ECMWF forecast system tends to yield higher prediction skill than the other two systems, in terms of both correlation and mean squared skill score. However, all three systems are found to exhibit large conditional biases in the tropics, highlighted using the mean squared skill score.

The sources of submonthly predictability are examined in the ECMWF hindcasts over the Maritime Continent in three typical years of contrasting ENSO phase, with a focus on the combined impact of the intraseasonal MJO and interannual ENSO. Rainfall variations over Borneo in the ENSO-neutral year are found to correspond well with the dominant MJO phase. The contribution of ENSO becomes substantial in the two ENSO years, but the MJO impact can become dominant when the MJO occurs in phases 2–3 during El Niño or in phases 5–6 during the La Niña year. These results support the concept that "windows of opportunity" of high forecast skill exist as a function of ENSO and the MJO in certain locations and seasons, which may lead to subseasonal-to-seasonal forecasts of substantial societal value in the future.

#### 3 models, boreal summer, weekly precipitation

Model	Grid Resolution	Ensemble	Frequency	# of Starts	Period
JMA	144 x 73	5	3/month	13	1979–2008
CFSv2	384 x 190	4	5-day	25	1982-2010
ECMWF	360 x 181	5	weekly	18	1992-2009

• Weekly averages were constructed from the GCM daily output, and CMAP pentad data

• Ensemble sizes are small so skill measures restricted to deterministic measures

• Hindcast frequency differ – MME not possible

# Skill metrics

- Correlation of anomalies (CORA)

  between the EPS ensemble mean and CMAP
  lead-dependent EPS weekly climo is subtracted
  weekly averages (week 1 = days 1–7, week2 = 8–14, week 3 = days 15–21), week 4 = days 22–28)
  all available start dates, 1992–2008 (17 yrs)
- Mean Squared Skill Score (MSSS)
   MSSS = (CORA)<sup>2</sup> + b<sup>2</sup>

## ECMWF Sub-monthly forecast skill

Weekly average precip

Jun–Aug anomaly correlation skill

Li and Robertson (2015, in press)



0.4

0.5

0.6

0.7

0.8

#### skill from atmos ICs

skill from MJO and atmos BCs

#### Anomaly correlation skill of weekly precipitation

ECMWF

ECMWF Precip Fcst vs CMAP: 1992-2008

CFSv2

CFSv2 Precip Fcst vs CMAP: 1992-2008

JMA

JMA Precip Fcst vs CMAP: 1992-2008



T255, coupled after day 9

T126, coupled

T159, persisted SST

#### MSSS: ECMWF Precip Fcst vs CMAP: 1992-2008



FIG. 15. Mean square skill score (MSSS) between ECMWF precipitation hindcast and CMAP rainfall data over weeks 1–4.

#### Mean Squared Skill Score



ECMWF Precip Fcst vs CMAP: 1992-2008

 $MSSS = (CORA)^2 + b^2$ 

Precip Fcst (Week-3) vs CMAP: Conditional bias

#### Conditional Bias



 $CORA - s_h/s_o$ 





(c) ECMWF



## Spatial averages of Correlation of Anomalies for 3 GCMs



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# Skill for ENSO Years

Weekly average precip

Jun–Aug anomaly correlation skill

#### ECMWF Precip Forecast (Week-3) vs CMAP



Figure 6: Correlation of anomalies between ECMWF lead-3 preci**Jinternational** Research Institute for Climate and Society start dates) and CAMP observation during (a) 5 ENSO years: 1EARTH INSTITUTE [COLUMBIA]UNIVERSITY

## ECMWF Performance over Borneo (Boreal summer)



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# ENSO & MJO Signals during boreal summer



CMAP pentad precip vs RMM: Jun-Aug 1992-2008



## Borneo Precipitation vs MJO Phase





## ECMWF Performance over Borneo



Li and Robertson (2015, in press)



### ECMWF Performance over Borneo



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Li and Robertson (2015, in press)



#### Mission

The main goal of the proposed WWRP/THORPEX/ WCRP joint research project is to improve forecast skill and understanding on the subseasonal to seasonal timescale, and promote its uptake by operational

#### Reports & Publications

 Subseasonal to Seasonal Prediction Research Implementation Plan

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 Report of the Subseasonal to seasonal prediction planning group







	Time-range	Resol.	Ens. Size	Freq.	Hcsts	Hcst length	Hcst Freq	Hcst Size
ECMWF	D 0-32	T639/319L91	51	2/week	On the fly	Past 18y	2/weekly	Ш
UKMO	D 0-60	N96L85	4	daily	On the fly	1989-2003	4/month	3
NCEP	D 0-45	N126L64	4	4/daily	Fix	1999-2010	4/daily	1
EC	D 0-35	0.6×0.6L40	21	weekly	On the fly	Past 15y	weekly	4
CAWCR	D 0-60	T47L17	33	weekly	Fix	1981-2013	6/month	33
ЈМА	D 0-34	T159L60	50	weekly	Fix	1979-2009	3/month	5
КМА	D 0-60	N216L85	4	daily	On the fly	1996-2009	4/month	3
СМА	D 0-45	T106L40	4	daily	Fix	1992-now	daily	4
Met.Fr	D 0-60	T127L31	51	monthly	Fix	1981-2005	monthly	П
CNR	D 0-32	0.75x0.56 L54	40	weekly	Fix	1981-2010	6/month	I.
HMCR	D 0-63	I.IxI.4 L28	20	weekly	Fix	1981-2010	weekly	10

