

Investigation of Snow Cover and Sea-Ice Impacts in coordinated experiments

Guillaume Gastineau

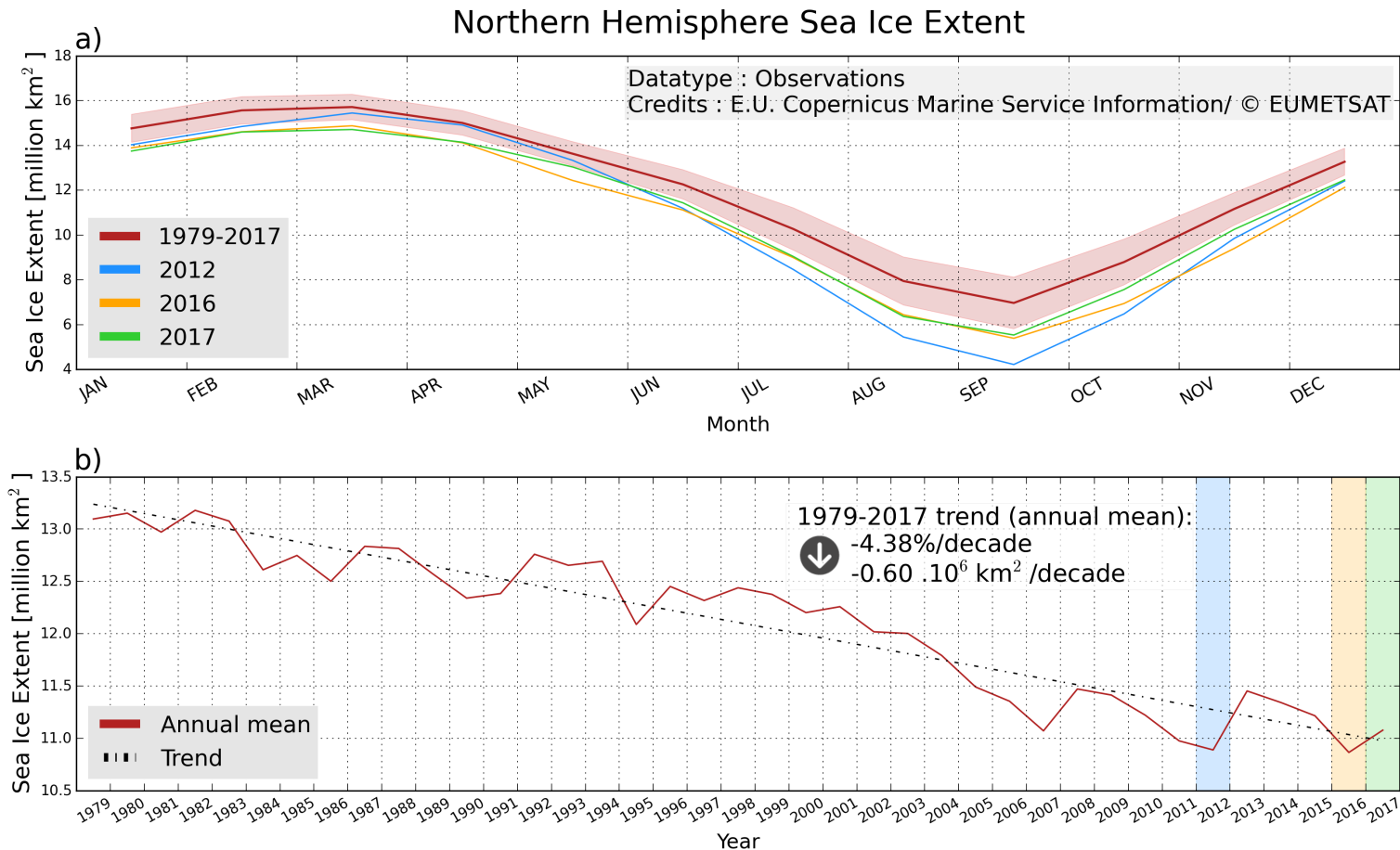
LOCEAN, Sorbonne Université, IPSL/CNRS, Paris, France

Collaborators: C. Frankignoul, J. Garcia Serrano, F. Ogawa, T.
Koenigk, N. Keenlyside, Y. Gao, S. Yang.



