Research and modelling center updates
Japan Meteorological Agency/Meteorological Research Institute

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Thanks to Kensuke Komatsu, Tomoki Iwakiri, Yutaro Kubo

気象研究所
Meteorological Research Institute

Configurations of seasonal prediction systems

A JMA/MRI-CPS3 description paper was published (**Hirahara et al. 2023, *J. Meteorol. Soc. Jpn.***)
https://www.jstage.jst.go.jp/article/jmsj/101/2/101_2023-009/_article/-char/ja

	JMA/MRI-CPS2 (June 2015-Feb. 2022)	JMA/MRI-CPS3 (Feb. 2022-)
Atmosphere model JMA global atmospheric model	Version: GSM1011C - SiB Resolution: ~110 km (TL159L60) Model top: 0.1hPa B.C.: CMIP5 RCP4.5 GHG, aerosol climatology (1D), Ozone climatology from MRI-CCM1	Version: GSM2003 – iSiB Resolution: ~55 km (TL319L100) Model top: 0.01hPa BC: CMIP6 SSP2-4.5 GHG, 3D aerosol climatology from aerosol MASINGAR model, Ozone climatology from MRI-CCM2, Volcanic aerosols in stratosphere (off-line)
Ocean model (MRI.COM)	Version: MRI.COM v3.2 Resolution: 1.0° x 0.3-0.5° , L52+BBL	Version: MRI.COM v4.6 0.25° x 0.25° L60
Initial condition	Atmosphere: JRA-55 Land: JRA-55 land analysis Ocean: MOVE/MRI.COM-G2 T, S, SSH 3DVAR Sea ice: no assimilation	Atmosphere: JRA-3Q Land: Land analysis forced by JRA-3Q Ocean: MOVE/MRI.COM-G3 T, S, SSH 4DVAR Sea ice: MOVE/MRI.COM-G3 3DVAR
Initial perturbation	Atmosphere: Bred vector in the tropics and N.H. Ocean: perturbations forced by the bred vectors	Atmosphere: Bred vector in the N.H. and S.H. Ocean: perturbation using ocean obs. errors
Model uncertainty	Stochastic physics (SPPT)	←
Ensemble	13 members/5 days x 4 LAF	5 members/day x 11 LAF (Predicted daily SSTs are used in Global EPS)

New system forecasts/reforecasts are now available from C3S and S2S

- Seasonal prediction skill was improved.
- Sub-seasonal prediction skill was improved in particular in Week 3-4, MJO skill was significantly improved.

JMA model for S2S was changed to CPS3 in Feb 2023.

https://confluence.ecmwf.int/display/S2S/News
https://confluence.ecmwf.int/display/S2S/JMA+model+description

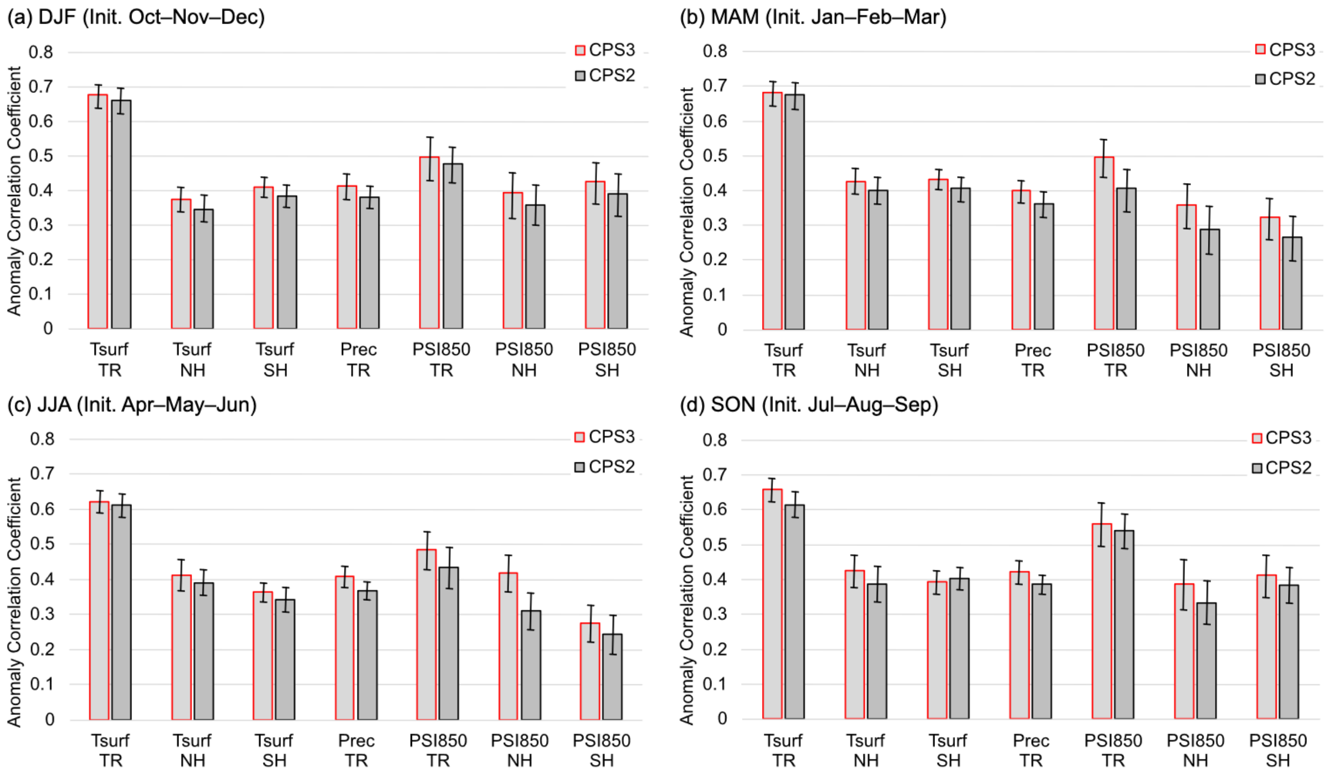
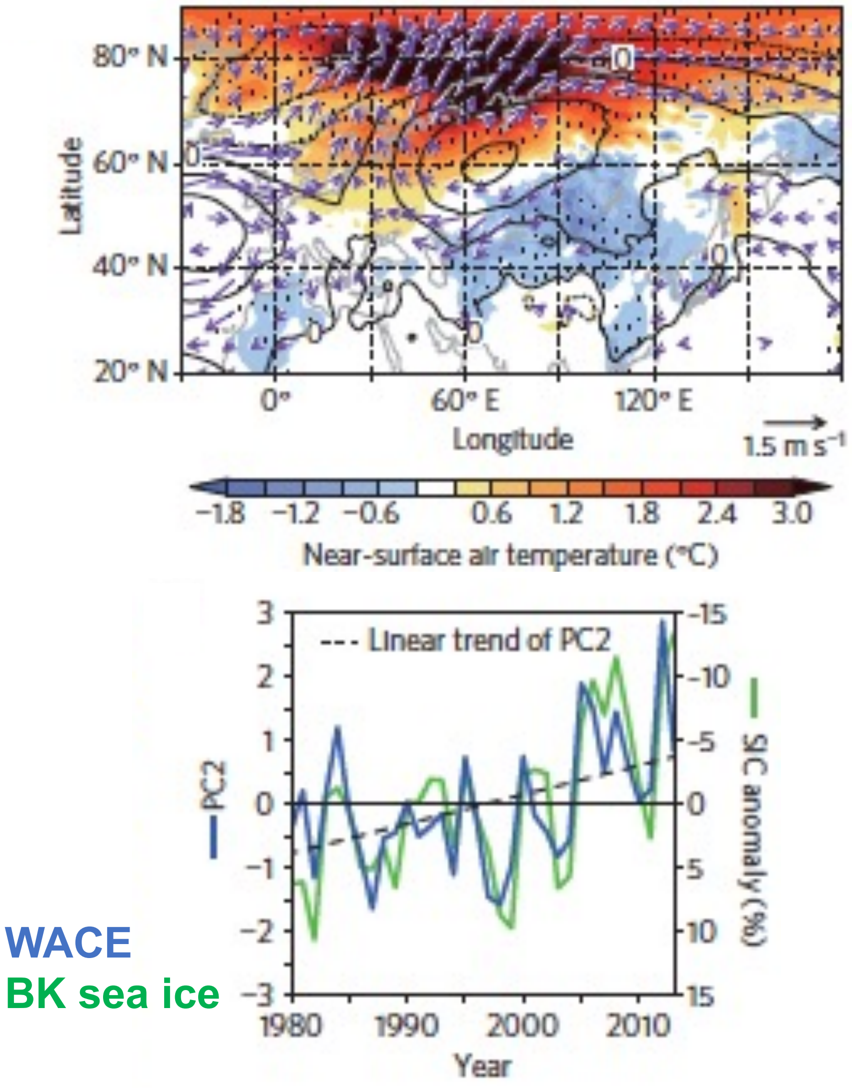


