



Drought Monitoring and Prediction Using Sub-Seasonal Predictions

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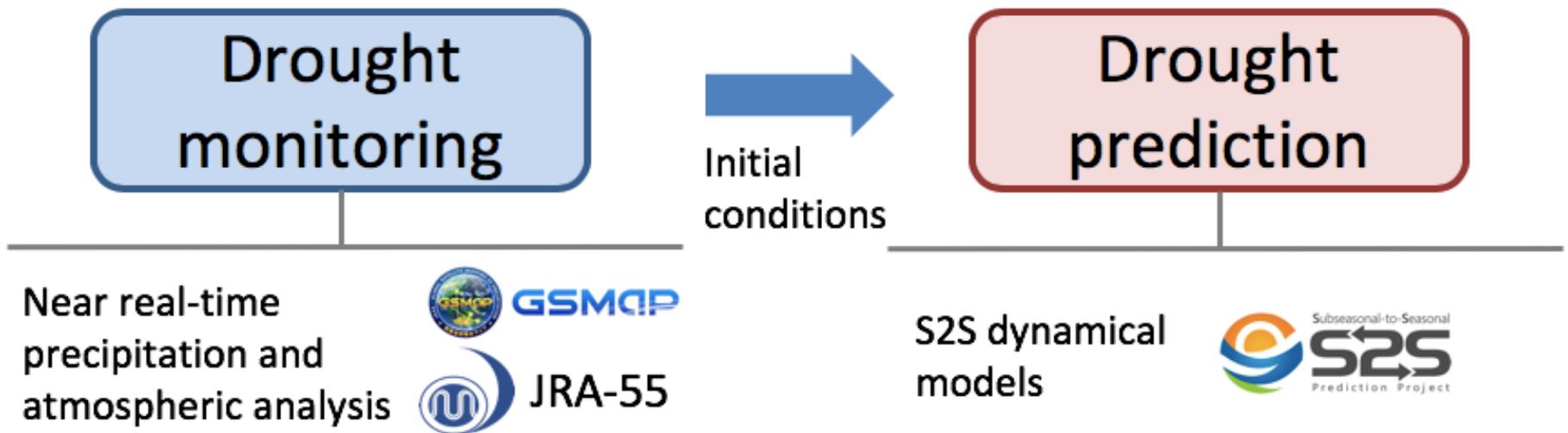
Acknowledgements

This study was supported by JAXA RA8 and JSPS KAKENHI (JP17K14395, JP17K01223).

Background and Aims

Persistent drought and flood create adverse results in various sectors, especially agriculture.

The aim of this study is to develop drought(/flood) monitoring and prediction capability using near real-time precipitation and atmospheric analysis as well as subseasonal predictions.



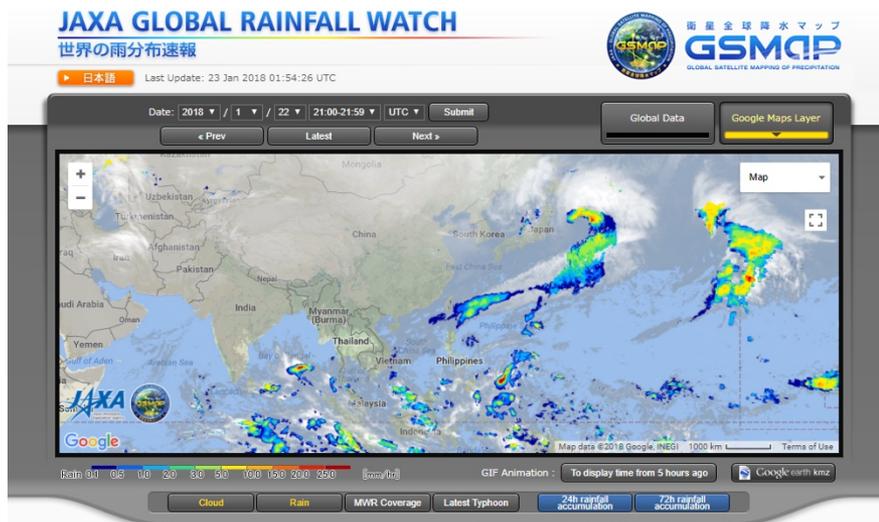
Data (1)

Analysis data

Precipitation: Global Satellite Mapping of Precipitation (GSMaP) data (Aonashi et al. 2009)
(available from JAXA web: <http://sharaku.eorc.jaxa.jp/GSMaP/>)



Atmospheric analysis: JRA-55 (Kobayashi et al. 2015)



Version: GSMaP NRT Version 6
Period: 2001 – 2015

<http://sharaku.eorc.jaxa.jp/GSMaP/>

Prediction data

	JMA	ECMWF	UKMO
Data	Hindcast data		
Period	2001-2010	2001-2015	2001-2015
Model Resolution	T319L60	T639/319/L91*	N96L85
Freq.	3/month	2/weekly	4/month
Ens. Size	5	11	3

(*T639 up to day 15 and T319 after day 15)



<https://www.ecmwf.int/en/research/projects/s2s>

Methods: Keetch — Byram drought index (KBDI)

Drought index

The Keetch — Byram drought index (KBDI, Keetch and Byram, 1968) was used in this study. The index estimates the soil moisture deficit, thus it is a useful indicator of drought conditions and wildfire risks. The index was calculated using meteorological variables by taking into account evaporation and plant transpiration.