The research leading to these results received funding from the H2020 project Blue-Action under grant agreement 727852.

I. Impacts of a warming Arctic



Amplification polaire du réchauffement climatique :

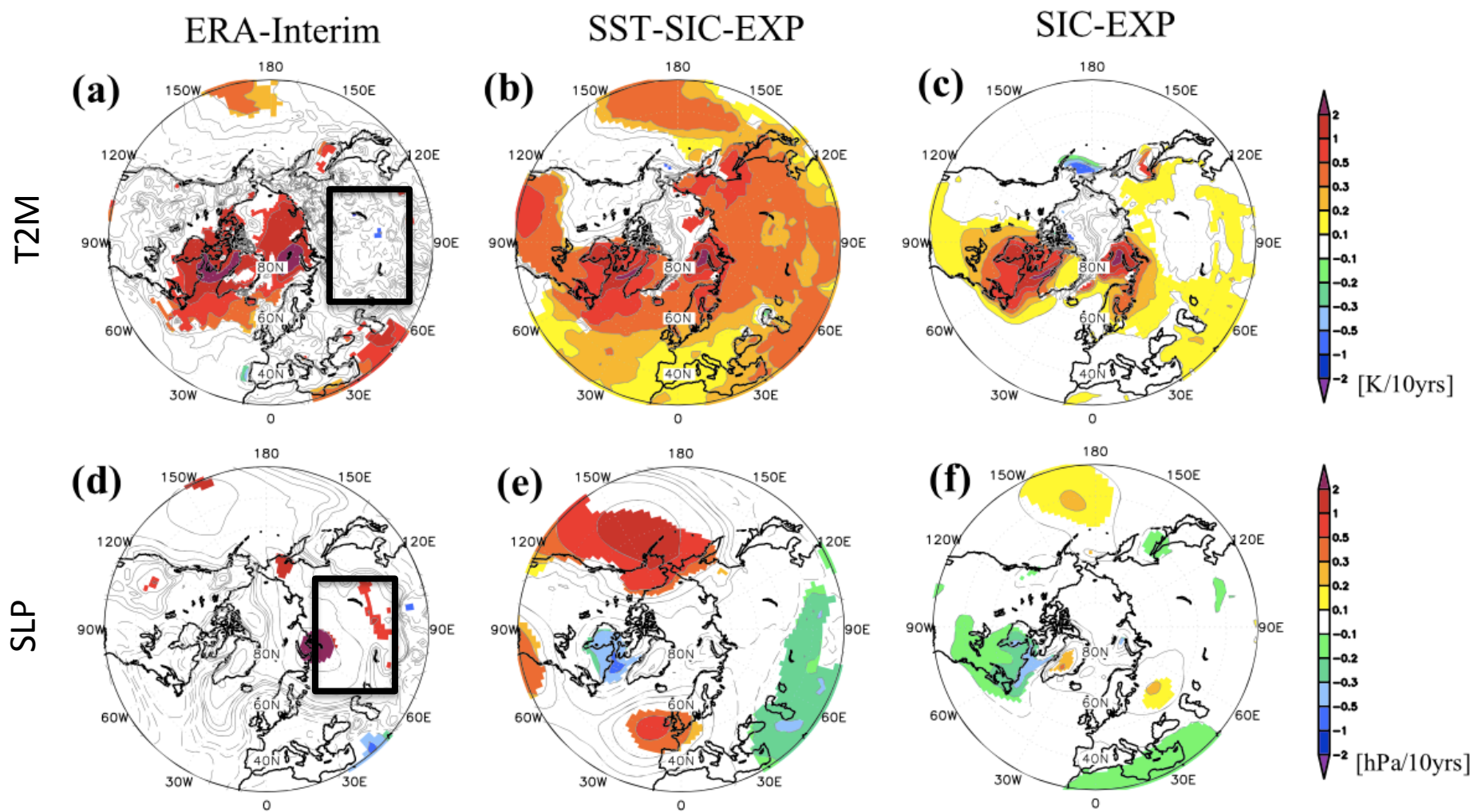
-> Implication pour les régimes de temps? Jet stream avec plus de méandres
(Francis and Varvus, 2015)? Plus d'extrêmes?