Fig. 13. Anomaly correlation coefficients (ACCs) for the average of months 1–3. The vertical and horizontal axes represent the ACC and variable name and region, respectively. The variable names “Tsurf”, “Prec”, and “PSI850” denote 2-m air temperature, precipitation, and the 850 hPa stream function, respectively. The region names “TR”, “NH”, and “SH” indicate that ACCs are averaged over the tropics (20°S–20°N) and the northern (20–90°N) and southern (20–90°S) hemispheres, respectively. ACCs are computed for Months 1–3 averages for forecasts starting from each initial month and are summarized by the season to which Month 2 belongs. The error bars represent 95 % confidence intervals estimated over 1000 bootstrap trials for all forecast initial dates in each season.

Hirahara et al. (2022)
J. Meteorol. Soc. Japan.
doi:10.2151/jmsj.2023-0

Barents Kara sea ice and Eurasian climate
Warm Arctic–Cold Eurasia (WACE) pattern

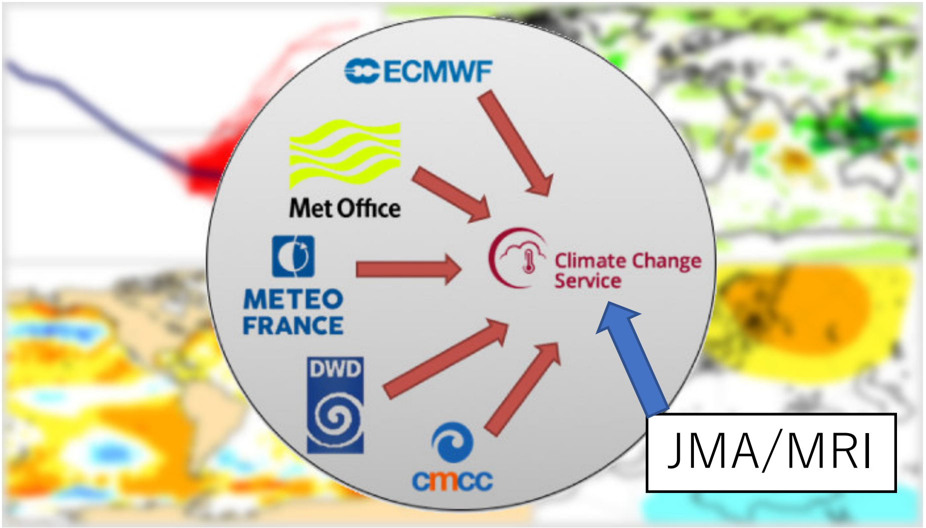


- Dipole temperature pattern that correlates to the Barents-Kara (BK) sea ice. (Mori et al., 2014).
- Obtain as a **sea ice forced-response** in the atmospheric model simulation. (Mori et al., 2014, 2019).
- **NOT** identified as a response in observation and coupled model simulation if focusing on the surface heating over BK sea. (Sorokina et al., 2016, Blackport and Screen 2020)
- Closely relates to the atmospheric blocking (Ural blocking high) which may **NOT** be driven by sea ice. (e.g., Tyrlis et al., 2020, Luo et al., 2016, He et al., 2020)

➢ **The impact of the sea ice condition on Eurasian temperature (or WACE) is highly controversial.**

Komatsu, Takaya et al. (2022) *GRL*

Data



https://cds.climate.copernicus.eu/cdsapp#!/dataset/seasonal-postprocessed-single-levels?tab=overview

- **Reforecast by operational seasonal prediction system**
  - SEAS5 (ECMWF)
  - GloSea5-GC2-LI (Met Office)
  - Météo-France System 7 (Météo-France)
  - SPS3.5 (CMCC)
  - GCFS 2.0 (DWD)
  - JMA/MRI-CPS2 (JMA)

✓ the **atmosphere-ocean coupled model**.

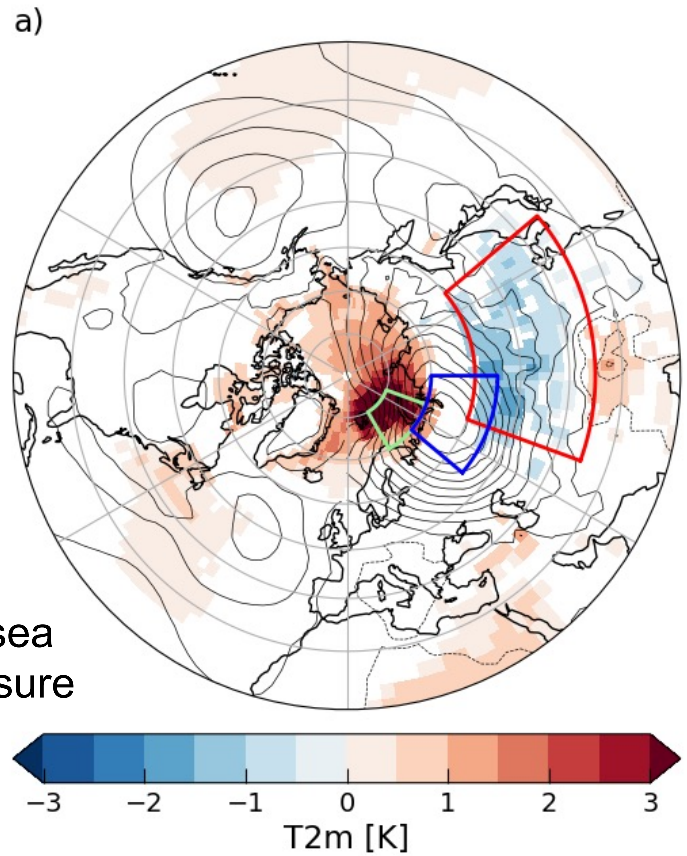
✓ Prediction starts **at around 01 November** in per year.
✓ **1993-2016: 24 years**
✓ Ensemble members = 25 in each system (10: JMA)
(identify 3,240 winters by ensemble predictions)

- **ERA5 Monthly product (1981-2020)**

✓ Focused the forecast averaged from December to February (DJF) .
✓ The correlation analysis using several indices focused on the interannual variability.

Indices

☐ **WACE** (Mori et al. 2014)
- Second EOF mode for the DJF temperature over Eurasian continent (20-90N, 0-180E).