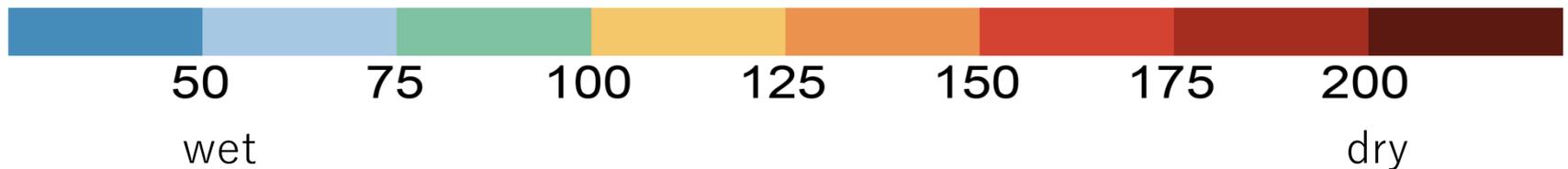
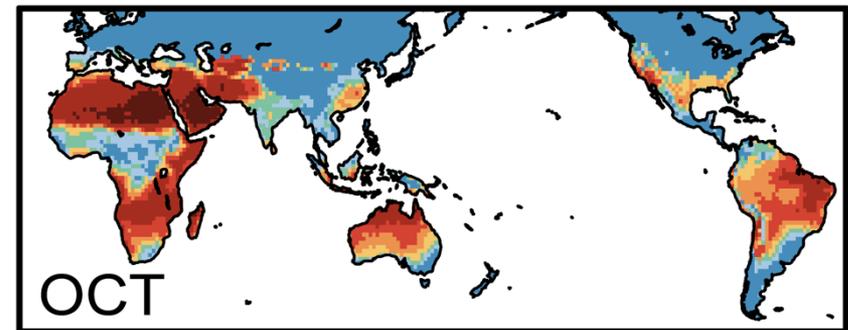
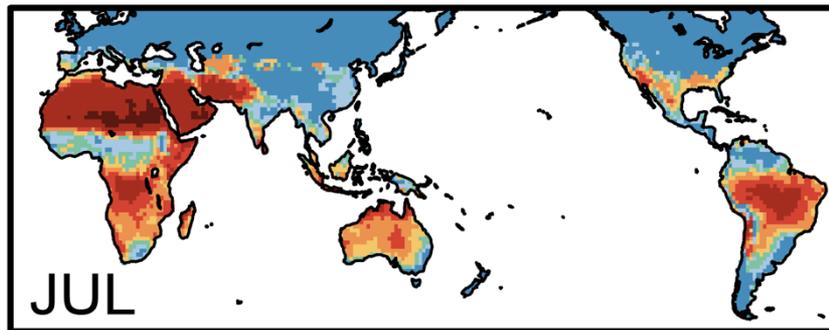
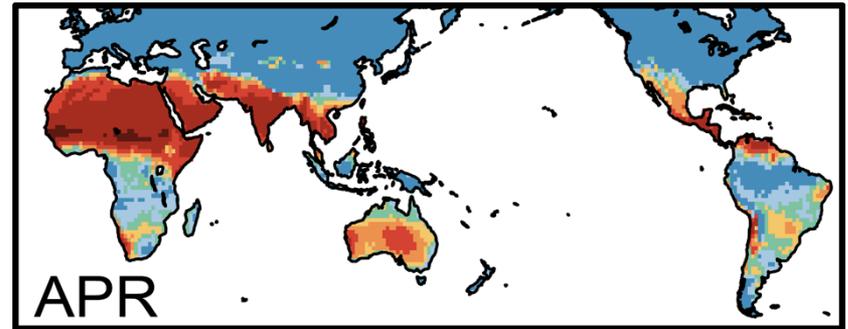
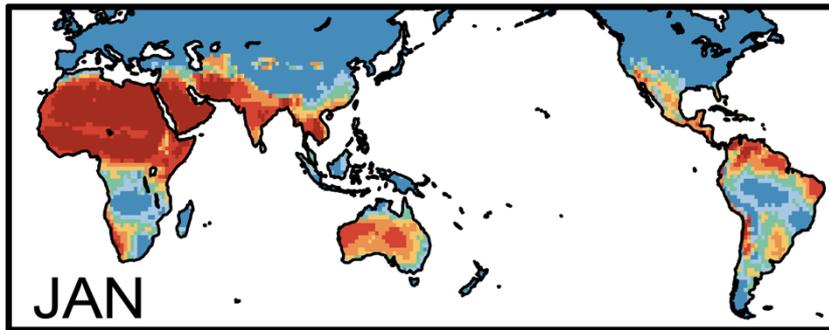
$$\text{KBDI}^t = \frac{\text{KBDI}^{t-1}}{\text{KBDI 1-day before}} + \text{DF}^t - \text{RF}^t$$