Data and methods

- Snow cover and SLP from the 6 atmosphere-only models GREENICE simulations of 1982-2014 :
 - SST-SIC-EXP : SST and SIC vary (from OI-SST)
 - SIC-EXP : SST clim, SIC vary (from OI-SST)

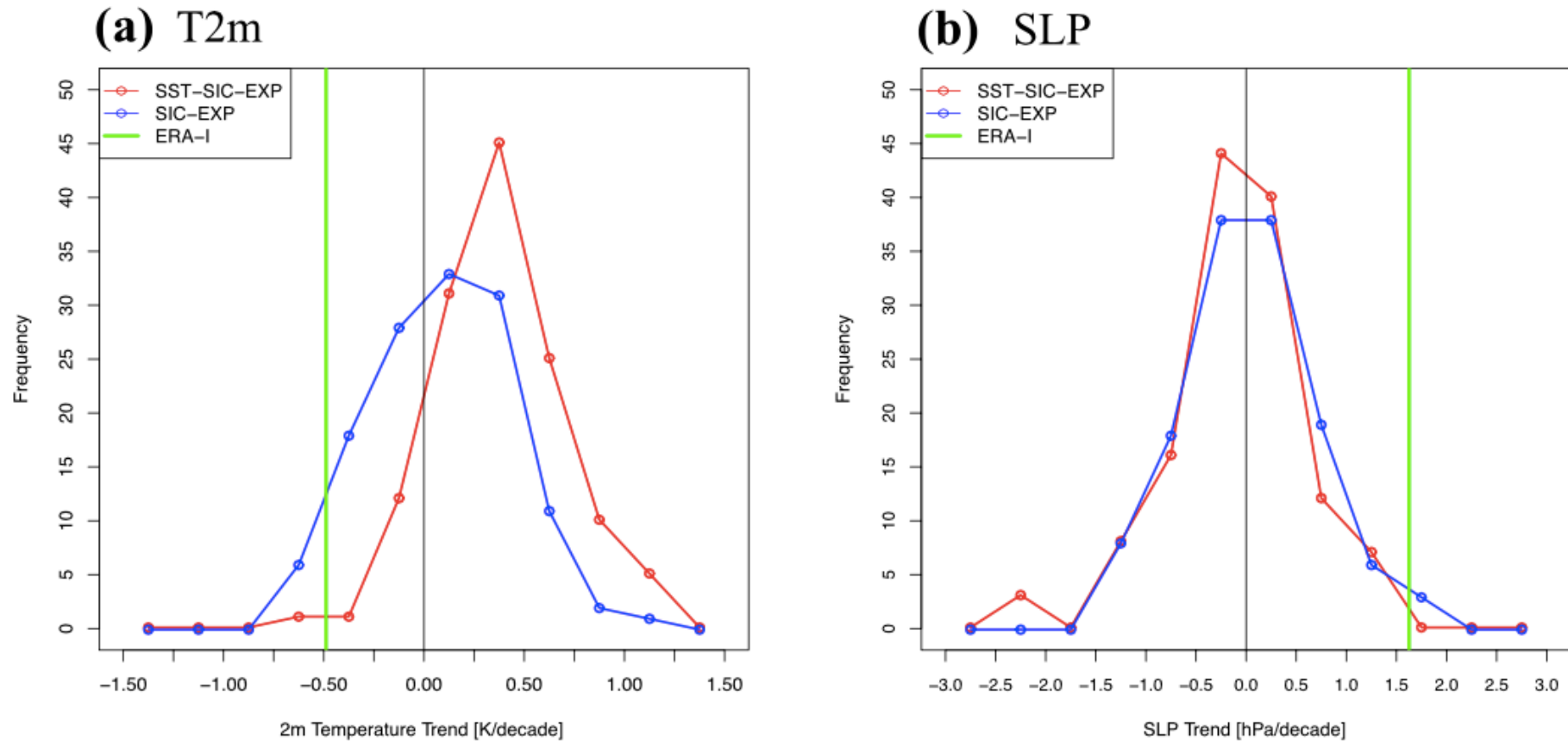
Group	Model	Number of members
SHMI	IFS	20
IAP	IAP4	10
IPSL	LMDZOR	40
UoB	CAM4	20
UoB	WACCM	20
HU	AFES3.1	30

