The influence of snow cover over Eurasia on surface air temperature variability and its impacts on sub-seasonal prediction

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Komatsu, K. K., Y. Takaya, T. Toyoda, and H. Hasumi, (2023): A submonthly scale causal relation between snow cover and surface air temperature over the autumnal Eurasian continent. *J. Climate*, 36, 4863–4877.

Takaya, Y, K. K. Komatsu, N. Ganeshi, T. Toyoda, H. Hasumi: A sub-monthly timescale causality between snow cover and surface air temperature in the Northern Hemisphere inferred by Liang–Kleeman information flow analysis, *Clim. Dyn.* (in revision)

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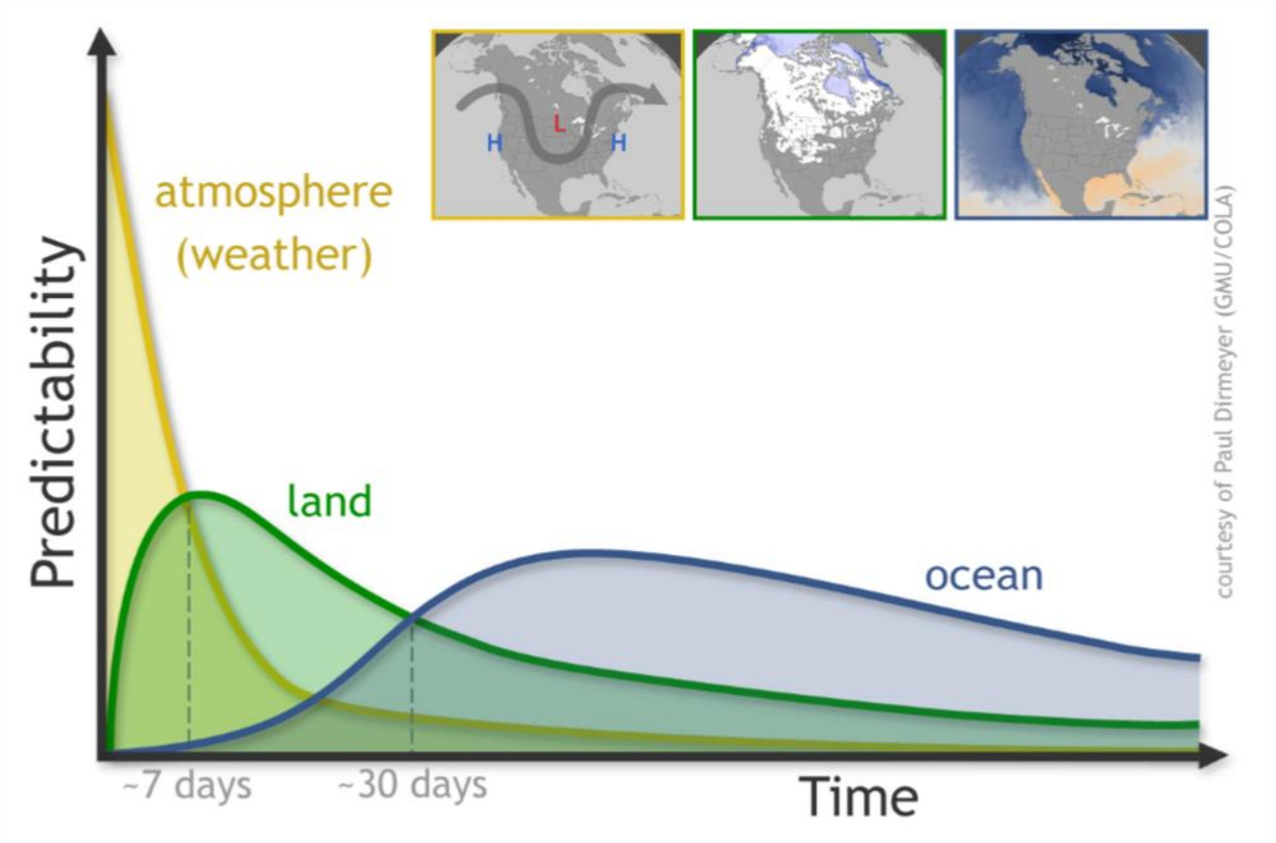
Introduction : Land impacts in the S2S prediction

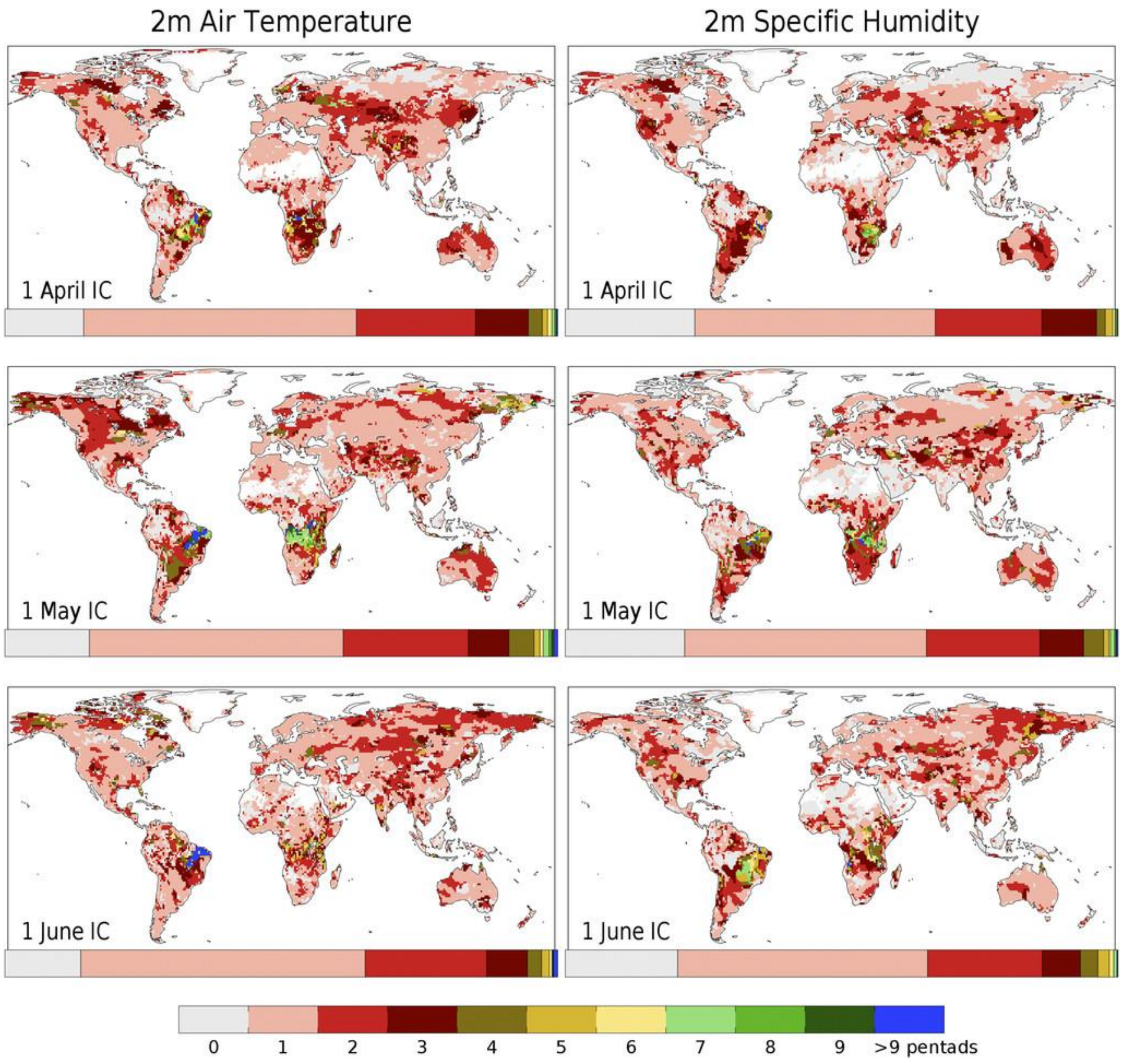


The ocean and land conditions are important sources of the predictability for the S2S prediction.

In particular, roles of the land are considered important over mid-latitude continents, where the S2S forecast skill remains low.