evaporation rainfall
transpiration



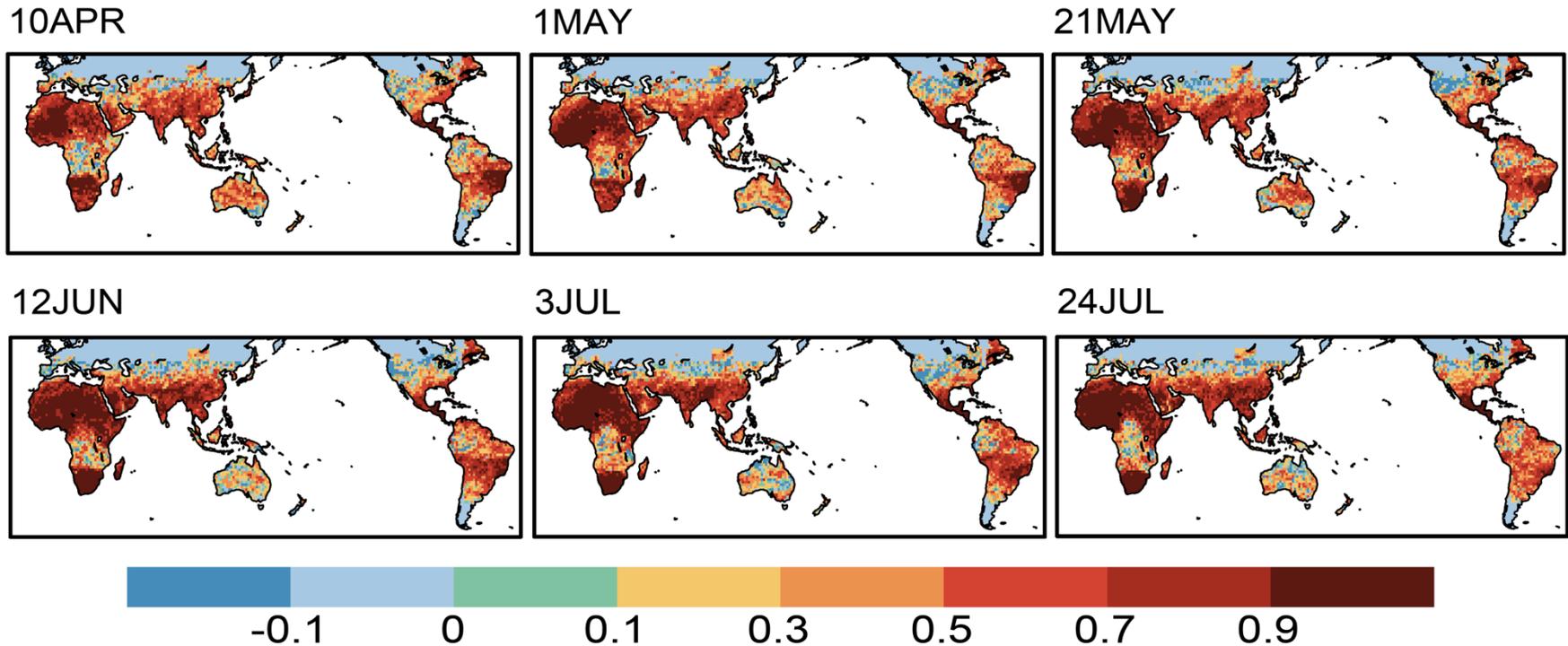
rainfall amount &
daily maximum surface temperature

KBDI monthly climatology (2001-2013)



KBDI was calculated with GSMaP precipitation and JRA-55 Ts.

Predictive skill of KBDI (ECMWF model)

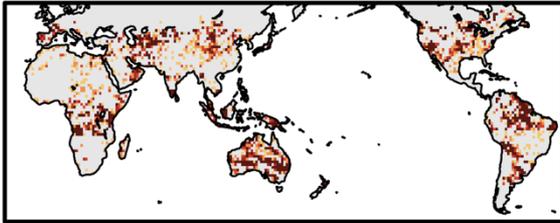


Rank correlations (Kendall's τ) between observations and predictions with a 28-day lead. Four consecutive 11-member ensemble mean predictions 7 days apart starting from dates denoted above figures were verified.

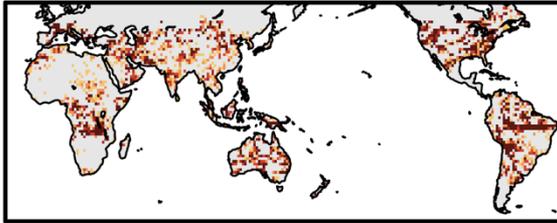
KBDI predictive skills are generally high in the tropics including South and Southeast Asia.

