

# IMPACT OF STATISTICALLY FORECASTED SEA-ICE BOUNDARY CONDITION ON THE SUB-SEASONAL PREDICTION USING ATMOSPHERIC GENERAL CIRCULATION MODEL

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# INTRODUCTION:





Kim et al (2014, Nature Communications)

# INTRODUCTION:

- Recently, an enhanced year-to-year variability of the Arctic sea-ice has been emphasized in its role for controlling mid-latitude climate variability.
- For the prediction of sea-ice on sub-seasonal to seasonal time-scale, statistical methods are most widely used. The statistical methods provide prediction of seaice concentration (SIC) over a specific area of interest or total sea ice extent over the entire Arctic [Drobot et al., 200; Lindsay et al., 2008; Tivy et al., 2007, Kim et al., 2013, Kim et al., 2016, Jun et al., 2018].
- However, the regional SIC variability over the Arctic domain (i.e., spatial-temporal anomalies) is highly necessary for many practical purposes. The coupled GCMs do have reliable skills in predicting the total sea ice extent in the Arctic, but still have very limited skills in predicting local SIC anomalies due to theirs serious bias in simulating sea ice and ocean over the Arctic.



## TODAY'S TALK:

We introduce a newly developed sub-seasonal prediction model named Korea Polar Prediction System (KPOPS) based on the Community Atmosphere Model version 4 (CAM4) by incorporating statistically predicted sea-ice boundary condition.

- The main idea of S-EOF is to find dominant spatio-temporal variations of a target variable by considering their seasonally evolving patterns from one-year to another (Wang and An, 2005).
- S-EOF analysis was applied to Arctic sea-ice in order to capture the major spatiotemporal mode of Arctic sea-ice (Jung et al, 2018; will be submitted to ERL).
- S-EOF analysis constructs a covariance matrix by treating the data for a year (up to 12 months) as a one time-step for the specific year.





Year



#### S-EOF VS. DYNAMIC MODEL

Spatial patterns of correlation coefficient between predicted and observed sea ice concentration anomalies of September for 2, 3, 4, and 5-month lead for the statistical prediction product and NCEP CFSv2. Stippling indicates statistical significance at 5%.

#### INTRODUCTION TO KOREA POLAR PREDICTION SYSTEM (KPOPS)

### **KPOPS MODEL DESCRIPTION**

# KPOPS CFS (CFS-REFORECAST) MODEL: Community Atmosphere Model Version 4 (CAM4, AGCM) HORIZONTAL RESOLUTIONS: About 2 degree at the equator for each core DYNAMIC CORE: Spectral Elements (SE) Core GRID SYSTEM: A cubed-sphere grid system SIC: Forecast based on the S-EOF SST: NCEP CFS-Reforecast

#### INTRODUCTION TO KOREA POLAR PREDICTION SYSTEM (KPOPS)

#### **KPOPS MODEL**

FORECAST PERIODS: 2001 - 2015 ENSEMBLE NUMBERS: 5 MEMBERS

LEAD TIME: 101 DAYS FROM FORECAST REFERENCE TIME



#### CFS (CFS-REFORECAST)

FORECAST PERIODS: 2001 - 2015 ENSEMBLE NUMBERS: 4 ENSEMBLE MEMBERS (ONLY 3 ENSEMBLE MEMBERS FOR 2015)



# **RESULTS: KPOPS VS. CFS-REFORECAST**

#### Early Winter Late Winter (a) Arctic Region (b) Arctic Region [Early Winter] [Late Winter] T2M T2M C] ŝ -ERA -CFS CFS KPOPS KPOP 2001 2004 2007 2010 2013 2016 2001 2004 2007 2010 2013 2016 Year Year (c) East Asia (d) East Asia [Early Winter] [Late Winter] T2M S S -2 -EBA -ERA -CFS CFS KPOPS KPOPS 2004 2007 2010 2013 2016 2001 2004 2007 2010 2013 2016 2001 Year Year (e) North America (f) North America [Early Winter] [Late Winter] T21 S σ .2 -ERA -FRAI -CFS -CFS KPOPS KPOP 2001 2004 2010 2013 2016 2001 2004 2007 2010 2013 2016 2007 Year Year

T2M Area-averaged Time Series

**Table.** Correlation coefficients of T2M anomalies area averaged over the Arctic region, East Asia, and North America by ERAI with KPOPS, CFS. R values in parentheses are the corresponding detrends, R exceeding the 95% significance levels are shown as red color and star marks (\*).

	EARLY WINTER		LATE WINTER	
	KPOPS	CFS	KPOPS	CFS
Arctic	0.59*	0.36	0.17	0.53*
	(0.54*)	(0.19)	(-0.04)	(0.32)
East Asia	0.25	-0.14	0.60*	-0.27
	(0.25)	(0.08)	(0.65*)	(-0.19)
North	0.50	0.38	0.45	0.11
America	(-0.36)	(-0.03)	(0.67*)	(-0.16)

The anomaly time-series of T2M area-averaged over the Arctic region, East Asia, and North America during early winter, and late winter. ERAI, CFS, and KPOPS are indicated by the black, blue, and red line, respectively. Color shades represent spreads of ensemble members by the CFS (blue) and KPOPS (red).

# RESULTS: KPOPS VS. CFS-REFORECAST

# ANOMALY CORRELATION COEFFICIENT



The anomaly correlation coefficients for 2m-air temperature (T2M) by KPOPS, CFS with ERAI during the early winter and late winter. The black dots indicate statistical significance at the 95% confidence level. Each color box denote the East Asia (red box), and North America (blue box).

# DISCUSSION AND SUMMARY

- One-month prediction skill of the KPOPS and CFS-Reforecast are compared for the early winter (November – December) and late winter (January – February) from 2001/2002 to 2014/2015.
- Overall forecast skill of KPOPS outperformed the CFS-Reforecast. Especially, in the early winter, the forecast skill of the KPOPS was superior in the Arctic region, apparently.
- In the late winter, the forecast skill over East Asia and North America was significantly higher than the CFS-Reforecast.
- In conclusion, we find that the sub-seasonal prediction using statistically forecasted sea-ice boundary condition exhibits a new possibility of better sub seasonal to seasonal prediction.