## Workplan

#### Year 1:

- 1. Downloading of datasets from NCEP and S2S database
- 2. Evaluation of skill of individual models;
- 3. Predictability diagnostics using individual models;
- 4. Development of MME methodology;
- 5. Publication on individual models.

#### Year 2:

- 6. Further development and testing of MME methodology;
- 7. Evaluation of skill of multi- model combinations;
- 8. Predictability diagnostics of MMEs;
- 9. Porting of MME methodology to NCEP;
- 10. Publication on MME.



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This table shows the centres that provide data to this project together with the latest configuration of their systems. Follow the link of each Data Prov of retrievals.

Status on 1st July 2015	Time range	Resolution	Ens. Size	Frequency	Re- forecasts	Rfc length	Rfc frequency	Rfc size
BoM (ammc)	d 0-60	T47L17	33	2/week	fix	1981-2010	6/month	33
CMA (babj)	d 0-60	T106L40	4	daily	fix	1994-April 2014	daily	4
EC (cwao)	d 0-35	0.6x0.6 L40	21	weekly	on the fly	past 15y	weekly	4
ECMWF (ecmf)	d 0-46	T639/319 L62	51	2/week	on the fly	past 20 years	2/week	11
ISAC-CNR (isac)	d 0-32	0.75x0.56 L54	40	weekly	fix	1981-2010	6/month	1
HMCR (rums)	d 0-63	1.1x1.4 L28	20	weekly	fix	1985-2010	weekly	10
JMA (rjtd)	d 0-34	T319L60	25	2/week	fix	1981-2010	3/month	5
KMA (rksl)	d 0-60	N216L85	4	daily	on the fly	1996-2009	4/month	3
Meteo-France (Ifpw)	d 0-60	T255L91	51	monthly	fix	1993-2014	monthly	15
NCEP (kwbc)	d 0-44	T126L64	16	daily	fix	1999-2010	day	4
UKMO (egrr)	d 0-60	N216L85	4	daily	on the fly	1996-2009	4/month	3

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YR S2SMME MURI WebofSci D	OCP seminars HIW Lamont weather TimeZone IRIcloud irap IRI_intranet ECMWFdata EI C&G Bascmp DL >>			
Home   S2	S Project Subseasonal to Seasonal Instantaneous and Accumulated +			
CECMWF	Home My room Contact Search ECMWF			
About Forecasts Computing	Research Learning			
Origin	Subseasonal to Seasonal Instantaneous and Accumulated			
BoM CMA	Please login before retrieving data from this dataserver.			
► ECMWF	This dataset is available Mondays and Thursdays. read more			
HMCR	Select date			
JMA Météo France	• Select a date in the interval 2015-01-01 to 2015-06-22			
NCEP         Start date:         2015-01-01         End date:         2015-06-22				
Statistical process	Reset			
► Instantaneous and	O Select a list of months			
accumulated	Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec			
Daily averaged	2015			
Type of level	Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec			
Potential temperature	Select All or Clear			
Pressure levels	Select sten			
► Surface				
Туре				
Control forecast	http://oppo.com/ufipt/			
Perturbed forecast				
About				
Conditions of was	datasets/data/s2s/			
Documentation				
Documentation				

# Data Download



```
#!/usr/bin/env python
import calendar
year list=range(1999,2015)
month list=range(1,13)
month name list=["01","02","03","04","05","06","07",
"08", "09", "10", "11", "12"]
for dy in year list:
    for dm in month list:
         end day=calendar.monthrange(dy, dm)[1]
         string="";
         date range=[str(dy), month name list[dm-1],
"01/to/", str(dy),
month name list[dm-1],str(end day)];
         file name=[ "NCEP SAm pf reforecast tp ",
str(dy)," ", str(dm), ".grib"];
         from ecmwfapi import ECMWFDataServer
         server = ECMWFDataServer()
         server.retrieve({
                  "class": "s2",
                  "dataset": "s2s",
                  "hdate": string.join(date_range),
                  "date": "2011-03-01",
                  "expver": "prod",
                  "levtype": "sfc",
                  "origin": "kwbc",
                  "param": "tp",
                  "step": "24/to/1056/by/24",
                  "stream": "enfh",
                  "target": string.join(file name),
                  "area": "20/-90/-60/-30",
                  "time": "00",
                      "number":"1/2/3",
                  "type": "pf",
              })
```