Contour: sea level pressure

ERA5s' 2 m temperature and sea level pressure regressed by WACE index (1981-2020)

☐ **Barents-Kara Sea (BK)** (Blackport and Screen 2020)
Center of action for temperature of WACE

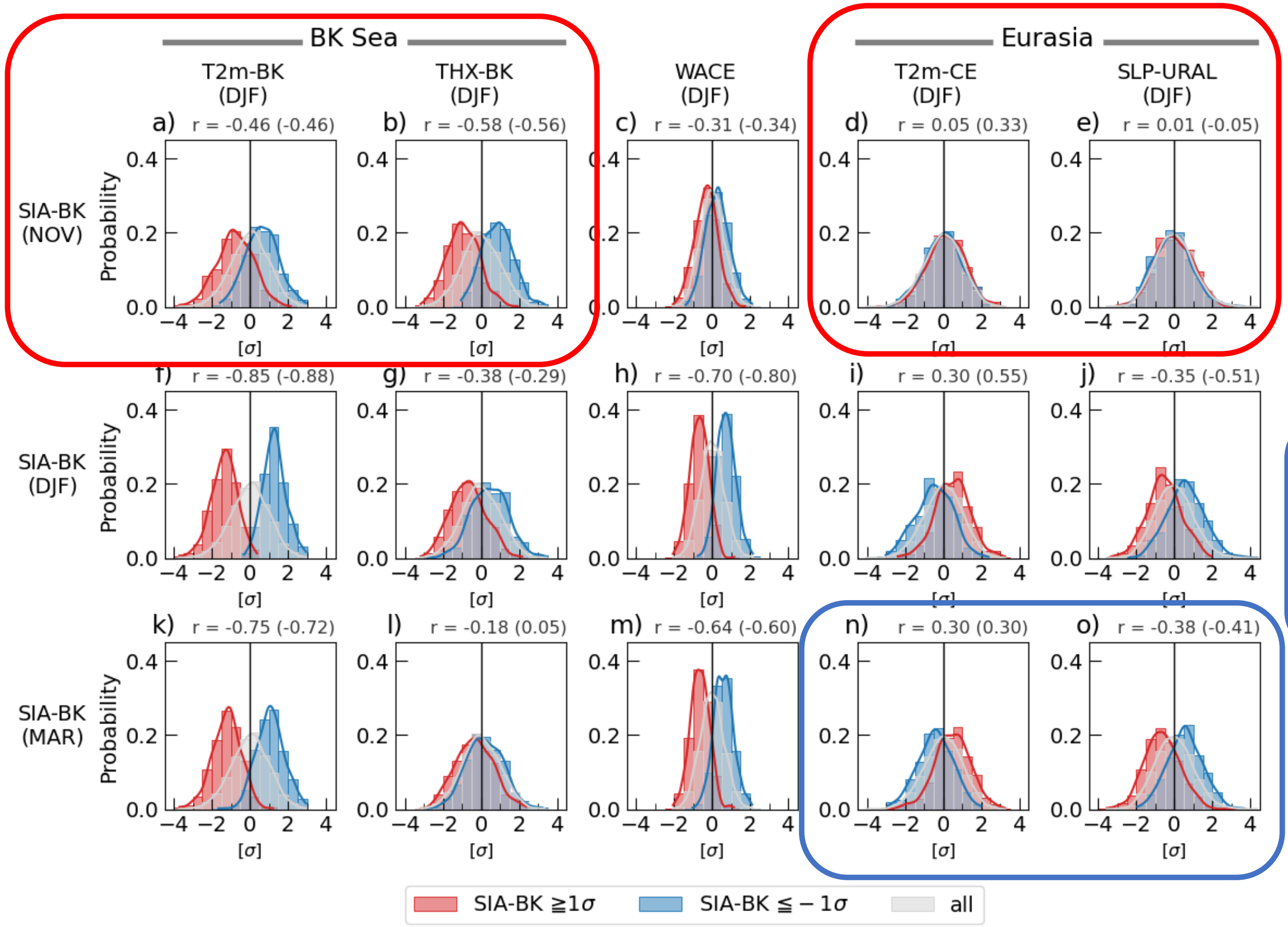
☐ **Central and East Eurasia (CE)** (Acosta Navarro et al., 2020)
Center of action for temperature of WACE

☐ **Around Ural mountain (URAL)**
Center of action for sea level pressure of WACE

Modification of indices
When we evaluate the correlation in each index, we linearly removed the Interannual variability related to Arctic Oscillation (AO) to emphasize the relation to the WACE.

AO strongly correlates to the first EOF mode of temperature over the Eurasian continent.

Probability distributions of ensemble predictions (3,240 samples) for Lead-Lag BK sea ice conditions



□ November SIA-BK

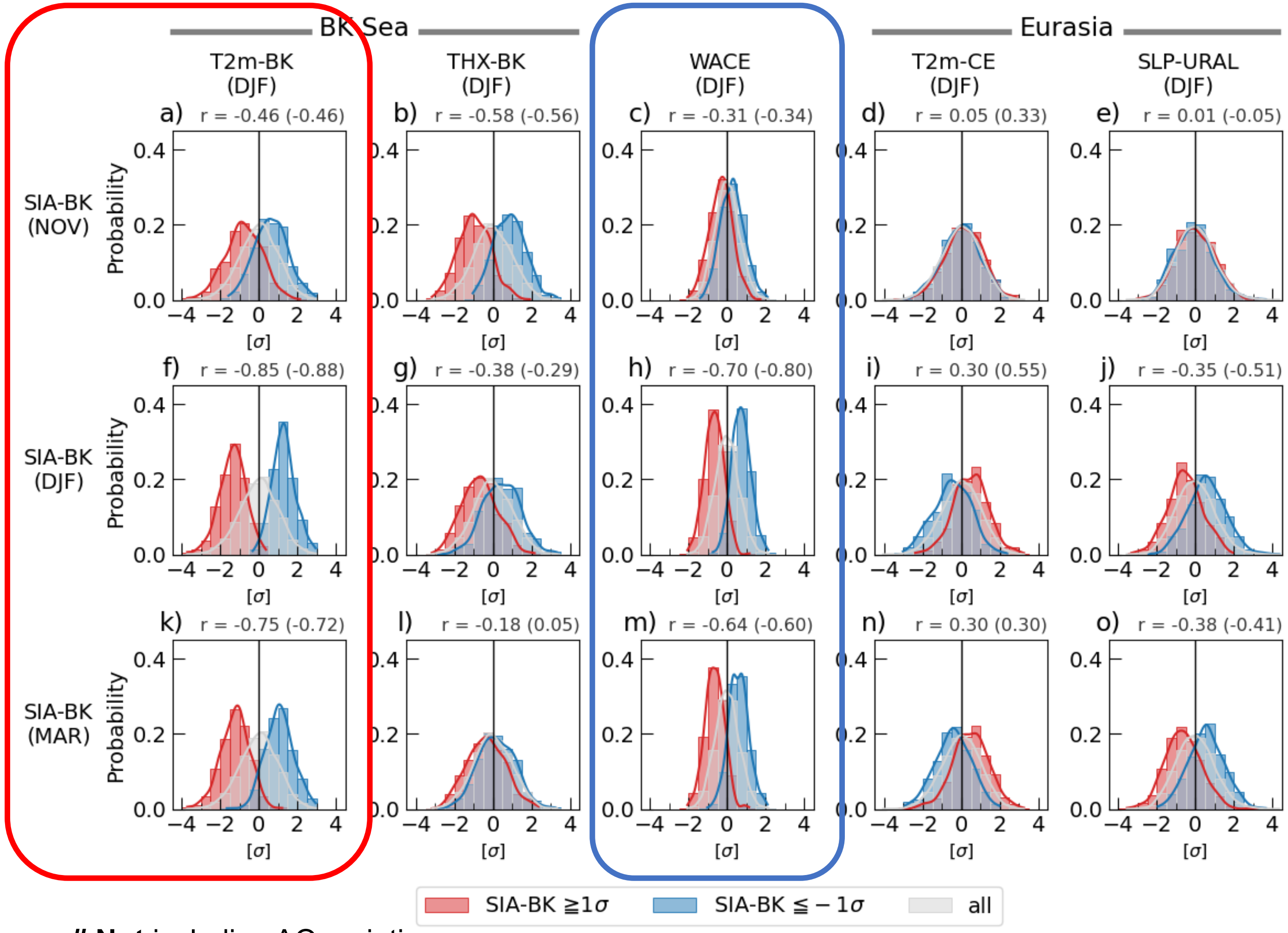
- Correlates to DJF temperature and surface heat flux in BK region.
- Preceding sea ice acts as **a precursor** for winter prediction for BK but not for remote regions.