Courtesy: Prof. Paul Dirmeuer (GMU/COLA)

Introduction : Land impacts in the S2S prediction



Timescale of land impacts

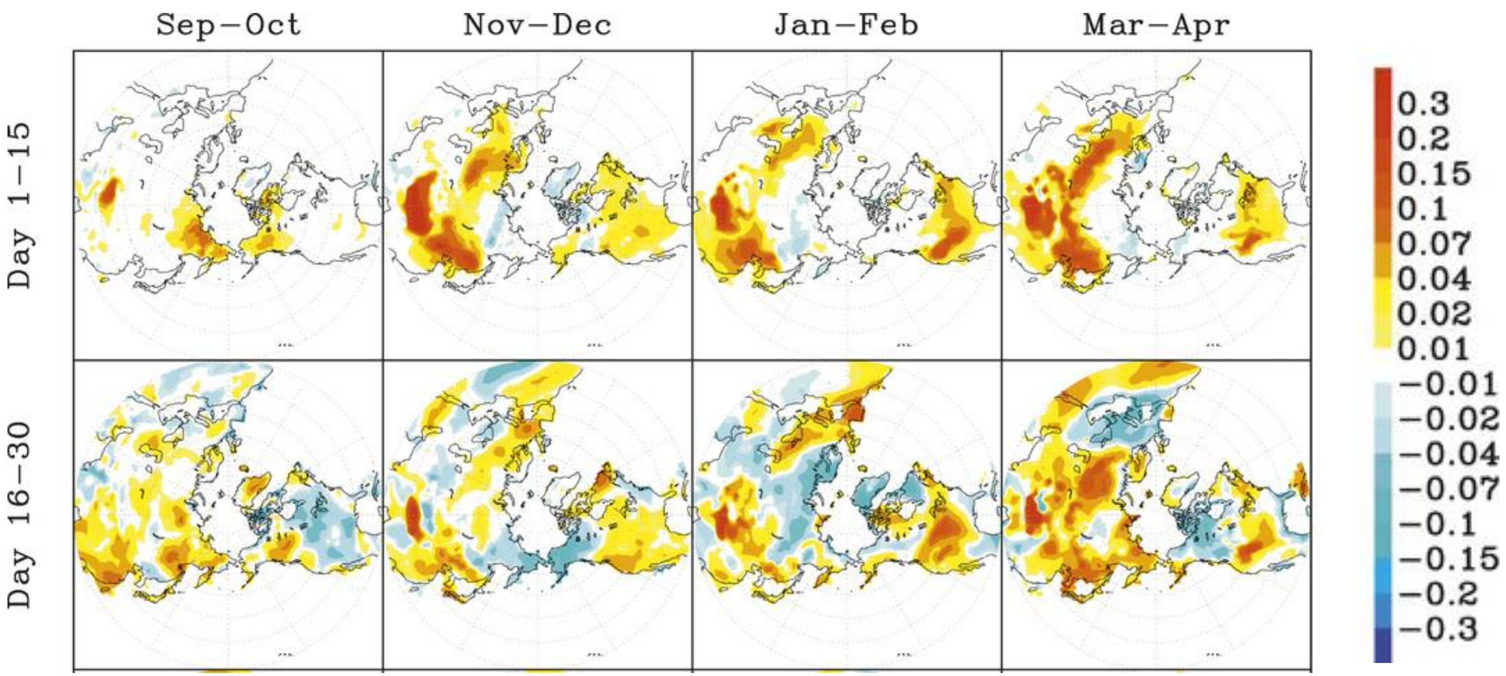
Maximum periods of increased prediction skill by land initialization (Based on NOAA CFSv2)

Number of pentads where the pentad mean forecast of the indicated variables in simulations with realistic land surface initialization at the indicated dates remains significantly better than forecasts with randomized initial land states, with skill quantified by ACC.

The colored bars beneath each map reflect the fraction of land area occupied by each skill duration category.

Source: Dirmeyer et al. (2007)

Introduction : Land impacts in the S2S prediction



Snow impacts

Change in potential predictability (r^2) of SAT hindcast using the snow depth initialization

(Experiment using the CAM3 model with the CMC land analysis)

During snowmelt season, snow–atmosphere coupling is strongest over many parts of midlatitude Eurasia and America.

Source: Jeong et al. (2013)

Purpose of this study

Previous studies

Assessed snow impacts using statistical analysis (correlation/regression) and model sensitivity experiments

This study (Komatsu et al. 2023, Takaya et al. in revision)

- Evaluating the snow impacts using a simplified transfer entropy analysis (Liang-Kleeman information flow).
- Diagnosing models' representation of snow-SAT interaction
- Underpinning the predictability originated from the snow condition in S2S models

Method: Liang-Kleeman information flow

Transfer entropy

$$T_{X\rightarrow Y} = H\left(Y_t \mid Y_{t-1:t-L}\right) - H\left(Y_t \mid Y_{t-1:t-L}, X_{t-1:t-L}\right)$$

Reduction of the uncertainty of Y by knowing X at the previous step

$$\frac{dx_1}{dt} = F_1(x_1, x_2, t) + noise$$

$$\frac{dx_2}{dt} = F_2(x_1, x_2, t) + noise$$

$$\frac{dH_1}{dt} = \frac{dH_{12}}{dt} + T_{2\rightarrow 1}$$

$$= \underbrace{\frac{dH_1^*}{dt}}_{\text{Change of } H_1 \text{ by } x_1} + \underbrace{\frac{dH_1^{noise}}{dt}}_{\text{Change of } H_1 \text{ by stochastic noise}} + T_{2\rightarrow 1}$$

Method: Liang-Kleeman information flow

Liang (2014) deduced rigorous formula to compute maximum likelihood estimate of information flow ($T_{2\to1}$) using variance and covariance of X_1 and X_2.

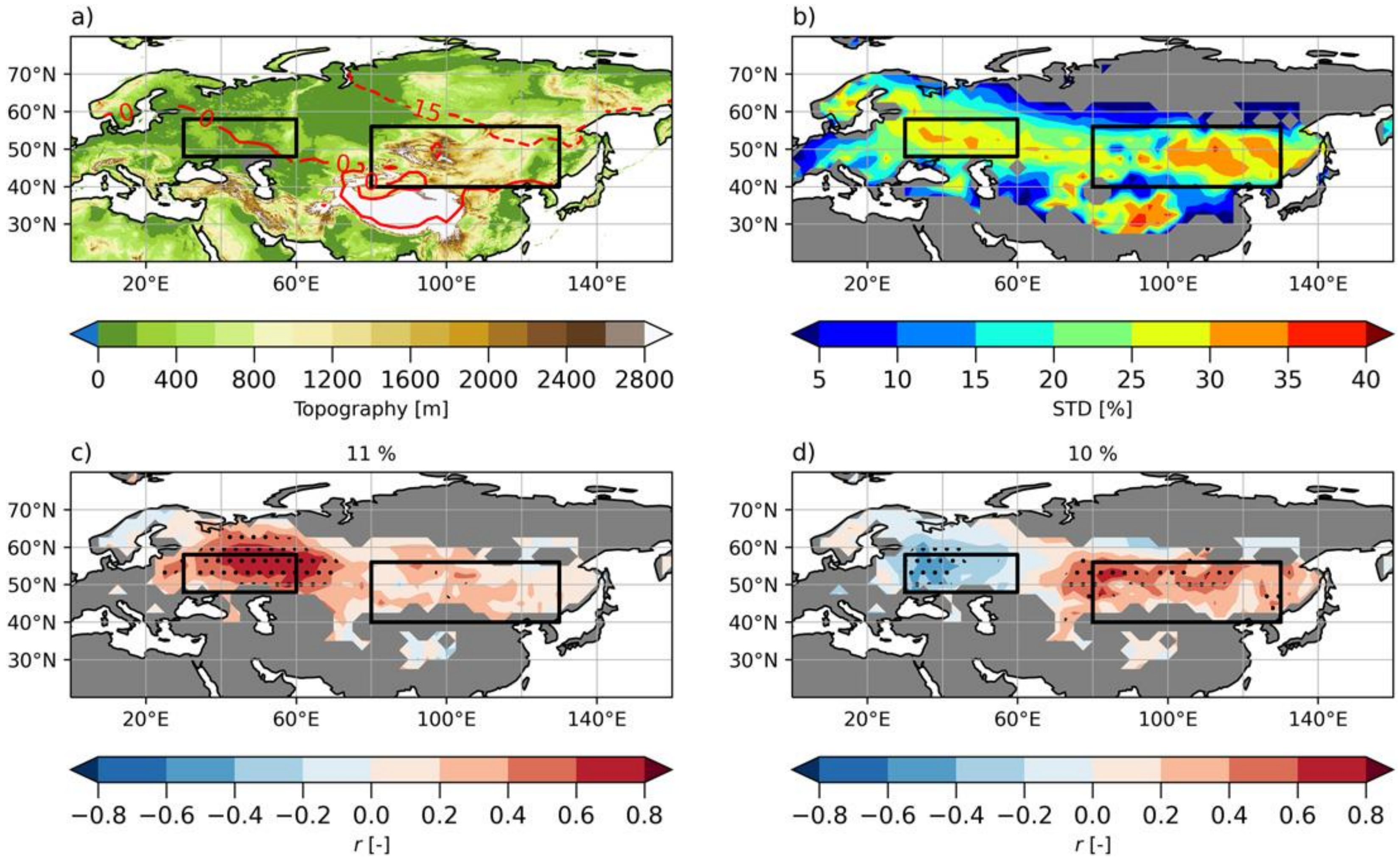
$$T_{2\to1} = \frac{C_{11}C_{12}C_{2,d1} - C_{12}^2 C_{1,d1}}{C_{11}^2 C_{22} - C_{11}C_{12}^2},$$

C : (co)variance, d1 : forward differential of X_1

This study uses the normalized information flow (Liang 2016)

$$\tau_{2\to1} = T_{2\to1}/Z_{2\to1}. \qquad Z_{2\to1} \equiv |T_{2\to1}| + \left|\frac{dH_1^*}{dt}\right| + \left|\frac{dH_1^{\text{noise}}}{dt}\right|.$$