Trend 1982-2014 in DJF, ensemble mean



Ogawa et al., 2017, GRL

Distribution of Trends over Siberia 1982-2014 in DJF

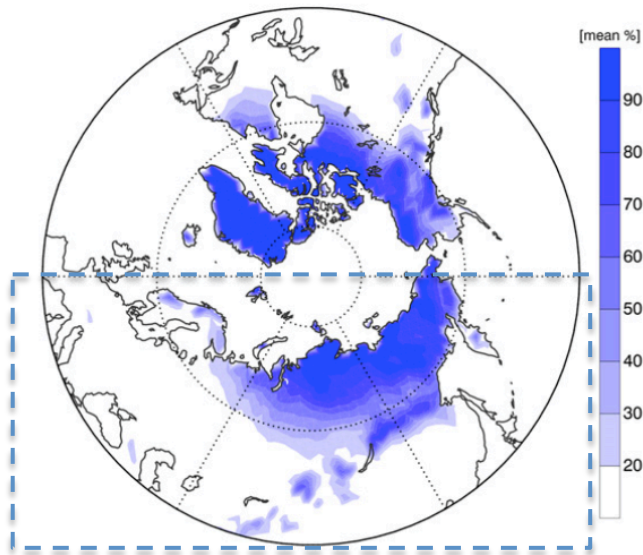


Ogawa et al., 2017, GRL

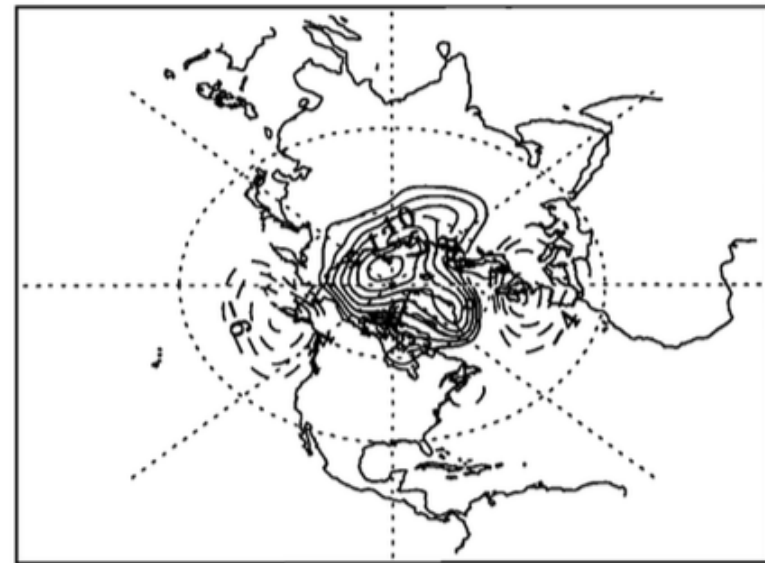
- Few members simulate a similar cooling trend over Siberia....
-> such cooling might be driven by internal climate variability

II. Interannual Eurasian snow cover and sea ice influence

Mean snow cover in October (SCE)