□ March SIA-BK

- Correlates to DJF T2m-CE and SLP-URAL.
- **a result** of winter atmospheric circulation.

Not including AO variation
all indices are detrended and normalized
r is correlation coefficient (parenthesis shows the observed value.)

Probability distributions of ensemble predictions (3,240 samples) for Lead-Lag BK sea ice conditions



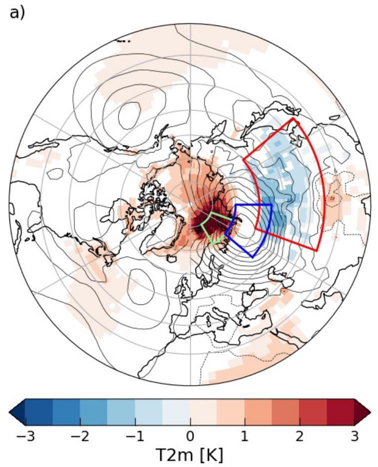
Not including AO variation
all indices are detrended and normalized
r is correlation coefficient (parenthesis shows the observed value.)

For the WACE index…

☐ **WACE-sea ice linkage**

- closely corresponds to the local link between temperature and sea ice in BK.
  (one center of dipole pattern action)

➢ The WACE index probably less reflects a remote link between sea ice and Eurasian temperature.



Conclusion

In the multiple seasonal prediction models….

- The measurable influence of sea ice anomalies on Eurasian winter temperatures is NOT found at least for the interannual variability.

- The actual benefit to prediction skill by representing the autumn sea ice's remote link is unclear.

- WACE–sea ice link is probably not suitable for assessing the remote link between BK sea ice and Eurasian temperature.

Influence of Eurasian Snow on surface temperature

A submonthly scale causal relation between snow cover and surface air temperature over the autumnal Eurasian continent

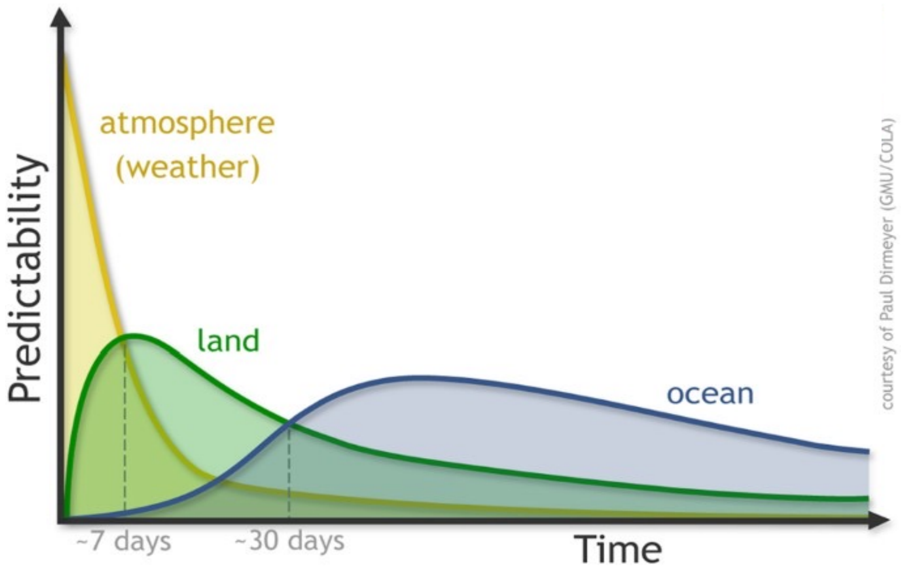
Komatsu, Takaya, et al. under review *J. Clim.*

Land (Snow)-Atmosphere coupling

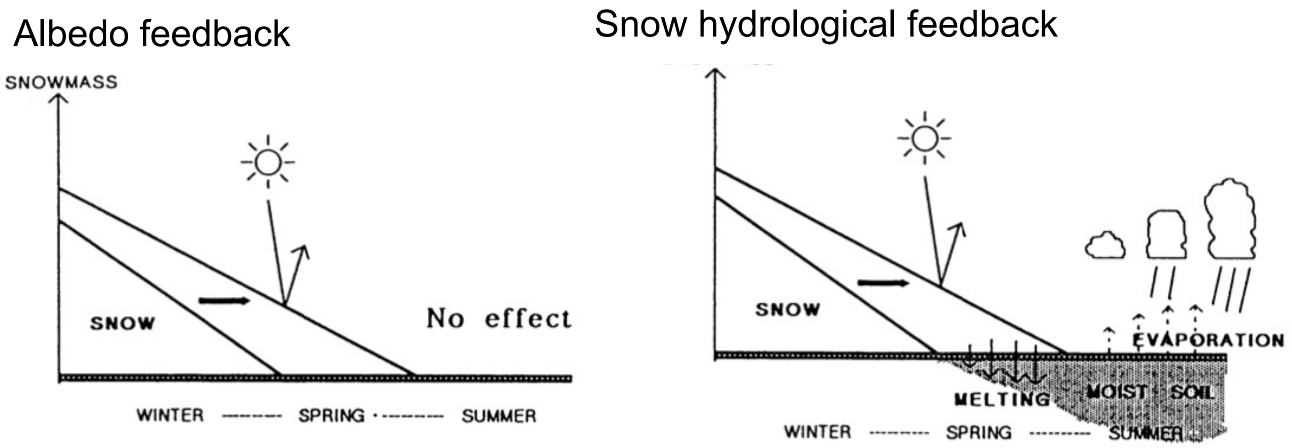
- Land-Atmosphere (L-A) coupling is regarded as a contributor to atmospheric predictability in sub-seasonal-to-seasonal (S2S) time scales.

- One of the most variant factors on the land surface is snow cover (SC).
  SC can interact with the atmosphere via albedo feedback and hydrological feedback.

- **To advance our knowledge of atmospheric predictability, we should clarify when and where the impact of snow cover becomes significant.**



(Mariotti et al. 2018)



(Yasunari et al. 1991)

Proposed metrics for evaluation of L-A coupling

- **L-A coupling strength** (Koster et al. 2006)

$$\Omega_{EXP} - \Omega_{CNTL} \quad \Omega: \text{Ensemble mean variance (e.g., precipitation)}$$

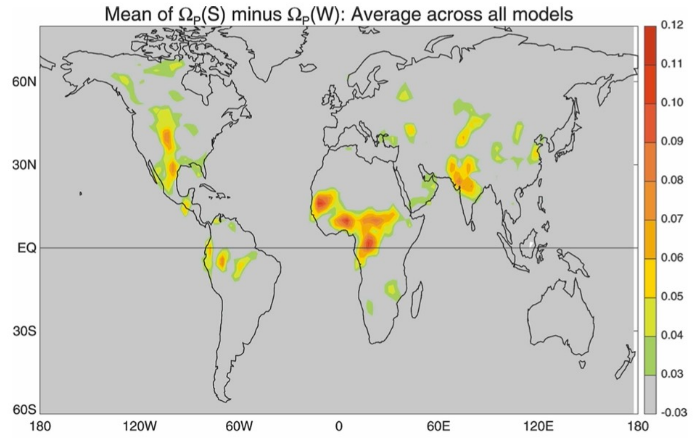
✓ Need ensemble atmospheric model simulation with fully interactive land-surface (CNTL) and prescribed land condition (EXP).