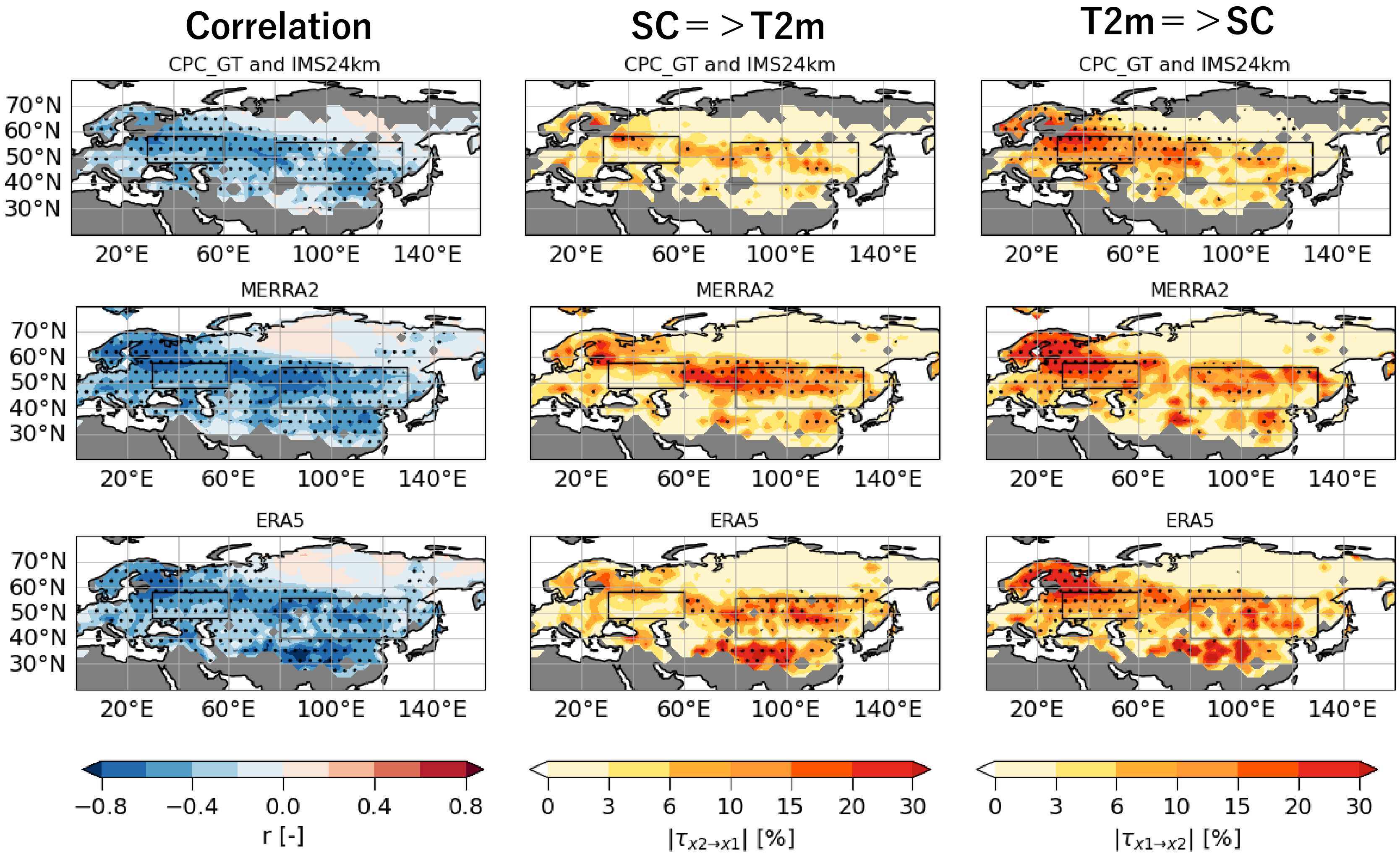
Topography and interannual SC variation in November between 1981 and 2020



(a) Map of Eurasian topography, (b) he observed interannual standard deviation (STD) of November SC.
(c, d) The correlation of SC for the first leading mode of the SC anomaly produced by the EOF analysis.

Causal relationship btw SC and T2m over Eurasia

Normalized Information Flow (SC & T2m)



Komatsu et al. (2023), using the simplified transfer entropy analysis, investigated the causal relationship between SC and T2m over Eurasia in Nov. 1999-2019

Correlation:
Negative over most of Eurasia

Causality:

West Eurasia
All data indicates prominent causality from T2m => SC.

East Eurasia
Relatively strong causality from SC＝＞T2m

We see some difference among data set.

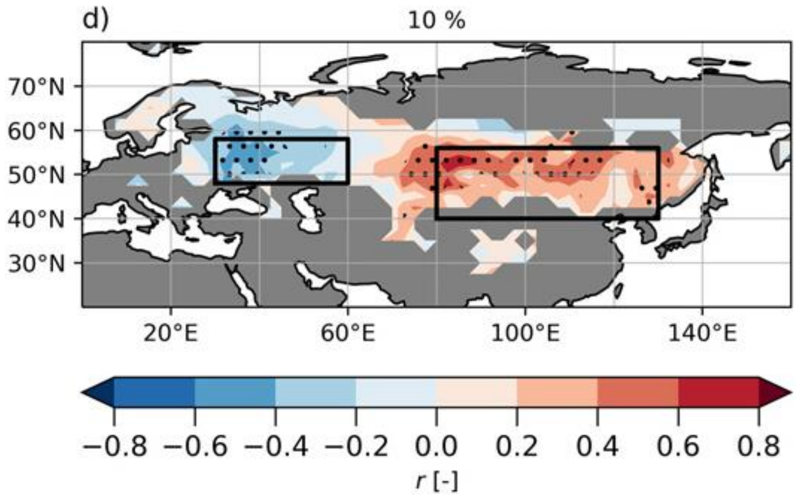
Komatsu et al. (2023)

Model sensitivity experiment

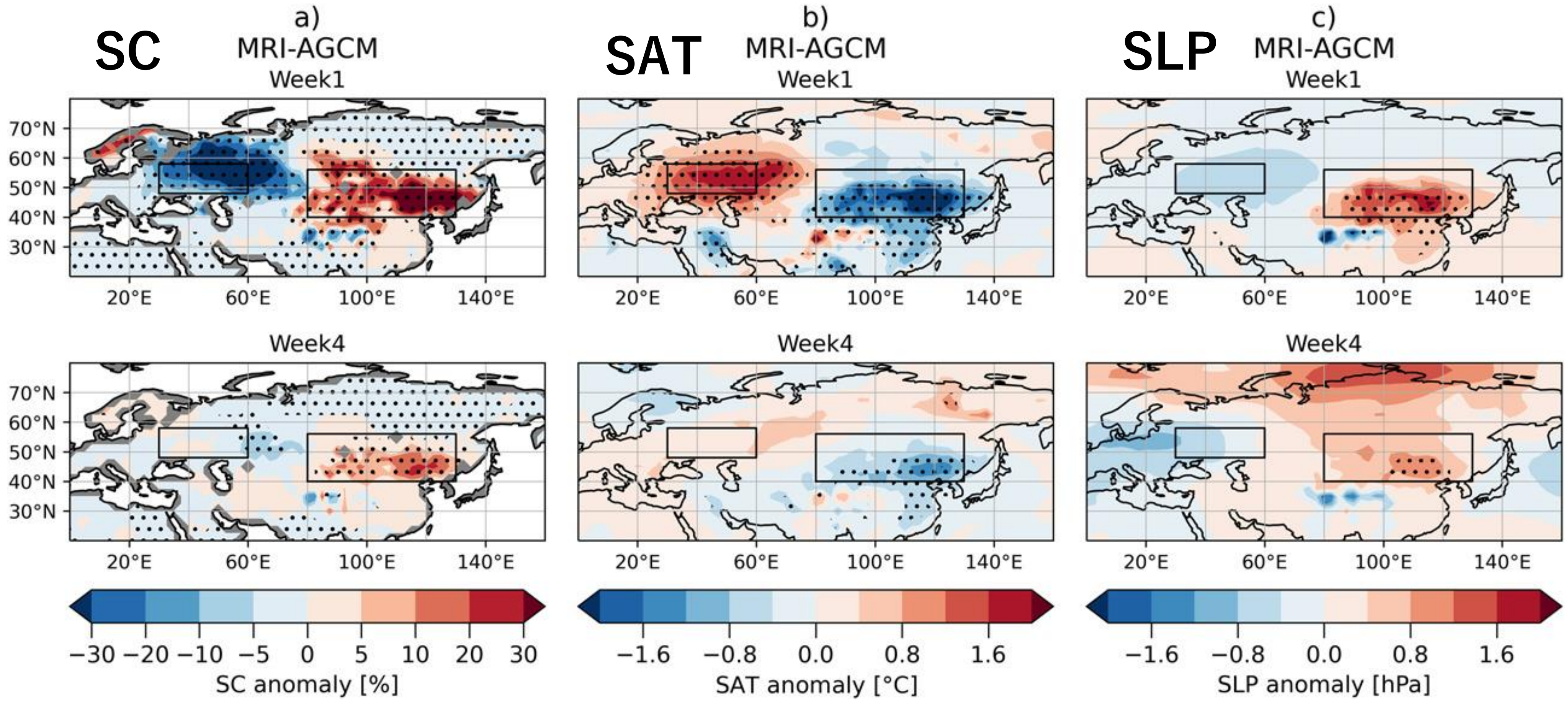
Model: MRI-AGCM3.2 (d4PDF model, Mizuta et al. 2012)

Land conditions: initialized with 5th highest and lowest years of the dipole pattern (based on a SC dipole index)

Ensemble size: Twin experiments of 300 simulations using different atmospheric initial conditions.