Skill improvement over persistent anomaly predictions

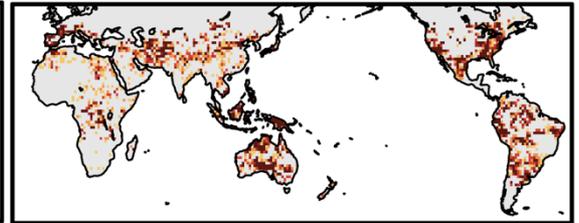
10APR



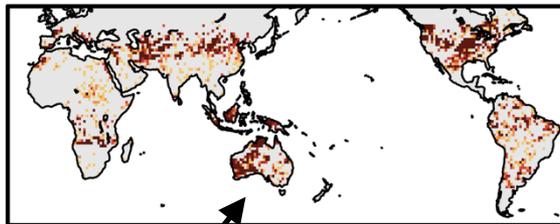
1MAY



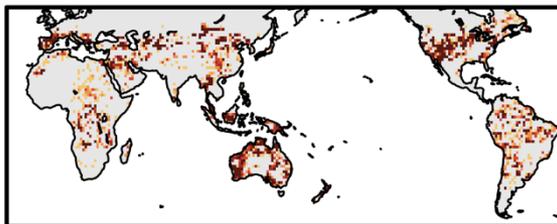
21MAY



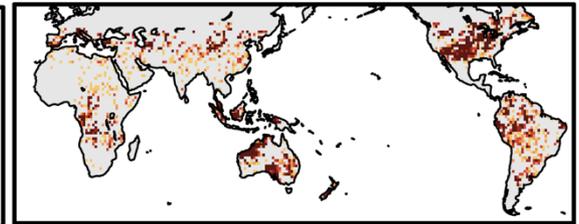
12JUN



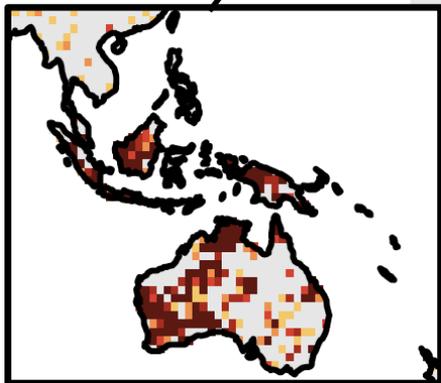
3JUL



24JUL



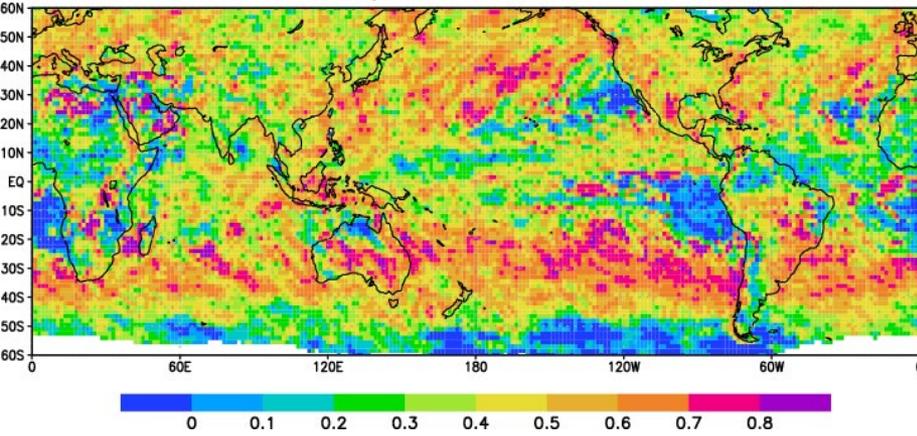
Same as the previous slide, but for rank correlation difference between model predictions and persisted anomaly predictions.