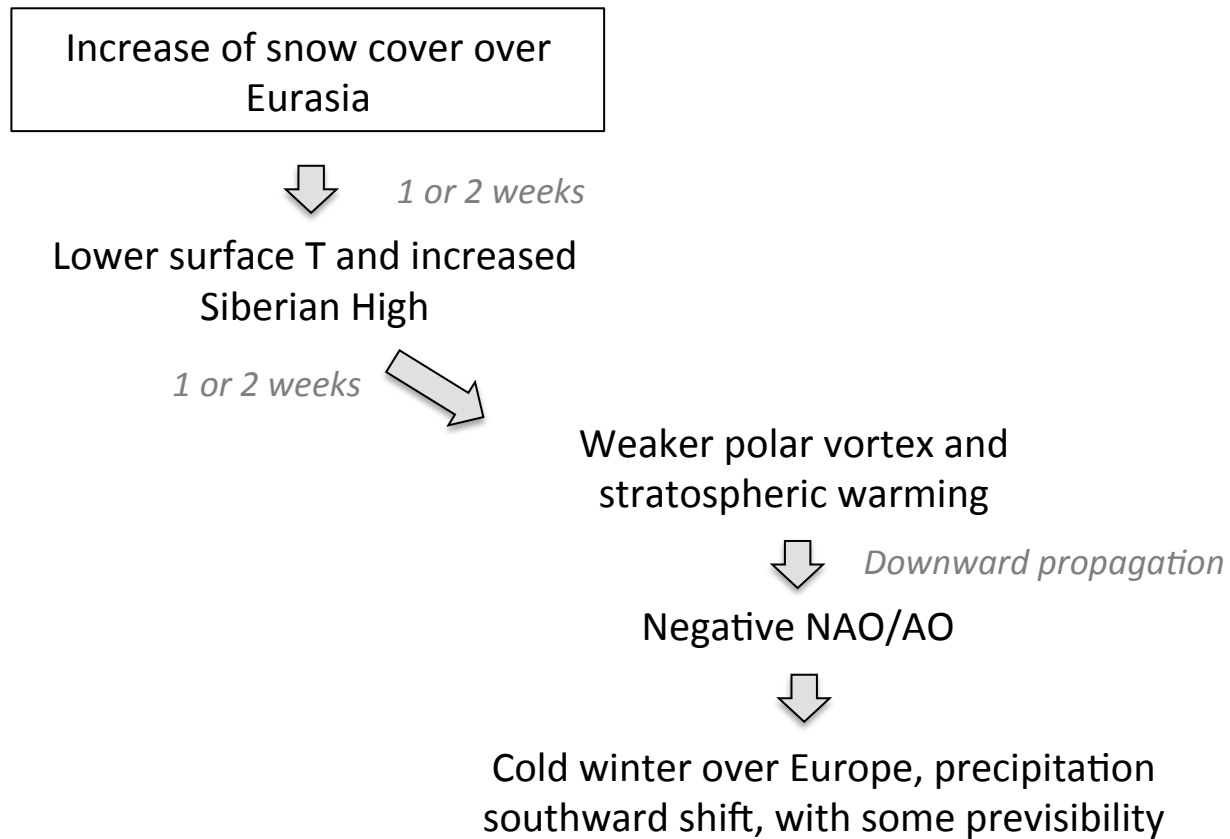
SLP DJF -> Difference high – low
SCE



Cohen and Entekabhi, 1999

- Snow cover in SON and October received most attention (Cohen and Entekabhi, 1999; Cohen et al. 2014)
- Influence confirmed by sensitivity experiments using snow cover anomalies (Allen and Zender, 2011; Orsolini et al., 2013; Orsolini et al., 2016)

Processes related to Arctic surface state influence



Data and methods

Datasets:

- Observation 1979-2014 from :
 - (1) ERA-Interim
 - (2) NOAA/NSIDC passive microwave sea ice concentration
 - (3) NOAA/NCDC snow cover (Comiso, 2012)

- Snow cover, sea ice concentration, and atmospheric variables from 12 CMIP5 ocean-atmosphere models, preindustrial simulations

Group	Model	length (year)
CCCma	CanESM2	995
CNRM-CERFACS	CNRM-CM5	850
CSIRO-QCCCE	CSIRO-Mk3-6-0	500
LASG-CESS	FGOALS-g2	700
MIROC	MIROC-ESM	630
MPI-M	MPI-ESM-LR	1000
MRI	MRI-CGCM3	500
NASA-GISS	GISS-E2-R	550
NCAR	CCSM4	600
NCC	NorESM1-ME	250
NSF-DOE-NCAR	CESM1-BGC	500
IPSL	IPSL-CM5A-LR	1000