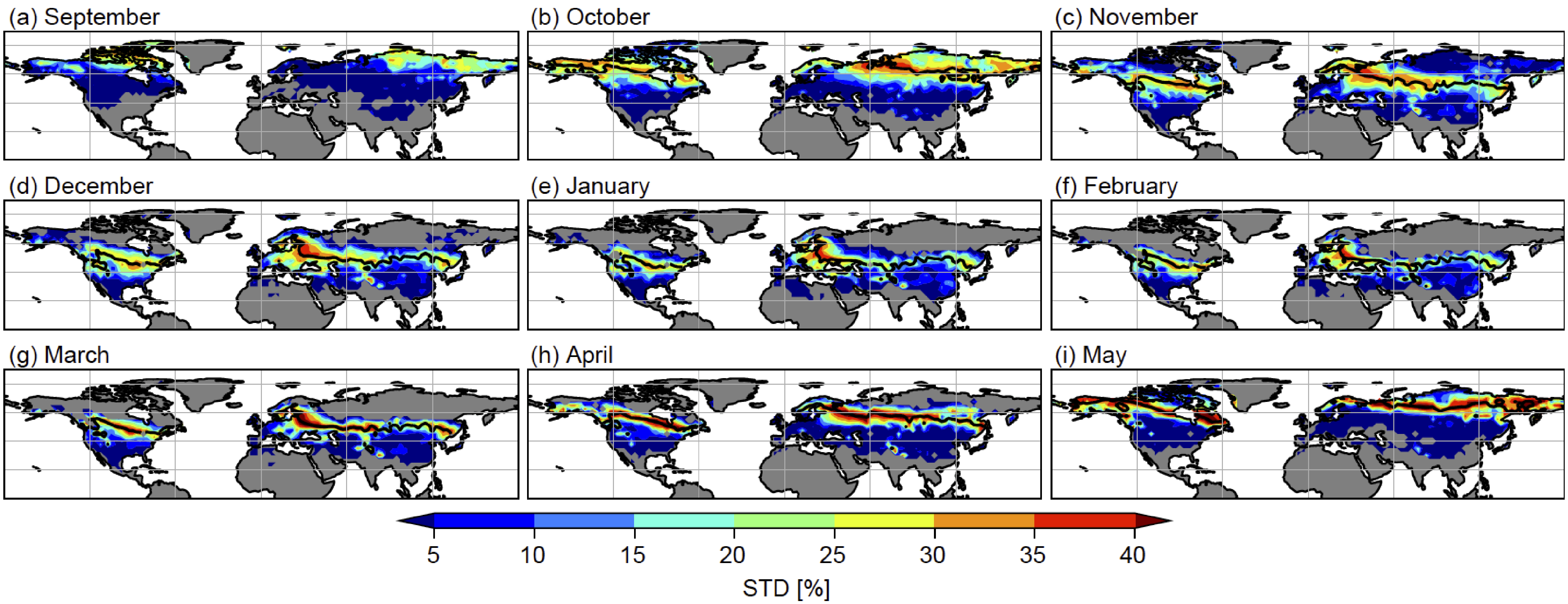


Model sensitivity experiment



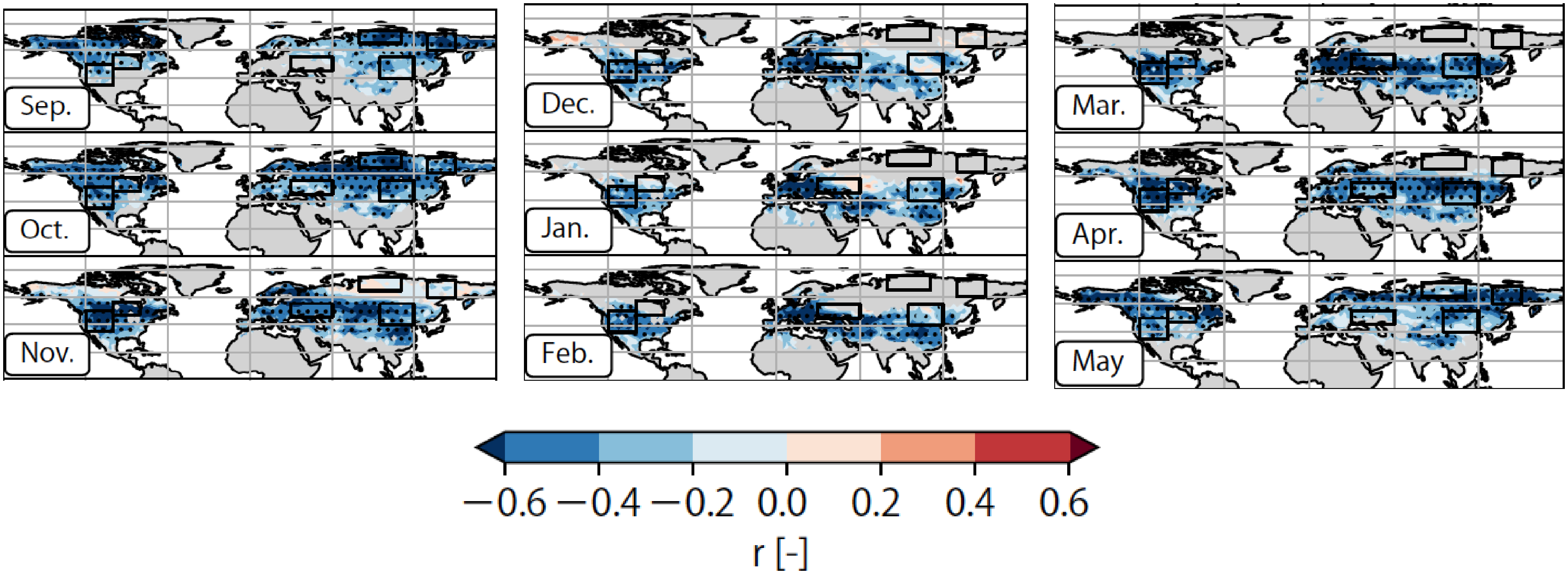
The ensemble-mean anomalies between positive and negative dipole experiments for (top) week 1 and (bottom) week 4 about (a) SC, (b) SAT, and (c) sea level pressure (SLP).
A positive value means that the positive dipole experiment yielded higher values than the negative dipole experiment.

Standard deviation of weekly average SC (MERRA-2)