Anomaly correlation coefficient: JMA control prediction, JJA

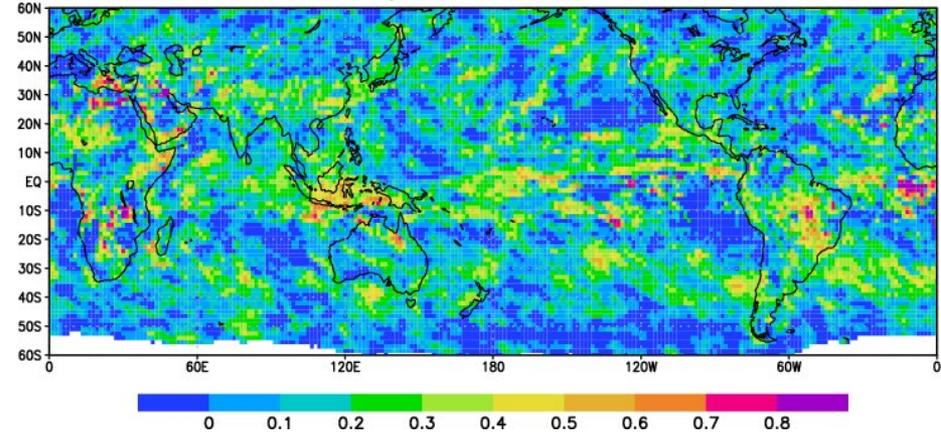
Week 1

7-day Accumulated Rain



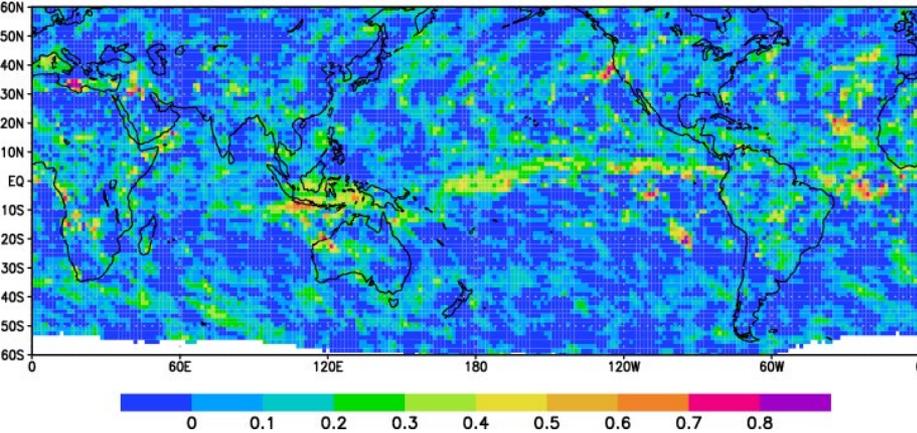
Week 2

7-day Accumulated Rain



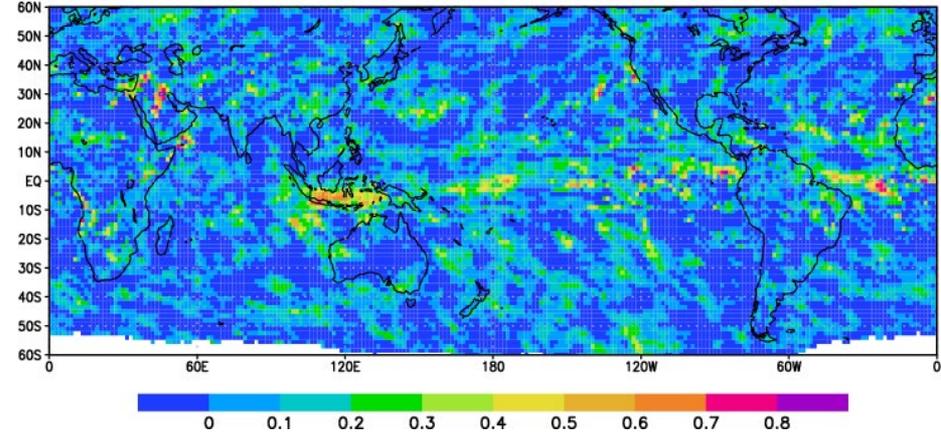
Week 3

7-day Accumulated Rain



Week 4

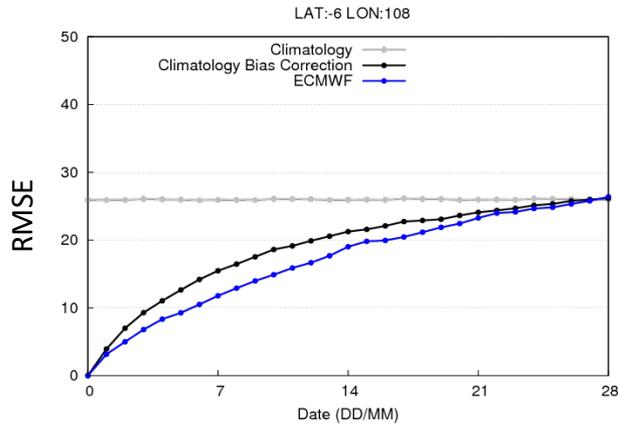
7-day Accumulated Rain



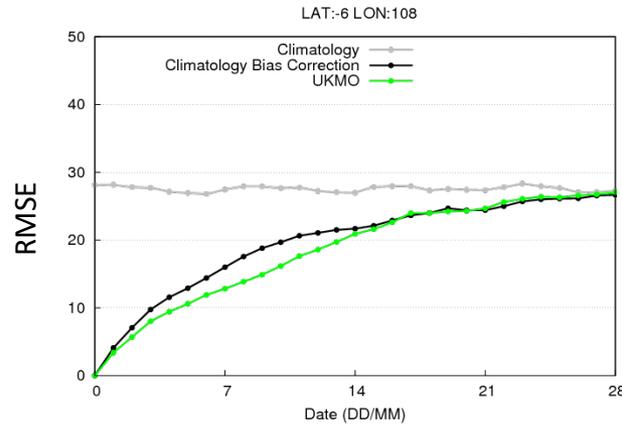
Skill of Indonesian drought prediction

RMSE of KBDI predictions near Jakarta

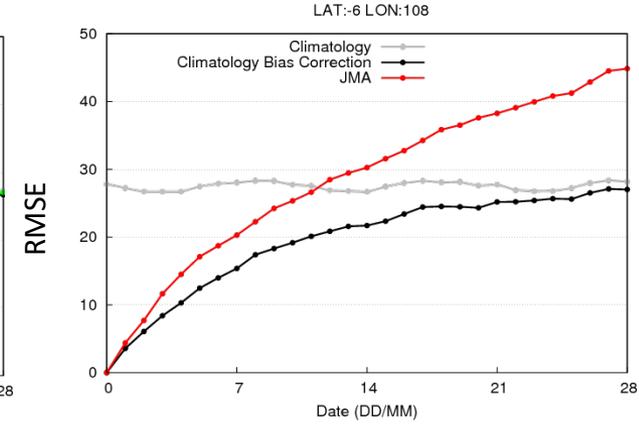
ECMWF



UKMO



JMA

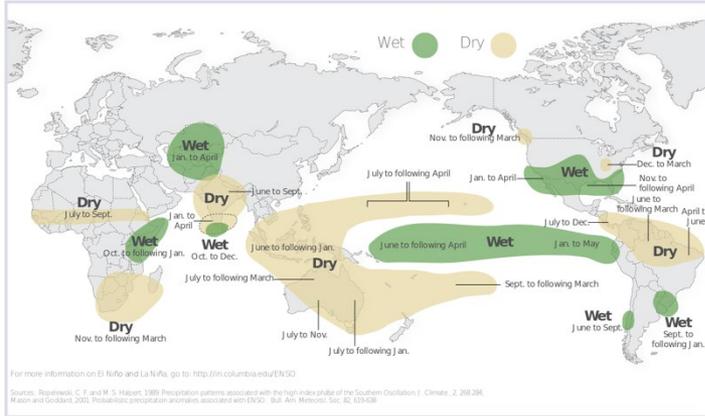


Models generally overperform climatological predictions up to at least 10-day lead, however, the model performance is a key to make a meaningful forecast.