- **Coupling index** (Dirmeyre 2011)

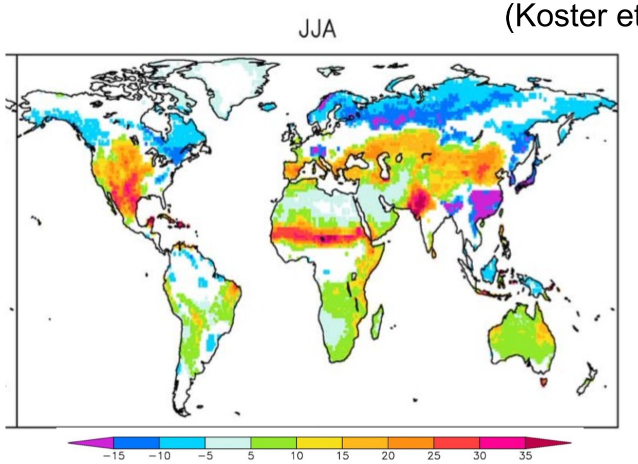
$$\sigma\beta_{\phi} \quad \begin{array}{l} \sigma\text{: standard deviation (e.g., soil moisture)} \\ \beta_{\phi}\text{: linear regression slope (e.g., latent heat flux)} \end{array}$$

✓ CI can be computed by observational dataset.
✓ But CI does not quantify the causal chain from soil to precipitation. (e.g., soil moisture => evaporation => precipitation)

Another indicator considering the cause and effect with time may be appropriate for evaluating the L-A coupling.



(Koster et al. 2006)



(Dirmeyer 2011)

Hot spots for the coupling between soil moisture and precipitation (latent heat flux)

Causality analysis based on the information theory

- **Liang-Kleeman information flow** (Liang and Kleeman 2005, Liang 2014)

  The information flow identifies the direction and magnitude of the cause-effect relationship.

  Taking the time series of X1 and X2, the information flow from X2 to X1 ($T_{2\text{->}1}$) is approximated by

$$|T_{2\to1}| = \left| \frac{C_{11}C_{12}C_{2,d1} - C_{12}^2 C_{1,d1}}{C_{11}^2 C_{22} - C_{11} C_{12}^2} \right|,$$

$C_{i,j}$: sample covariance between i and j
d_1: Euler forward difffential of X1

- **Ideally, $|T_{2\text{->}1}|$ will be zero if X2 does not affect the time-evolution of X1.**

  Even in X2 correlates to X1($C_{12} \neq 0$), information flow possibly takes 0.

  Correlation does not always promise causation. $|T_{2\text{->}1}| \neq 0$ or 0 when $C_{12} \neq 0$.

  Causation imply correlation. $C_{12} \neq 0$ when $|T_{2\text{->}1}| \neq 0$

  We can use the information flow to reveal the causal direction even in two time series correlate heavily.

SC-SAT coupling in autumnal Eurasia

- We demonstrate the information flow between **SC and surface air temperature (SAT) in autumnal Eurasia**.

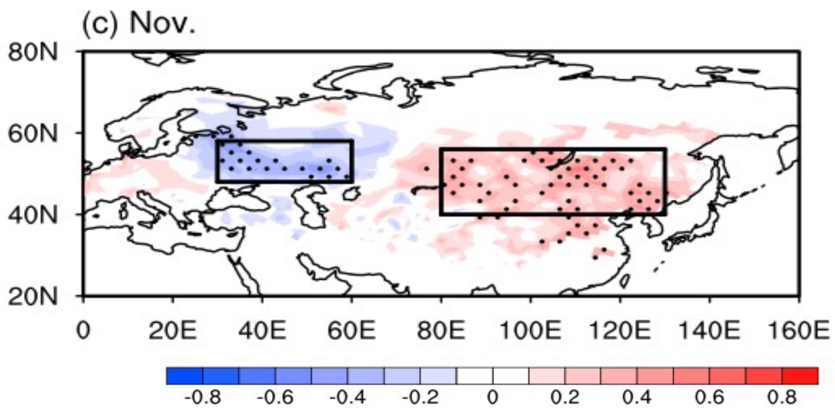
- Obtained causality is verified by using atmospheric model experiment and forecast.

- We focus on the eastern and western parts of the continent in **November**.

Why focusing on autumnal Eurasian SC ?

- ✓ Recent climate studies discuss whether a dipole-like snow pattern in November is a precursor of winter atmospheric circulation.
  (Gastineau et al. 2017; Han and Sun 2018; Santolaria-Otín et al. 2021; Wegmann et al. 2021)

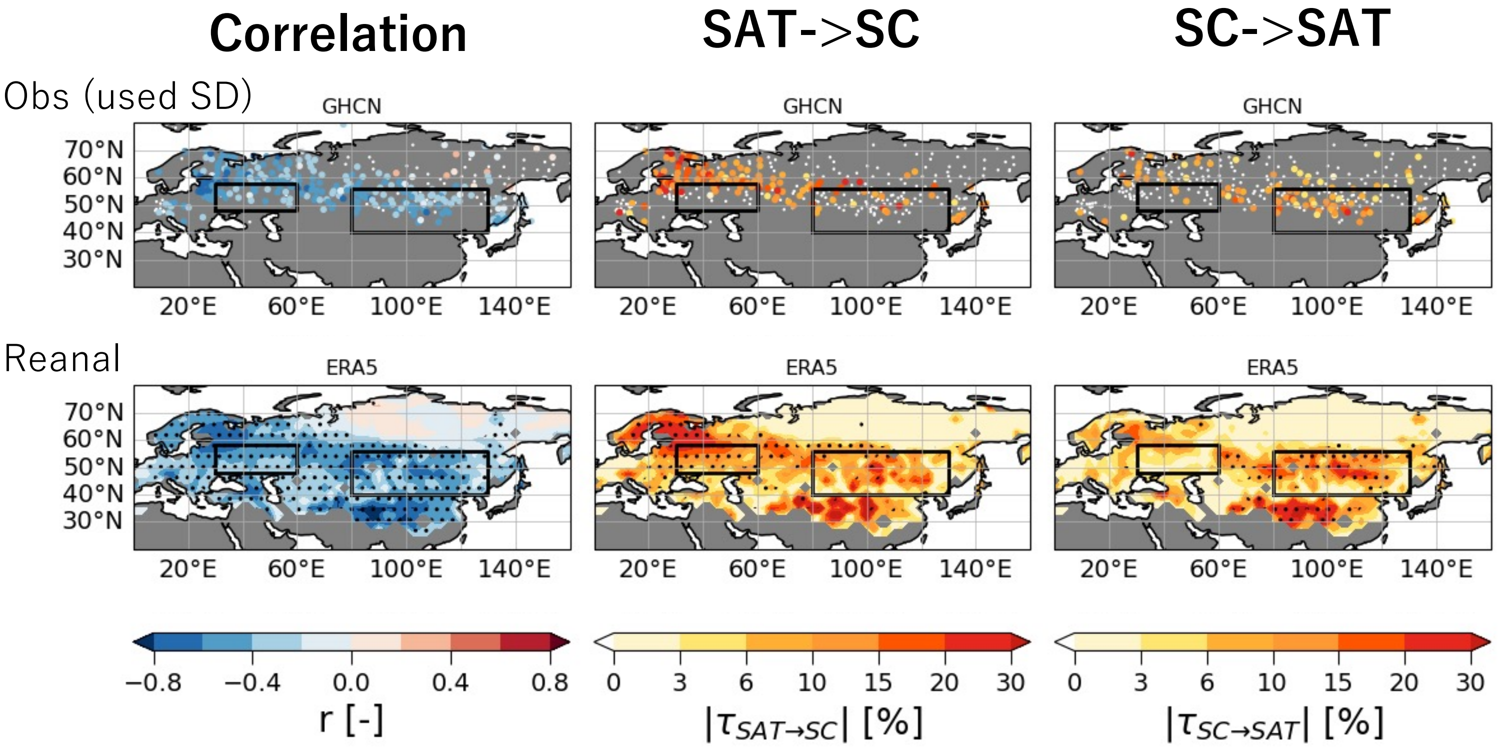
- ✓ But remote and local atmosphere responses forced by such snow cover are not fully understood yet..