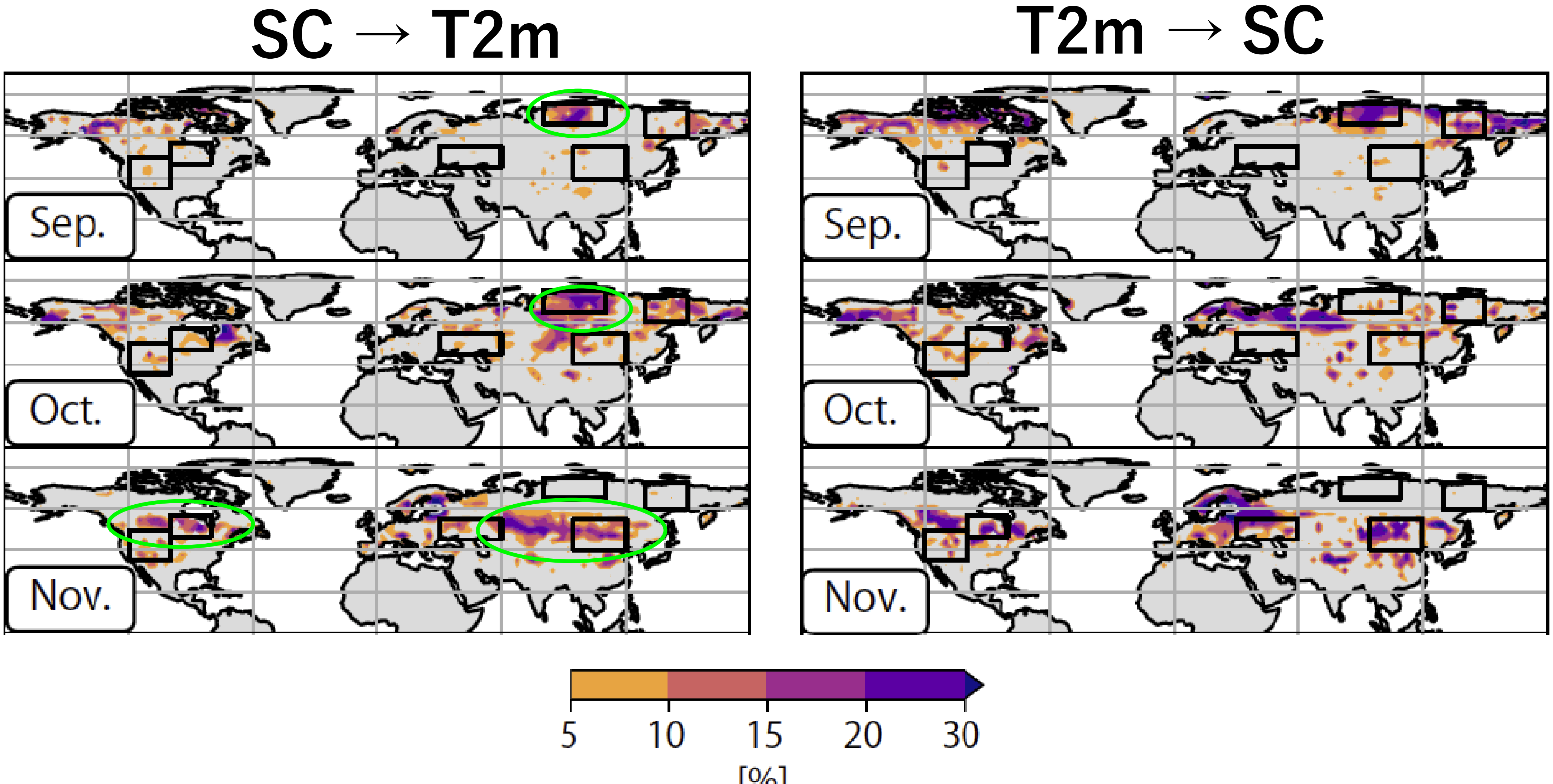


Black contours: mean SC of 50%

T2m-SC Correlation（MERRA-2）

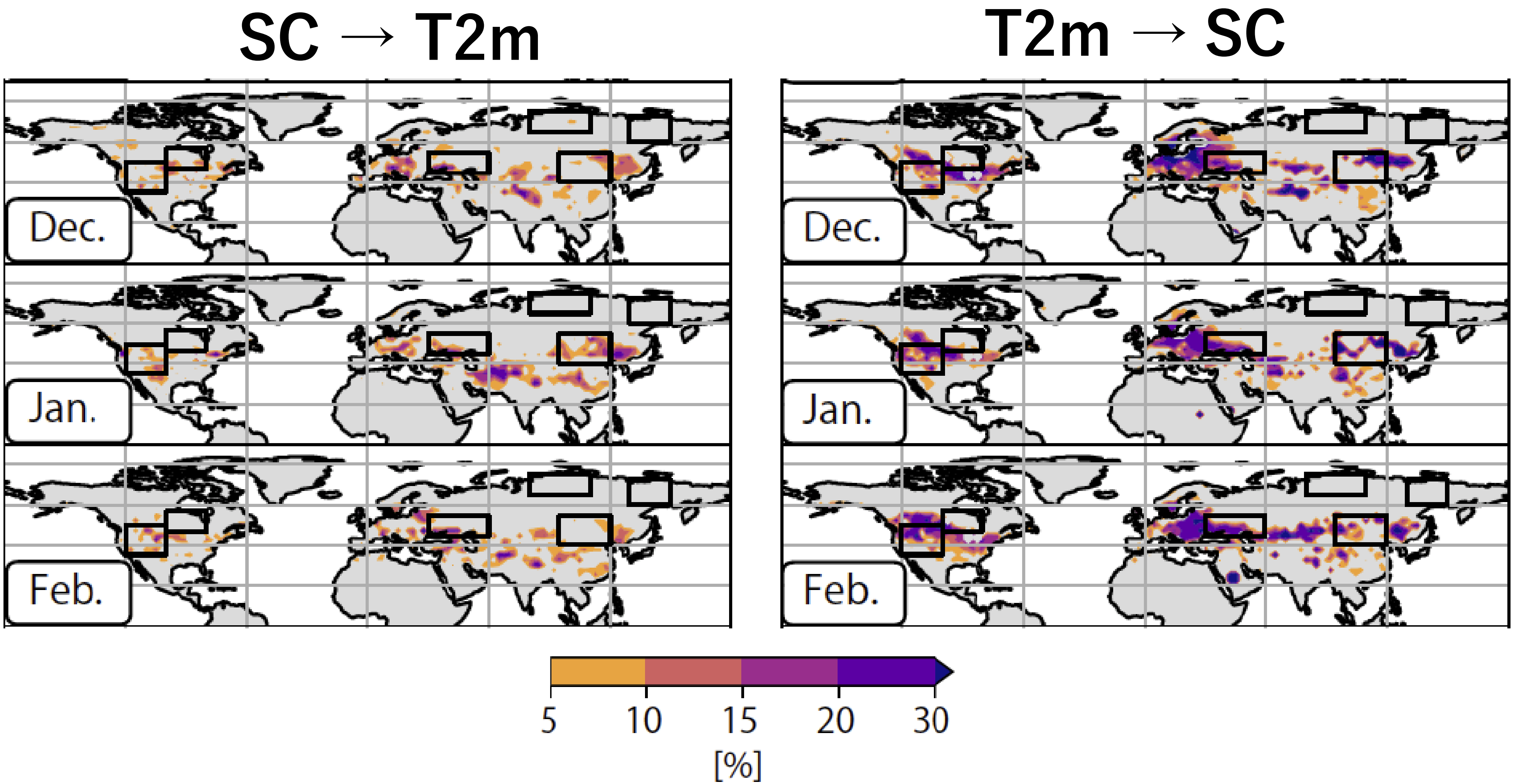


T2m-SC Liang-Kleeman information flow (MERRA-2)



Information flow was computed using four consecutive weeks.

T2m-SC Liang-Kleeman information flow (MERRA-2)