Indonesian drought and ENSO/IOD

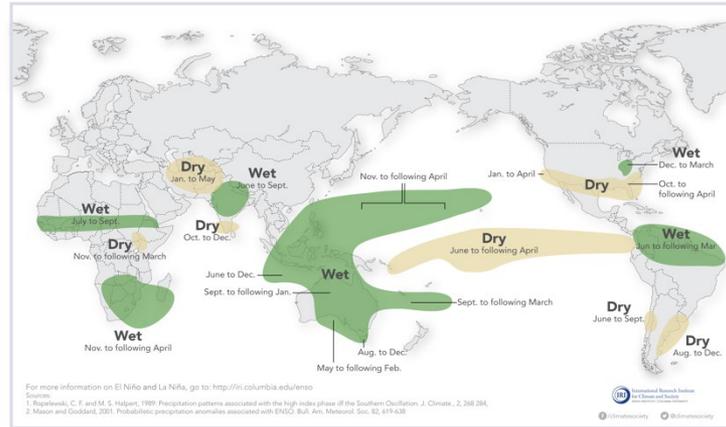
El Niño and Rainfall

El Niño conditions in the tropical Pacific are known to shift rainfall patterns in many different parts of the world. Although they vary somewhat from one El Niño to the next, the strongest shifts remain fairly consistent in the regions and seasons shown on the map below.

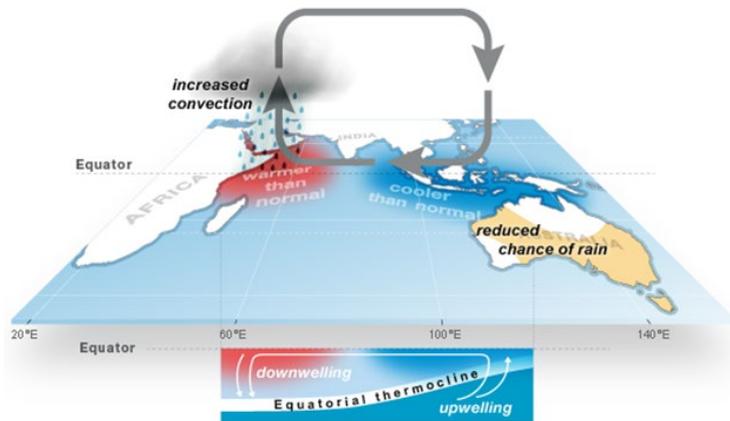


La Niña and Rainfall

La Niña conditions in the tropical Pacific are known to shift rainfall patterns in many different parts of the world. Although they vary somewhat from one La Niña to the next, the strongest shifts remain fairly consistent in the regions and seasons shown on the map below.

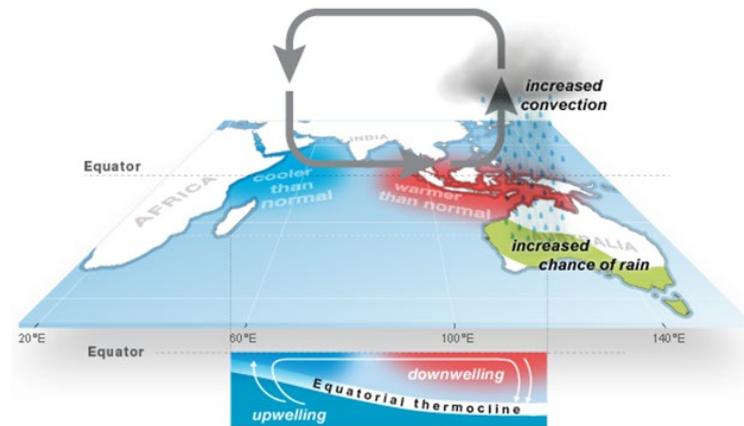


Source: NOAA
 cf. Lyon and Barnston 2005



Indian Ocean Dipole (IOD): Positive phase

© Commonwealth of Australia 2013.



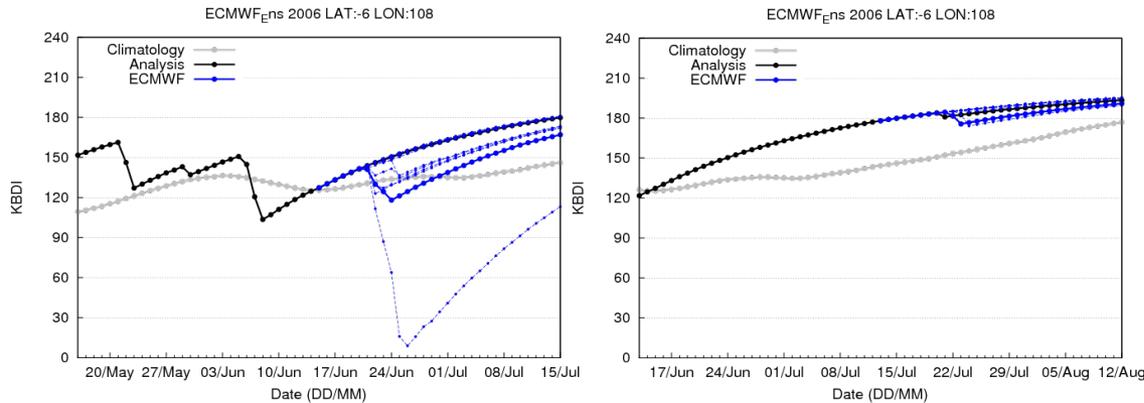
Indian Ocean Dipole (IOD): Negative phase

© Commonwealth of Australia 2013.