Data and methods

- Snow cover and SLP from the 6 atmosphere-only models GREENICE simulations of 1982-2014 :
 - EXP1 : SST and SIC vary (from OI-SST)
 - EXP2 : SST clim, SIC vary (from OI-SST)

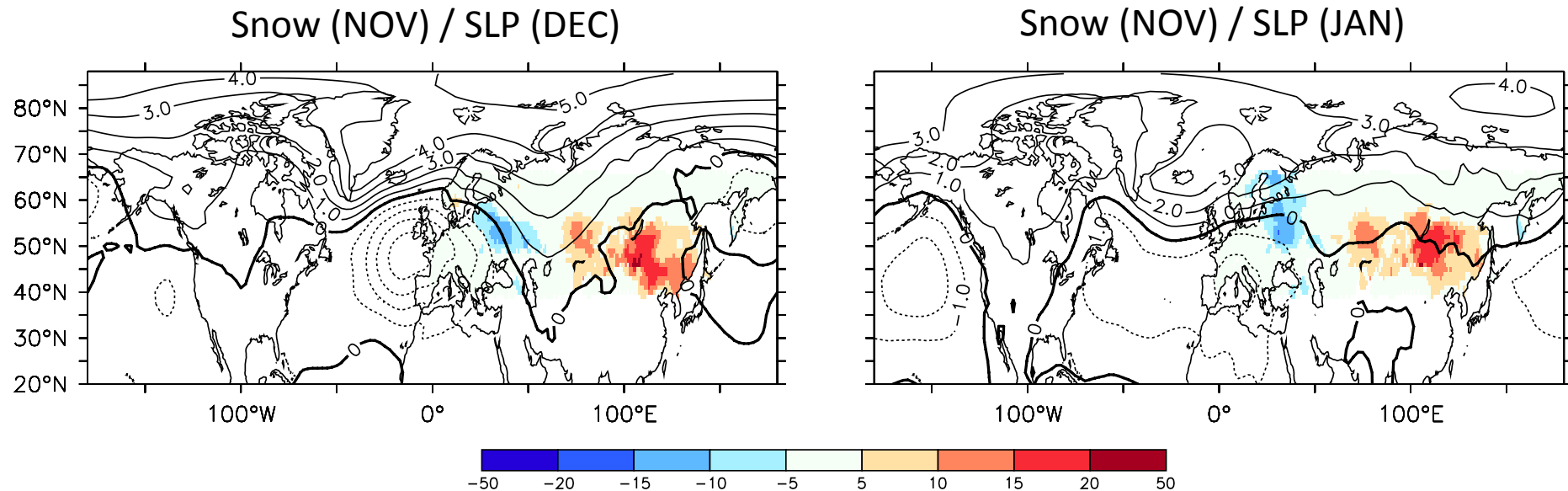
Group	Model	Number of members
SHMI	IFS	20
IAP	IAP4	10
IPSL	LMDZOR	40
UoB	CAM4	20
UoB	WACCM	20
HU	AFES3.1	30

Methods :

- A quadratic trend is removed from all data,
- Maximum Covariance Analysis (MCA) between snow cover and atmospheric sea-level pressure,
- Level of significance of R (correlation) and NSC (scaled eigen value) using Monte Carlo,
- For CMPI5 and observation, part of ENSO teleconnection removed using regression on the first PC of the Pacific ocean.

Snow influence in observations

Homogeneous snow (colors, in %) and heterogeneous SLP (contours, in hPa)