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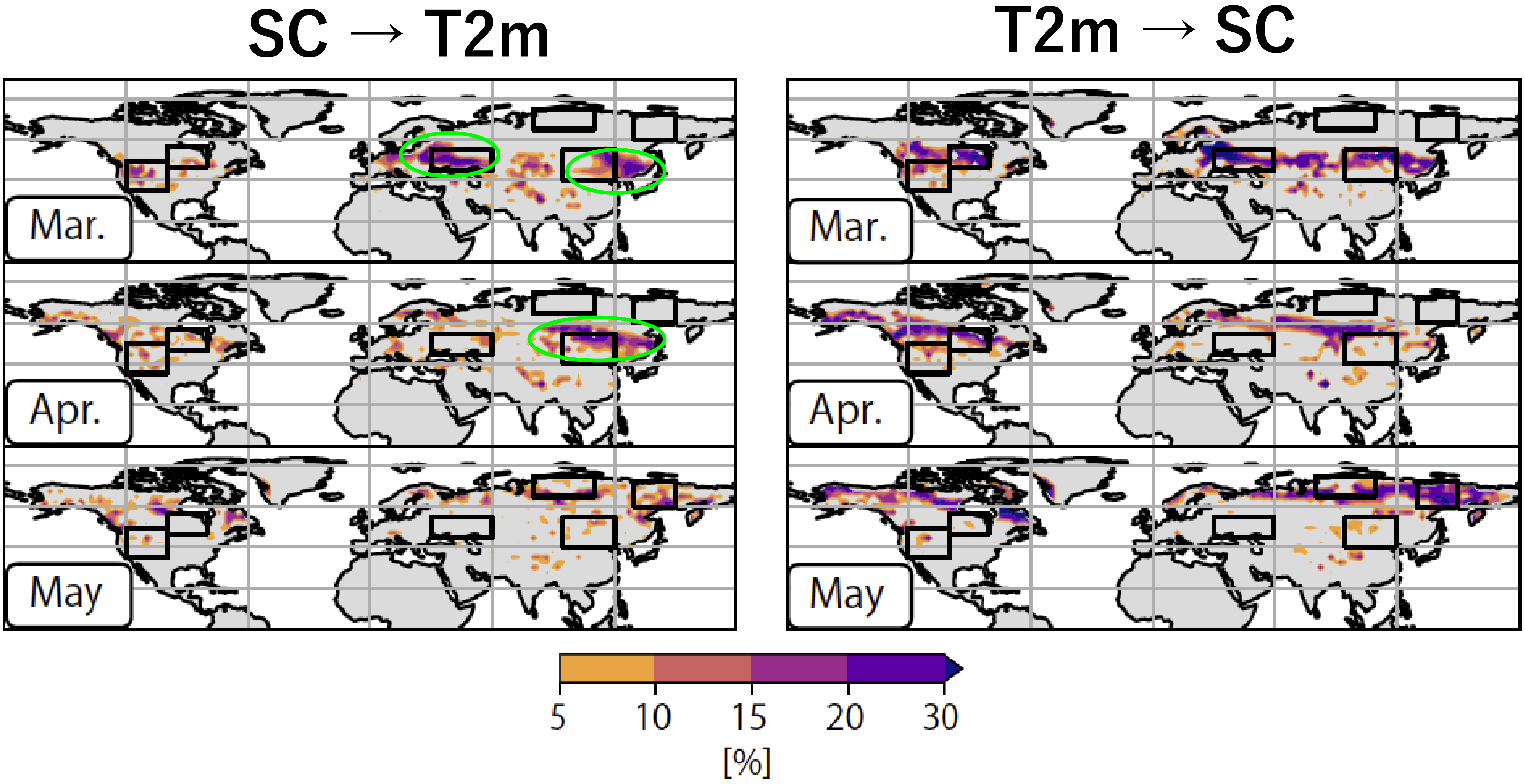
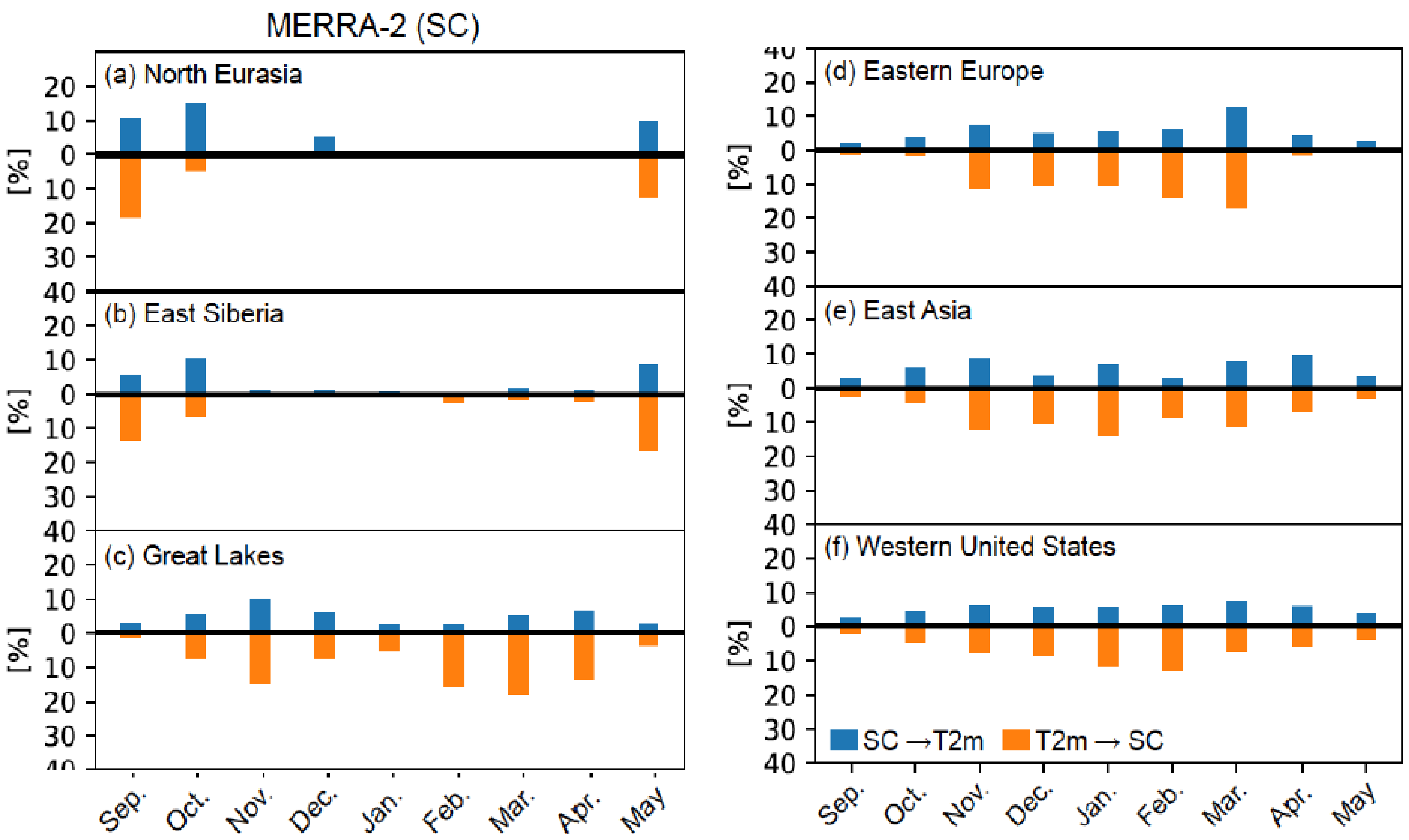
T2m-SC Liang-Kleeman information flow（MERRA-2）



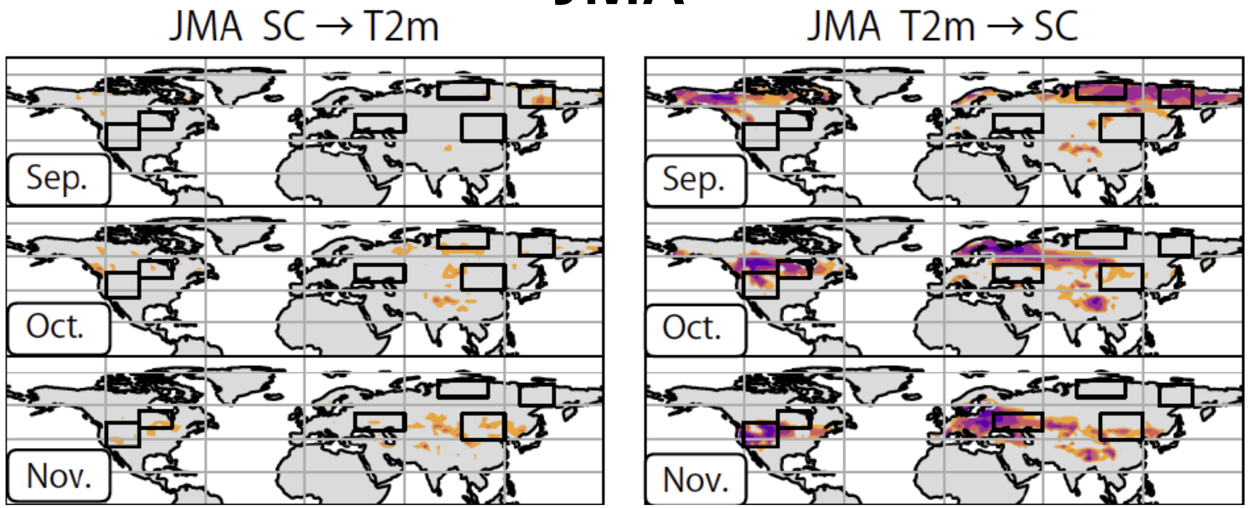
Information flow was computed using four consecutive weeks.

MERRA-2 T2m-SC Liang-Kleeman information flow

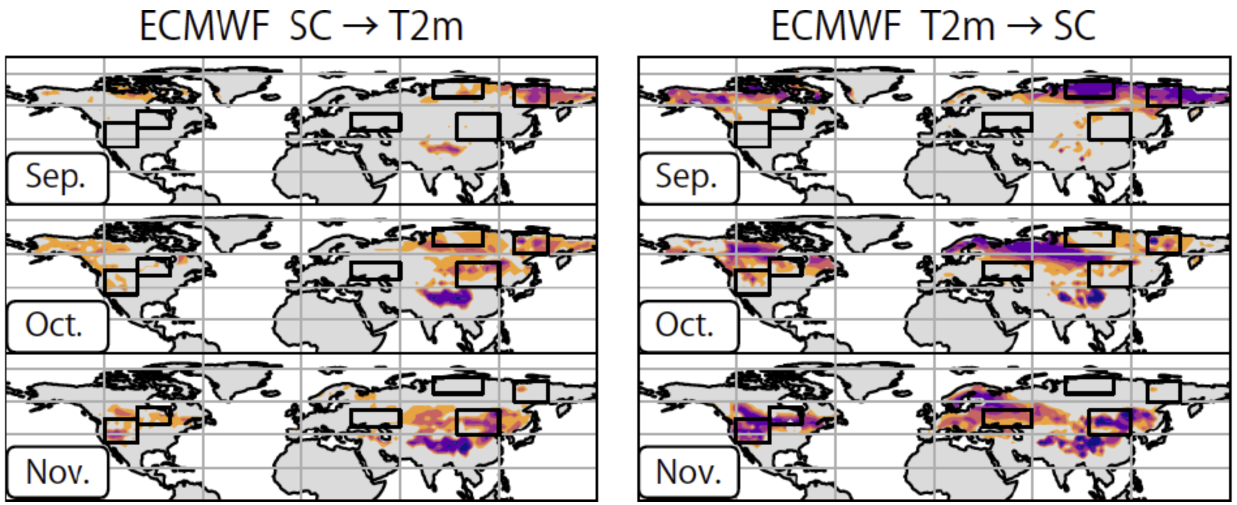


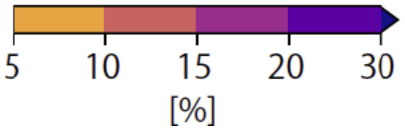
T2m-SC Liang-Kleeman information flow (S2S model)