Source: Bureau of Meteorology
 cf. Pan et al. 2018, 11

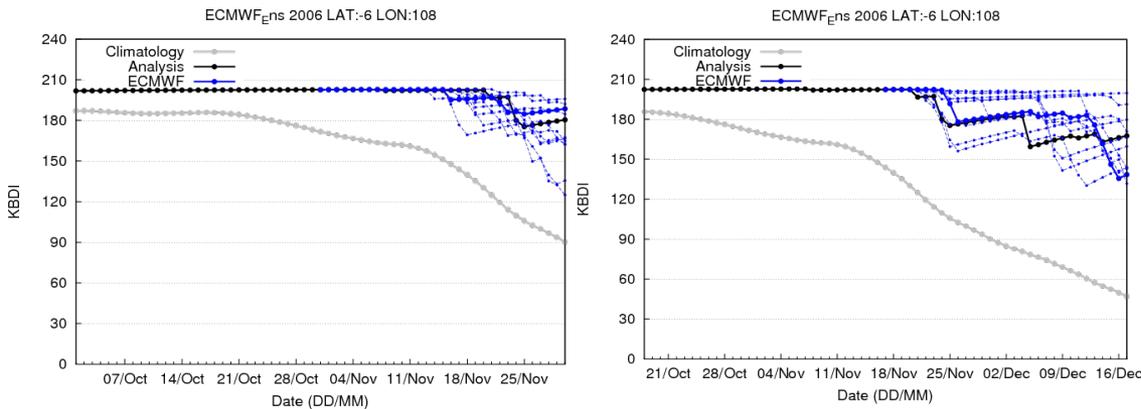
Case study: 2006

Early dry season



ECMWF predictions early (15Jun, 13Jul) and late (31Oct, 17Nov) dry seasons in 2006. Thick lines: control members, thin lines: perturbed members.