Han and Sun(2018)

Sub-monthly scale causality between SC and SAT

Used weekly averaged SC (or Snow depth) and SAT in November during 2000~2019.



* information flow is normalized following by Laing (2015).

- **SC and SAT strongly correlate in the whole Eurasia.**
  Low SAT is likely observed with high SC and vice versa.

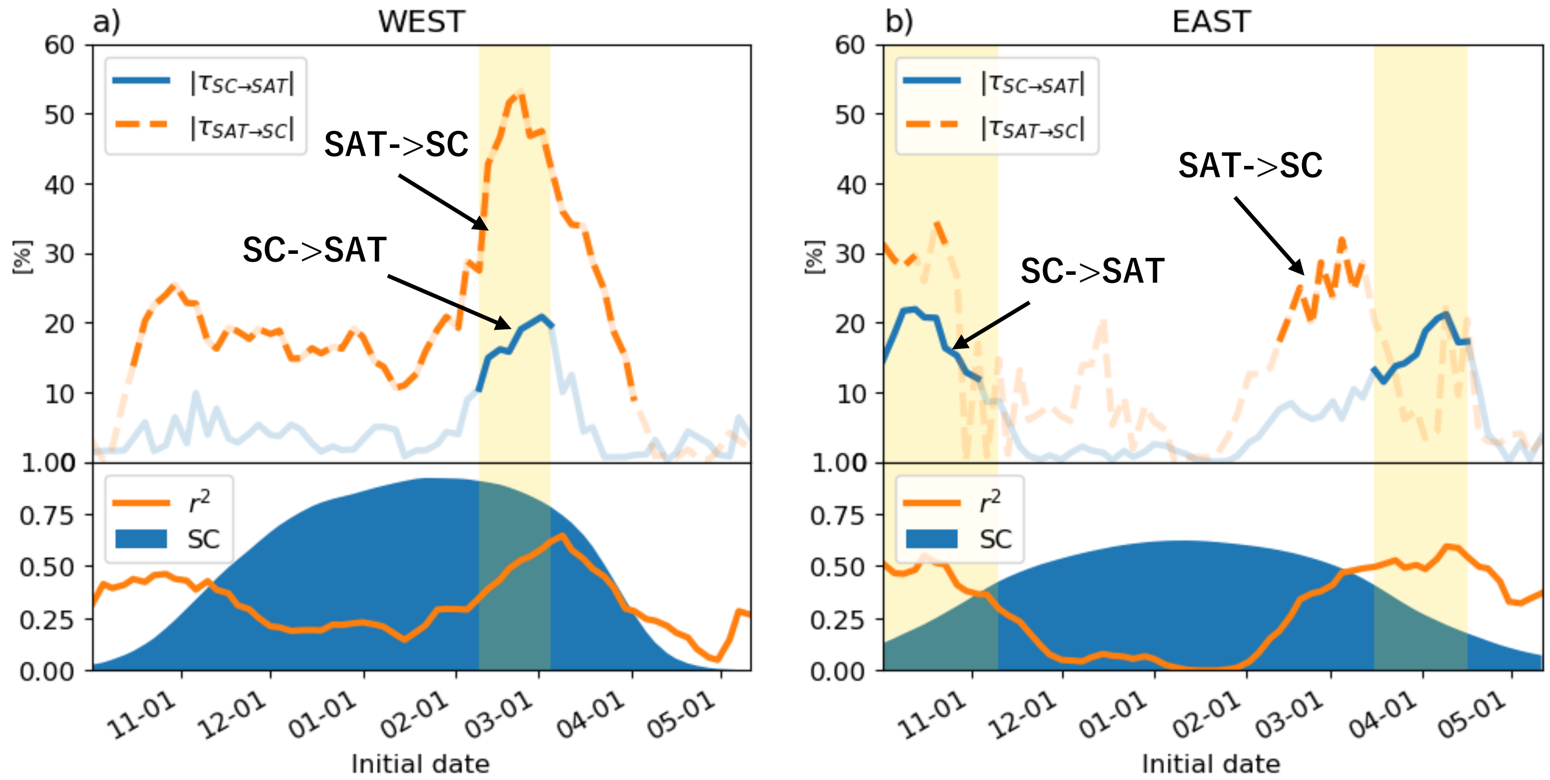
- West Eurasia.
  Large SAT->SC, insignificant SC->SAT.

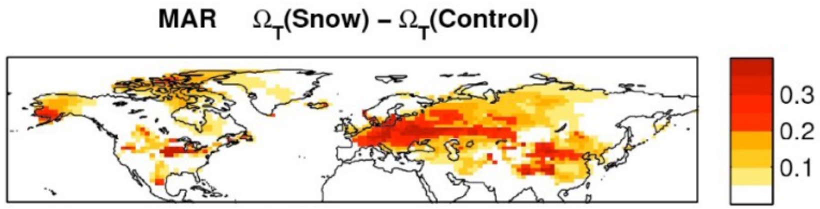
  SC hardly affects the time evolution of SAT. (**SC is not the cause of SAT**)

- East Eurasia.
  Insignificant SAT->SC, Large SC->SAT.

  SC surely affects the time evolution of SAT. (**SC is the cause of SAT**)

