KMA-APCC-CNU updates for dynamical seasonal climate prediction

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I. KMA-Met Office Joint Seasonal Forecasting System
## New Initialization schemes for GloSea5-KMA

<table>
<thead>
<tr>
<th></th>
<th>KMA</th>
<th>UKMO</th>
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<tr>
<td>Atmos</td>
<td>KMA NWP analysis</td>
<td>UKMO NWP analysis</td>
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<tr>
<td>Land Surf</td>
<td>ECMWF ERA-int</td>
<td>ECMWF ERA-int</td>
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<tr>
<td></td>
<td>⇒ JULES-JRA55</td>
<td>(preparing for JULES-JRA55</td>
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<td>Initial Field</td>
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<td>based init.)</td>
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<td><strong>Near real-time analysis ~2018</strong></td>
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<td>Ocean</td>
<td>UKMO NEMOVAR</td>
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<td>⇒ KMA NEMOVAR</td>
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• Offline land surface model, JULES, forced by reanalysis: atmosphere variables + precipitation.
2016 Mega-heatwave in East Asia and Korea, Dry-soil & land-atm interaction seems to contribute...
Soil moisture Initialization for GloSea5-KMA

- There is large bias between model and SM estimated, which lead to model’s drift which degrade forecasts.
- Soil moisture estimate from the JULES is further modified based on CDF matching technique.

“Dryness” in observation(analysis) Could be “Very wet” in the model
For further improve soil moisture quality,

1. Correction of precipitation dataset (forcing to drive LSM) with observation

\[
\text{precip}_{\text{JRA}}^{\text{scaled}} = \frac{\text{precip}_{\text{JRA}}^{\text{monthly}}}{\text{precip}_{\text{JRA}}^{\text{monthly}}} \times \text{precip}_{\text{JRA}}^{6\text{-hourly}}
\]

2010 Jul. precipitation time series
East Asia (lon 80–150, lat 30–75)

2. Blending satellite dataset into soil moisture derived by LSM

Soil Moisture - ESA Climate Change Initiative (CCI)

Satellite SM is nudged at the first two soil layers

1979~2015 daily 0.25 spatial resolution global dataset
Improvement of JJA soil moisture quality

North America (269-274E/33-35N) JJA soil moisture (~10cm)

- Corr are assessed with in-situ SM observation
- Better precipitation data and nudging satellite estimate lead to better SM quality
II. updates for APCC

Jin-Ho Yoo
APCC MME skill has been improved, why?

Hindcast Skill of each year’s operational MME set

Number of participating models in operational MME

Rmm = Rave / sqrt(r) (Yoo et al. 2005)

Increasing skill: collective impact of individual improvements + Increasing diversity?

Significant increase of skill of Grand MME when APCC/ClipAS and ENSEMBLES are combined.

Enhancing utility of DSP: Post-processing of DSP

ROK-PI CLIPS (Rep. of Korea – Pacific Islands Climate Prediction Services) project (‘15-’17)

Seasonal prediction in Pacific Islands Countries
- Region with the highest potential/actual predictability by DSP
- So far, rely mostly on statistical model (Nino3.4)

“Let’s make the best use of DSP in the region”

Multi Model Climate forecast
- Capacity building,
- Participatory development

SPREP (regional hub)

Localized/Tailored information
Post-processing of DSP

Statistical Downscaling is possible

Climate model can predict large scale structure related with islands’ rainfall variability to some degree (ENSO related and Non-ENSO signal)

Difference between Individual station’s rainfall variability is partly systematic (due to topography)
Post-processing of DSP

Local forecast is based on the relationship (Bayesian regression) between large scale pattern (MME) and individual station’s seasonal rainfall → Develop a tool for forecaster

① identification of pattern (predictor) and relationship

② Apply to new forecast

③ downscaling

The first operational attempts was made in Pacific Islands Climate Outlook Forum (PICOF, Setp. 2017)
Thanks!
We used ground-based soil moisture data from the USDA Soil Climate Analysis Network (SCAN; http://www.wcc.nrcs.usda.gov).
LSM experiment design

<table>
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<tr>
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<th>Exp1</th>
<th>Exp2</th>
<th>Exp3</th>
<th>Exp4</th>
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<tbody>
<tr>
<td>Precipitation correction</td>
<td>X</td>
<td>O</td>
<td>X</td>
<td>O</td>
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<tr>
<td>Blending Satellite dataset</td>
<td>X</td>
<td>X</td>
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- Monthly CMAP data is used to correct the climatological difference between JRA-55 forcing, but sub-monthly variation is adopted by JRA-55.

- Long-term merged soil moisture satellite date (ESA-CCI) provides surface (~5cm) volumetric soil moisture for 1979~2015.

- The soil moisture data is nudged about a half of top-level (~10cm) soil moisture derived by JULES offline simulation.

\[
SoilM'_{\text{diag}} = \alpha \times SoilM_{\text{diag}} + \beta \times SoilM_{\text{satellite}} \quad [\alpha=0.5, \beta=0.5]
\]
Experiment design (2016 heat wave)

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<td>Ocean/sea-ice initialization</td>
<td>Climatology</td>
<td>O</td>
<td>Climatology</td>
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<tr>
<td>Soil moisture initialization</td>
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- Initial date: 1~5, July 2016 (each starting date has 4 member ensemble simulations)
- Each experiment has 20 member ensembles
2016 East Asia heat wave (H300 - eddy)

- Teng sumun surface inferred from the eastern Asian monsoon season. (c.f. Exp4-Exp2)
- Experiment 4 in Exp1 high low level high surface. (c.f. Exp4-Exp3)
- Exp4-Exp# shows the surface h300 zonal eddy departure ±20 in the surface 10 regions exceeding in dotted.

해양/해빙 + 토양 수분 초기화 효과
토양 수분 초기화 효과
해양/해빙 초기화 효과
Improvement of JJA soil moisture quality

North America (269-274E/33-35N) JJA soil moisture (~10cm)

**Mean value = 0.15 m³/m³**

- RMSE and Corr are assessed with in-situ SM observation
- Better precipitation data and nudging satellite estimate lead to better SM quality