JMA

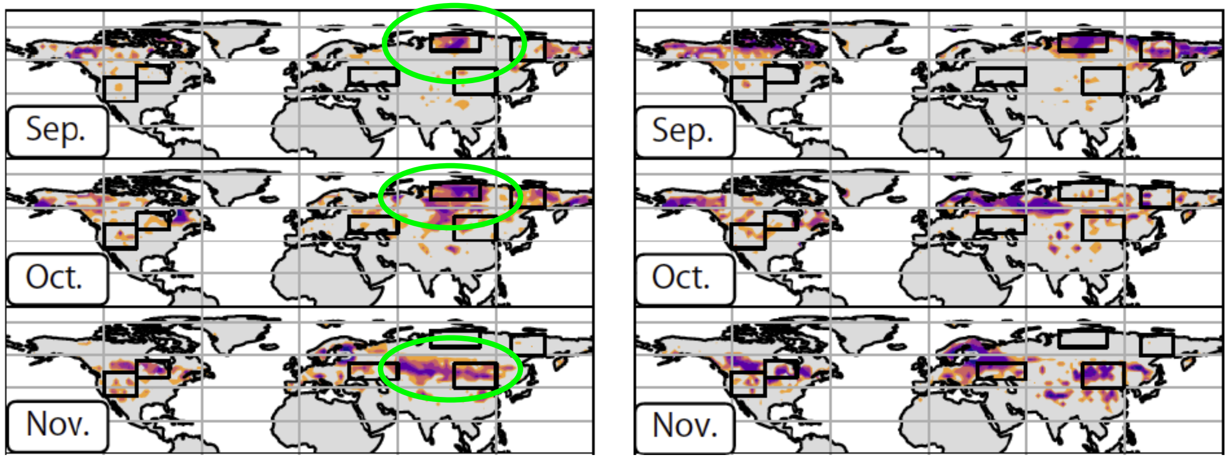


ECMWF



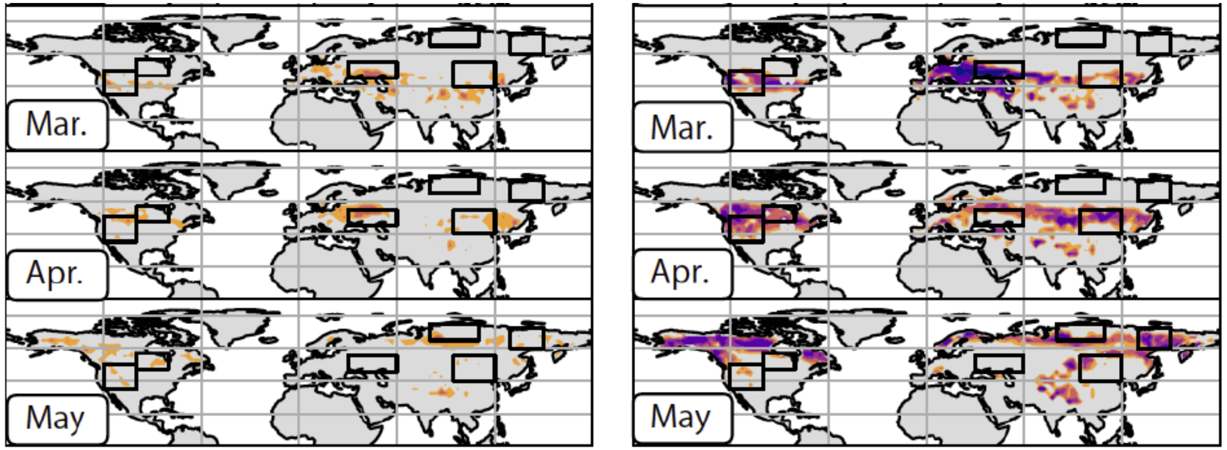


MERRA-2

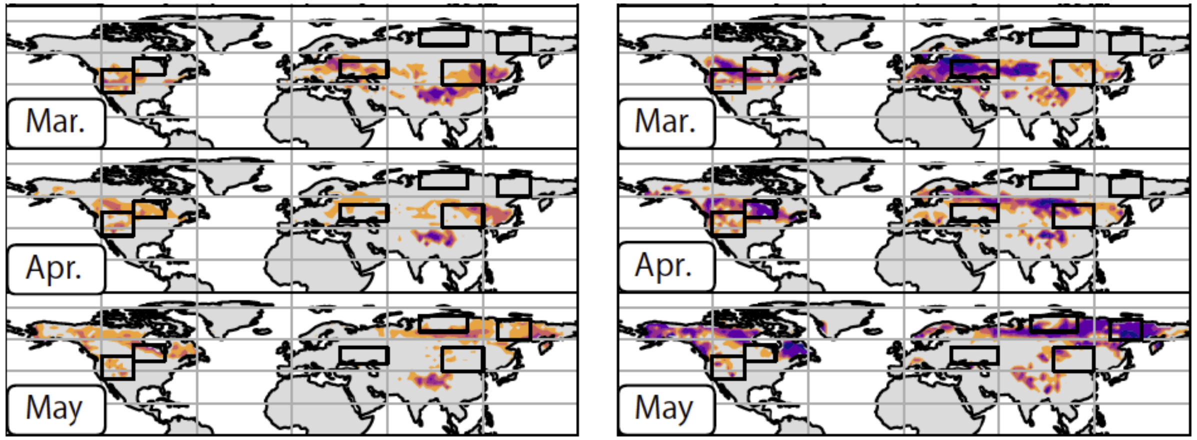


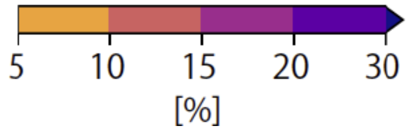
T2m-SC Liang-Kleeman information flow (S2S model)