Seasonality of causality





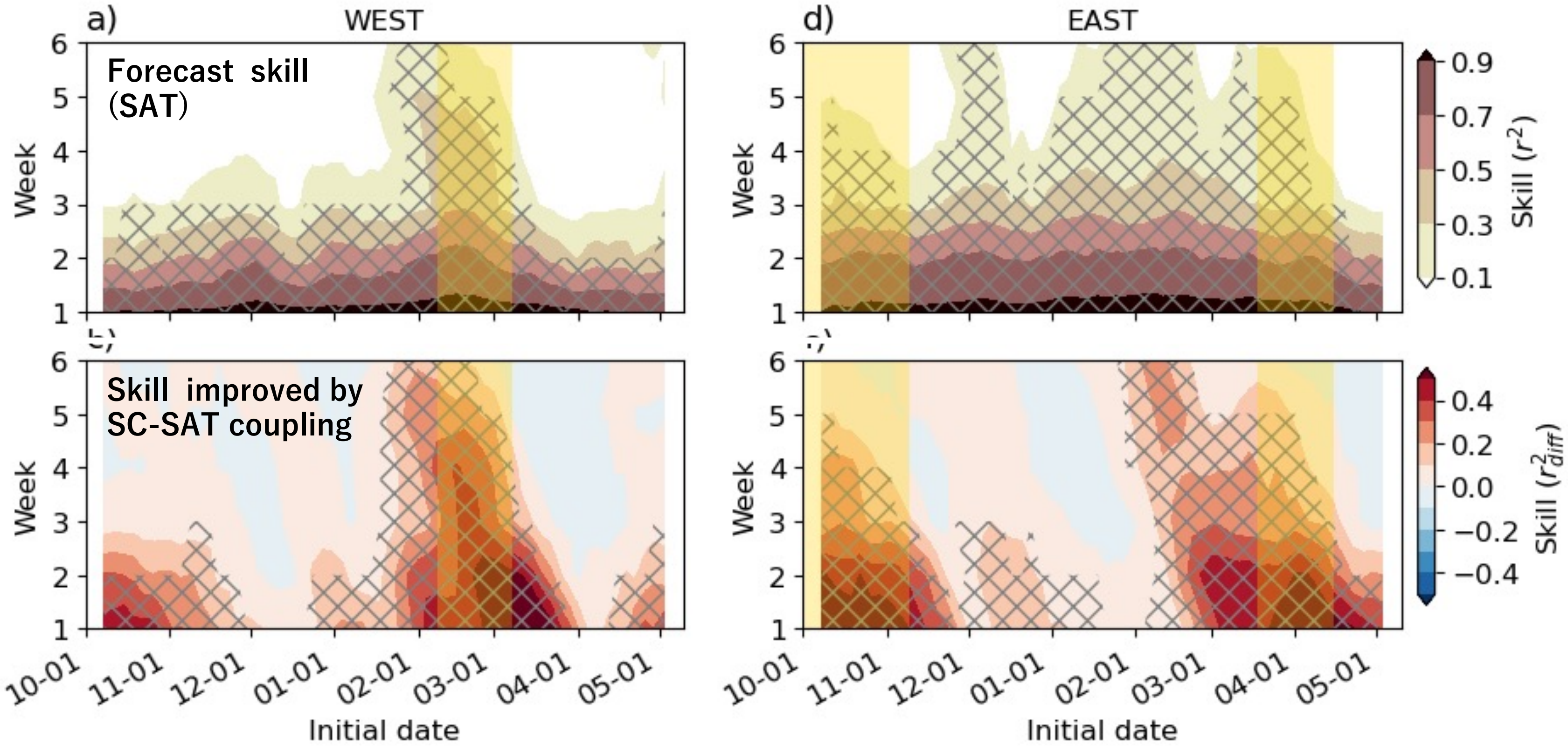
Coupling strength between SC and SAT (Xu and Dirmeyer, 2011)

*Transparent lines sho statistically insignificant information flow.

*Here, information flows were computed by weekly data during one month initiated on each date. We used ERA5 during 1980/81-2020/21.

- Correlation (r^2) between SC and SAT increases in autum and spiring at both regions.
- But, in autumn, the influence on SC on SAT is significant only in east Eurasia.
- In springtime, SC in both west and east Eurasia can affect SAT variation. It corresponds to the strong coupling of SC-SAT shown by Xu and Dirmeryer (2011).

Causality and Predictability



20 years reforecasts by ECMWF operational forecast model were used.

<u>Forecast skill</u>
Interannual correlation between forecast and reanalysis.

The seasonal tendency of causality relates to the predictability of SAT.

- The forecast skill of SAT tends to persist for a long lead time during periods when SC is the cause of SAT.

- The autumnal coupling of SC-SAT is important for the forecast of SAT, at least of east Eurasia..

Conclusion

- Liang-Kleeman information flow revealed the cause-effect relation of the SC-SAT coupling, which is hidden behind the traditional correlation analysis.

- The atmospheric model response and seasonal dependency of forecast quality agreed with the causal relation inferred by the information flow analysis.

- **East Eurasia is "hot spot" where SC certainly influence SAT, at least in autumn.**

Implications for future L-A coupling study

- The information flow can be easy to calculate only using two time series.
  Thus, it may be a helpful approach to quantifying a local L-A coupling with considering causal directions.

- Comparing the degree of information flows of observation and numerical simulation may help to identify a deficiency of the land surface process in a model system.

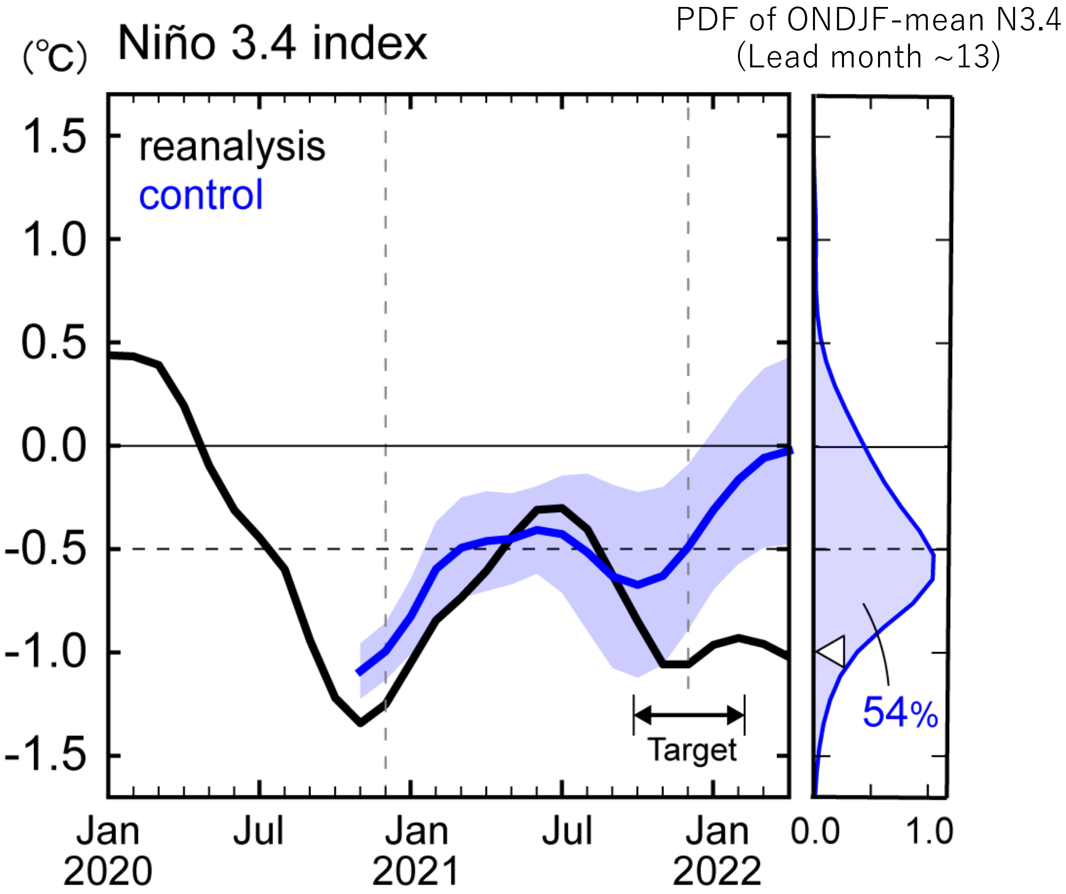
Japanese Multi-model Comparison of Seasonal Predictions