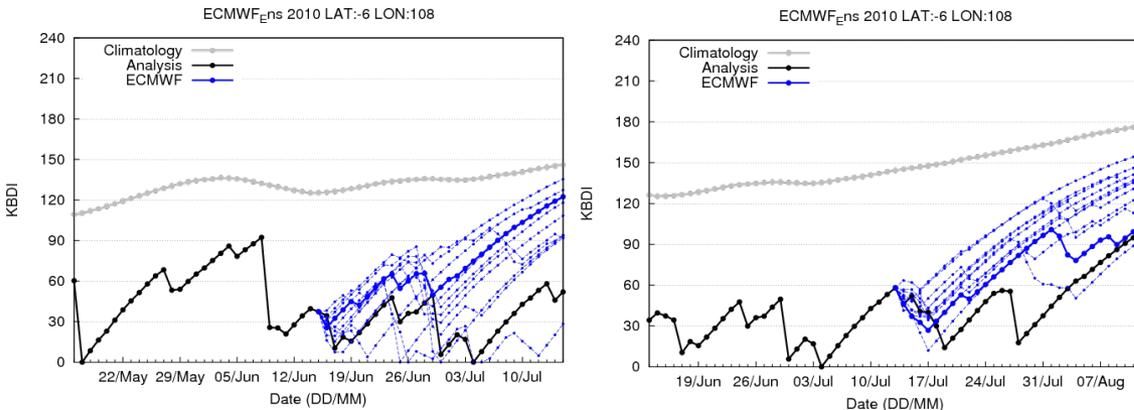
Late dry season



2006:
EP-El Nino and positive IOD

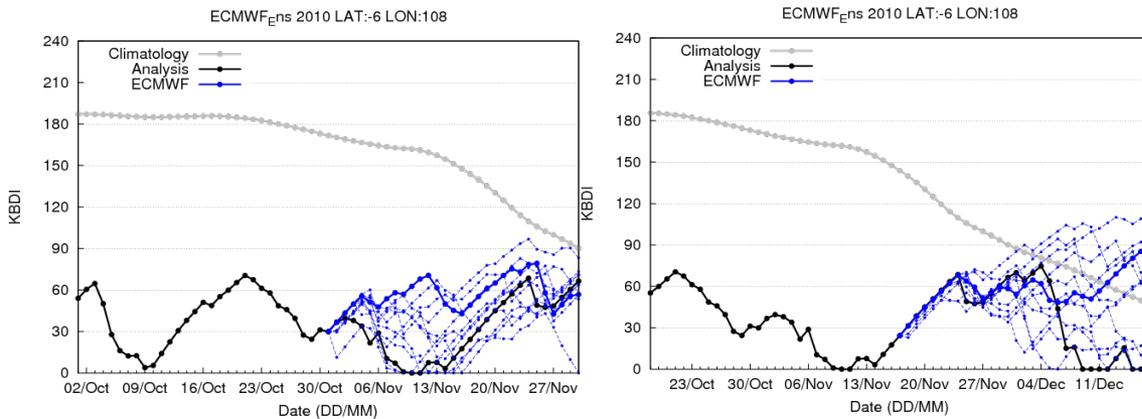
Case study: 2010

Early dry season



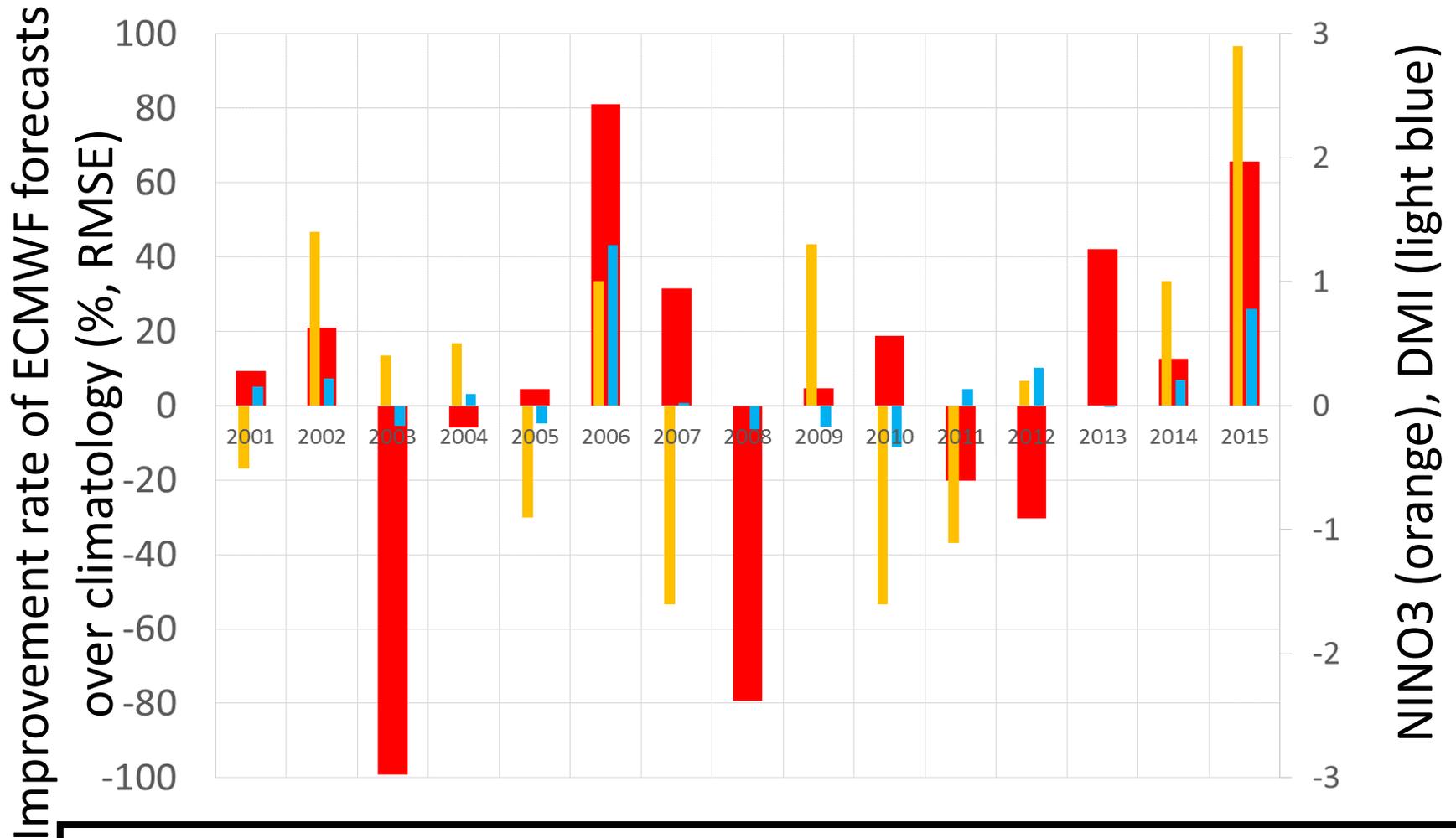
ECMWF predictions early (15Jun, 13Jul) and late (31Oct, 17Nov) dry seasons in 2010. Thick lines: control members, thin lines: perturbed members.

Late dry season



2010:
Strong negative IOD

Skill enhancement due to ENSO and IOD



Improvement rates are larger when both NINO3 and Dipole Mode Index (DMI) are both large positive value (i.e., 2006 and 2015)

Summary

- New products to monitor and predict the risk of drought based on the KBDI were developed using GSMaP, JRA-55 and S2S data.
- Skill evaluations of KBDI showed benefits of using S2S model outputs in some regions.
- Drought forecast in Indonesia is expected to provide useful information for decision making disaster risk managements.
- The subseasonal KBDI predictability arises from slow-varying SST conditions (IOD and El Nino), in addition to the subseasonal variability (e.g., MJO).
- For the drought prediction, substantial prediction information provided from the real-time monitoring capability, S2S models could add information/value to monitoring products.