JMA

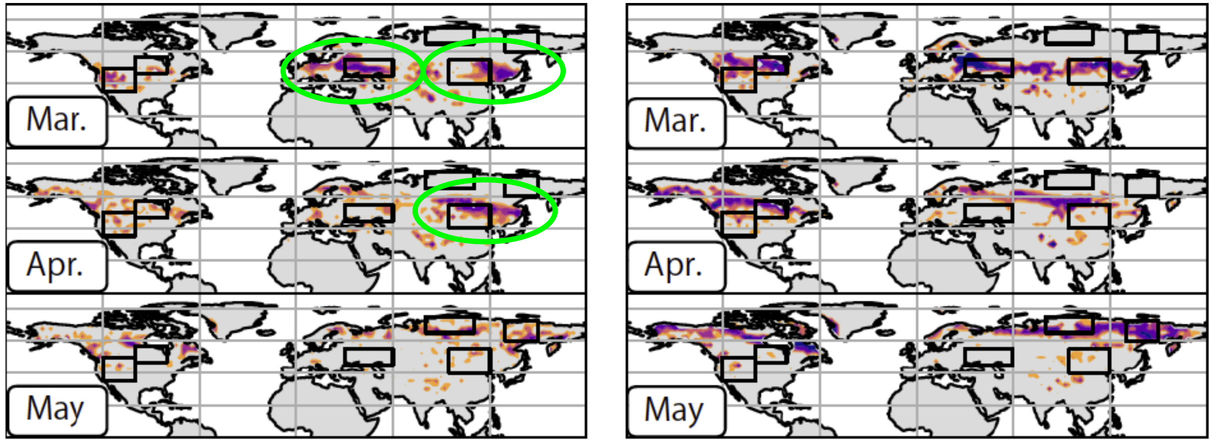


ECMWF

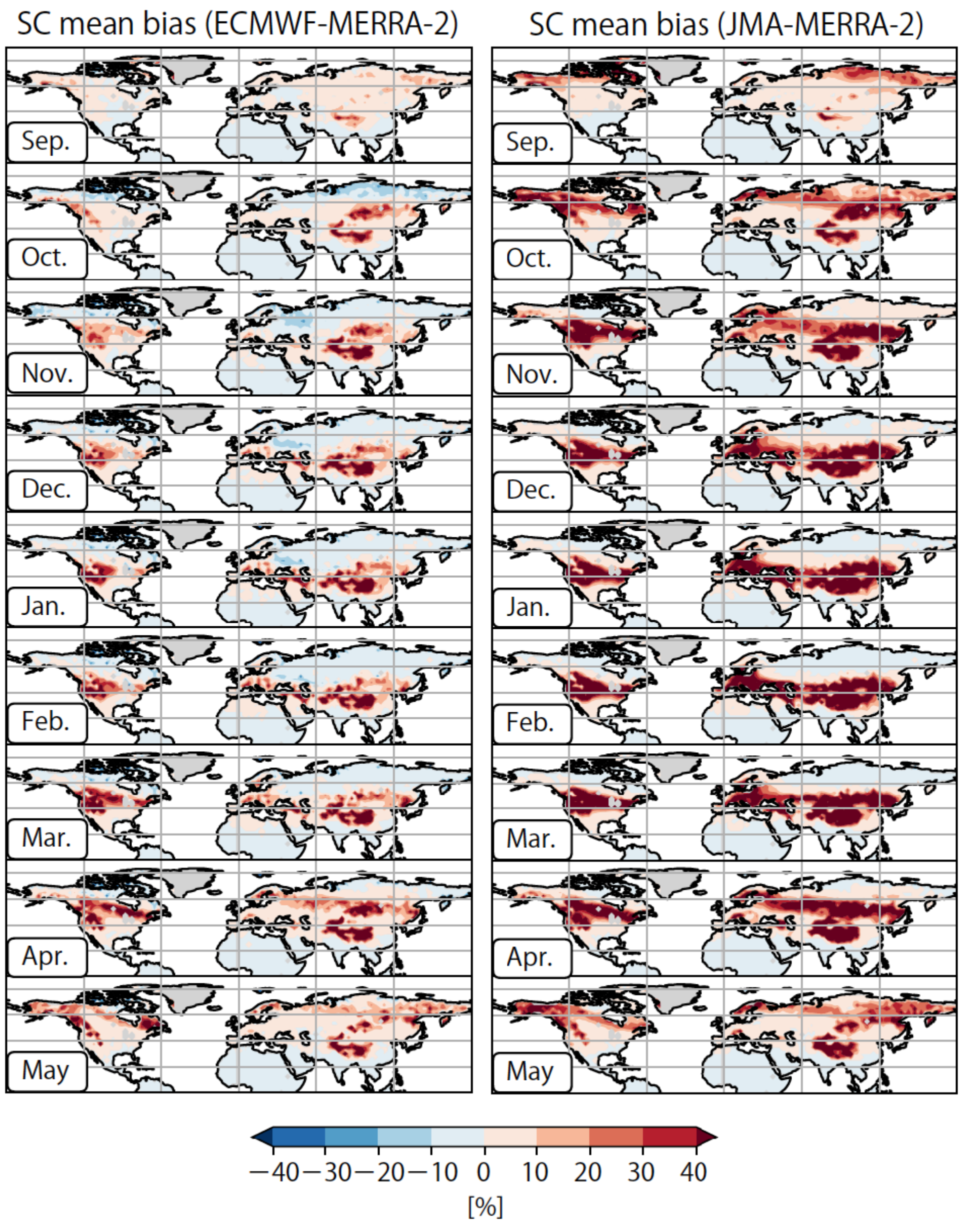




MERRA-2



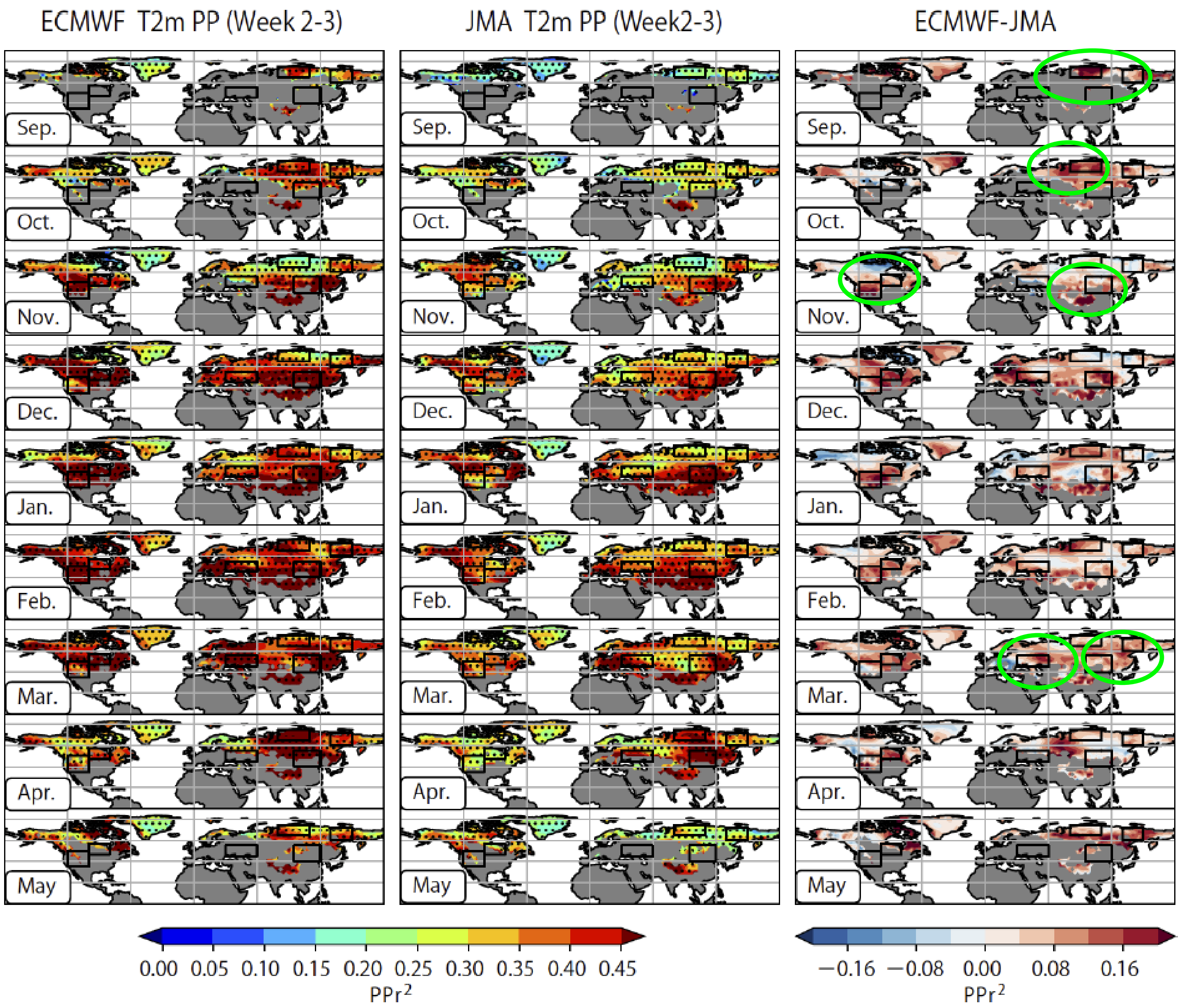
Model Bias of Snow Cover (climatological mean)



Large SC bias is seen in the JMA model.

The verification results of the model climatology imply that the SC biases in mean and variance may account for the underestimated causality in the JMA model.

Impacts on the potential predictability of SAT



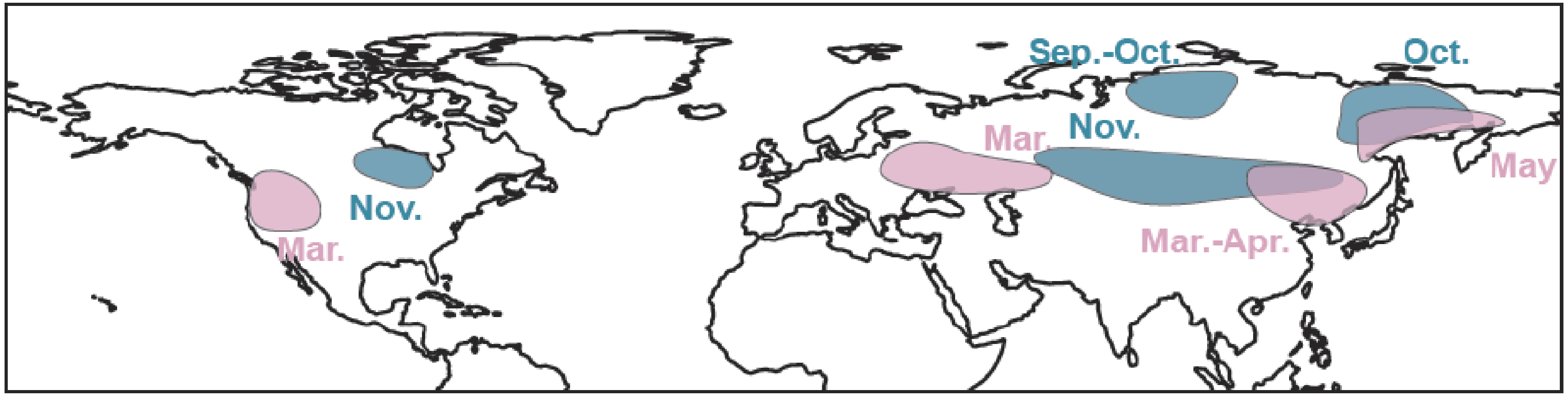
Strong SC effect on SAT
→ High potential predictability of SAT

Weak SC effect on SAT
→ Low potential predictability of SAT

Summary

- This study investigated the sub-monthly causal relationship between observed snow cover (SC) and surface air temperature (SAT) in the Northern Hemisphere.
- Evaluation of S2S models revealed the shortcomings of the model in representing snow influence on SAT.
- The diagnostics of this study are useful for advancing our understanding of S2S predictability and contributing to the future improvement of S2S prediction.

'Cold spots' identified by Liang-Kleeman information flow analysis



Takaya, Y et al. : A sub-monthly timescale causality between snow cover and surface air temperature in the Northern Hemisphere inferred by Liang–Kleeman information flow analysis, *Clim. Dyn.* (in revision)