- Predicting Triple-dip La Nina episode -

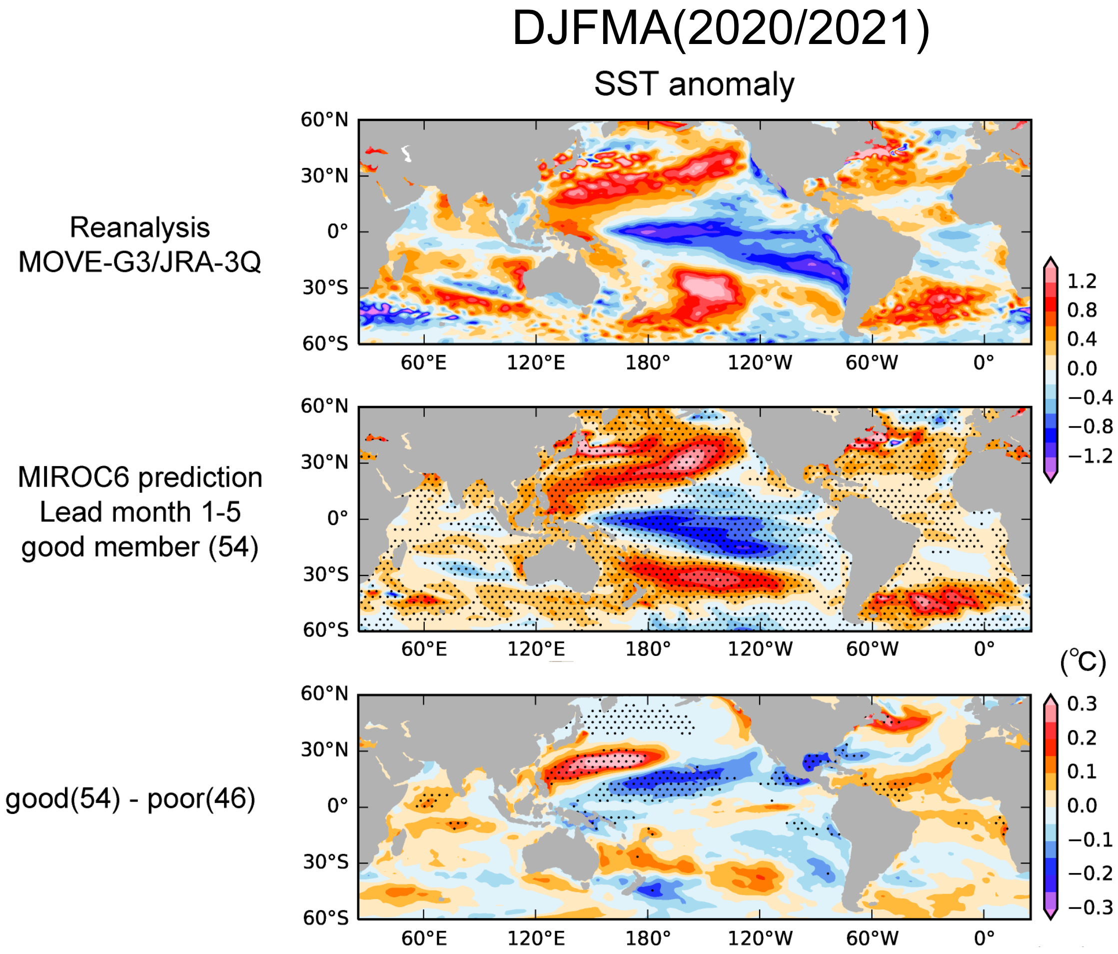
Iwakiri et al. to be submitted
Iwakiri et al. in prep.

Cause of 1st to 2nd year La Niña in 2020-2022

based on MIROC6's 100-member extended seasonal hindcast



MIROC6 captures 2nd year La Niña one year ahead.



Members characterized by broad spatial pattern successfully predict 2nd year La Niña (Iwakiri & Watanabe, 2022).

Comparison among Japanese seasonal forecast models just started

✓ **MIROC6** (Tatebe et al., 2019)

Ensemble size : 10-member
Forecast length : 122 month

✓ **MRI-ESM2.0** (Yukimoto et al., 2019)

Ensemble size : 10-member
Forecast length : 62 month

✓ **SINTEX-F2** (Doi et al., 2016)

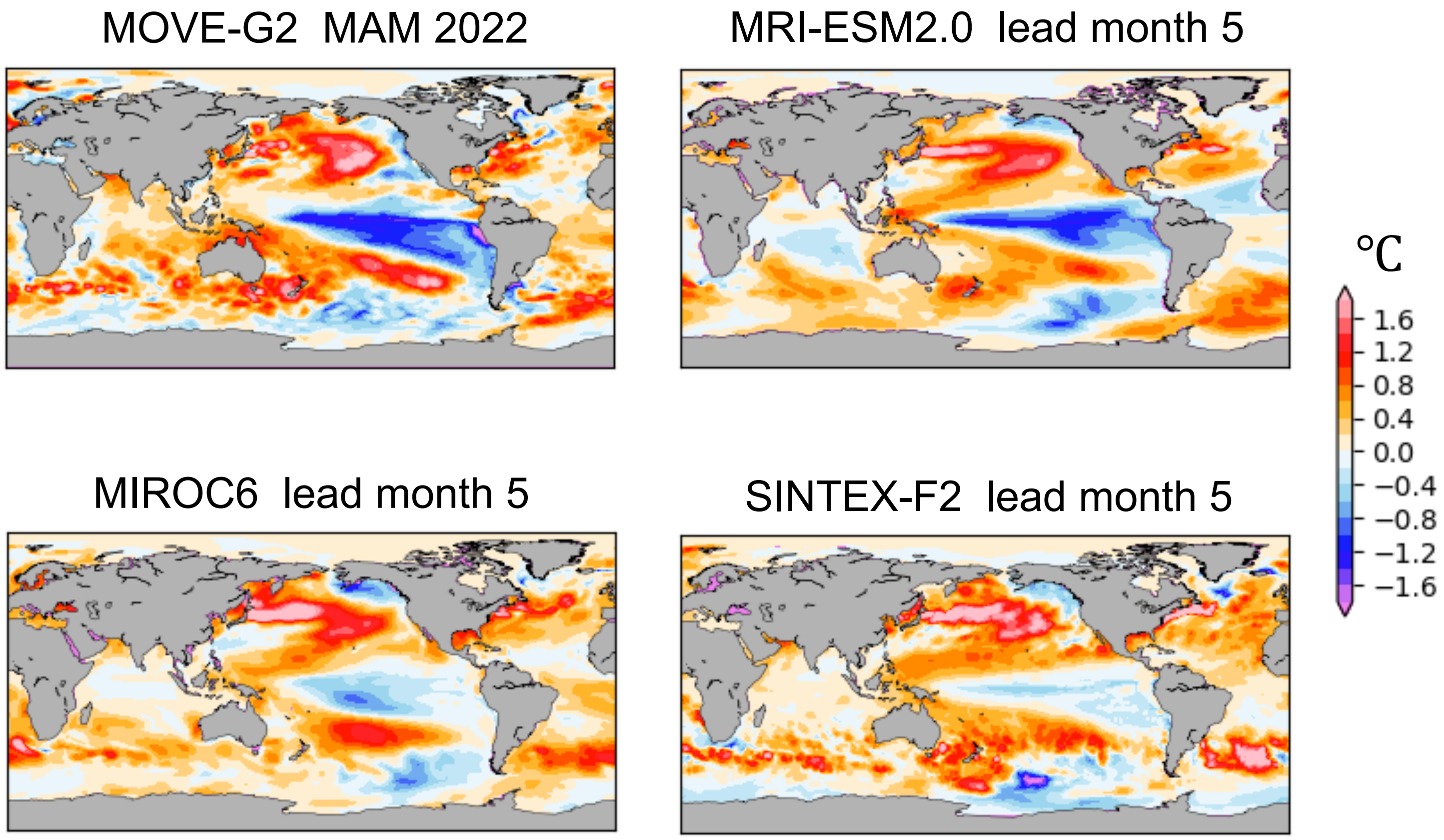
Ensemble size : 12-member
Forecast length : 12 month

✓ **JMA/MRI-CPS3** (Hirahara et al., 2023)

Ensemble size : 10-member
Forecast length : 13 month

Initial time of Nov. 2021

SST anomaly



Comparison of DCPP models is difficult due to the huge data size
→ A comparison project started in Japanese four models