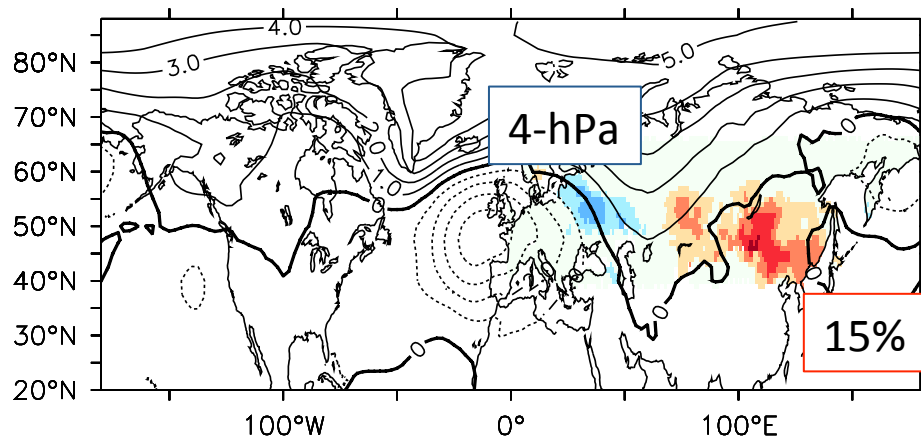


- MCA statistics only show statistical significance with p-values < 5% for Snow in November and SLP in December/January
- The snow cover pattern that influence most the AO is a dipole,

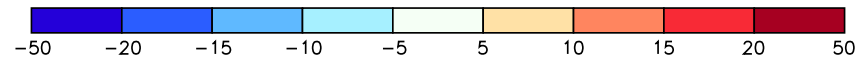
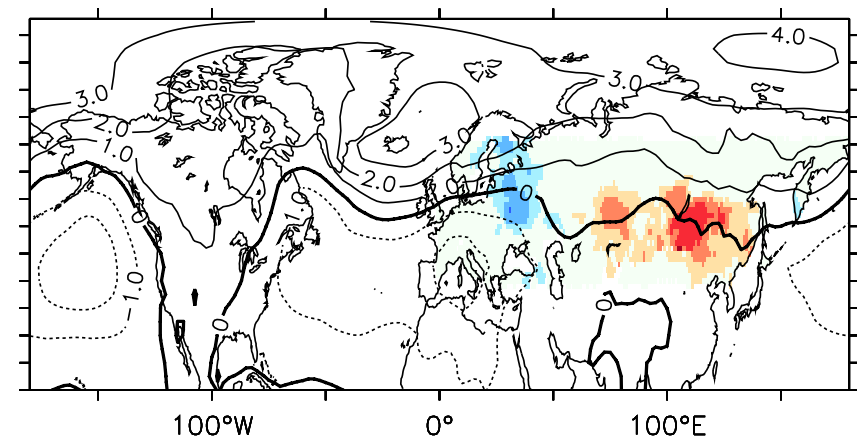
Snow influence in observations

Homogeneous snow (colors, in %) and heterogeneous SLP (contours, in hPa)

Snow (NOV) / SLP (DEC) $R=0.82$



Snow (NOV) / SLP (JAN)

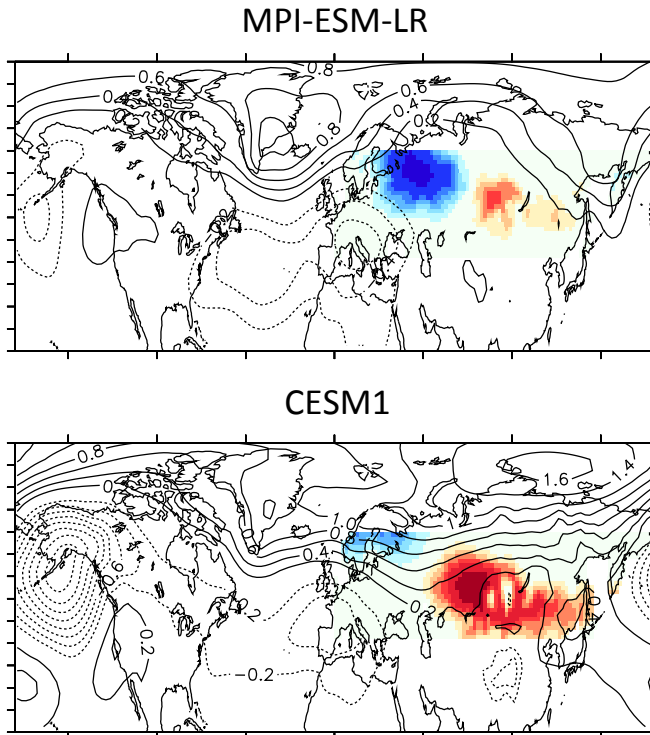
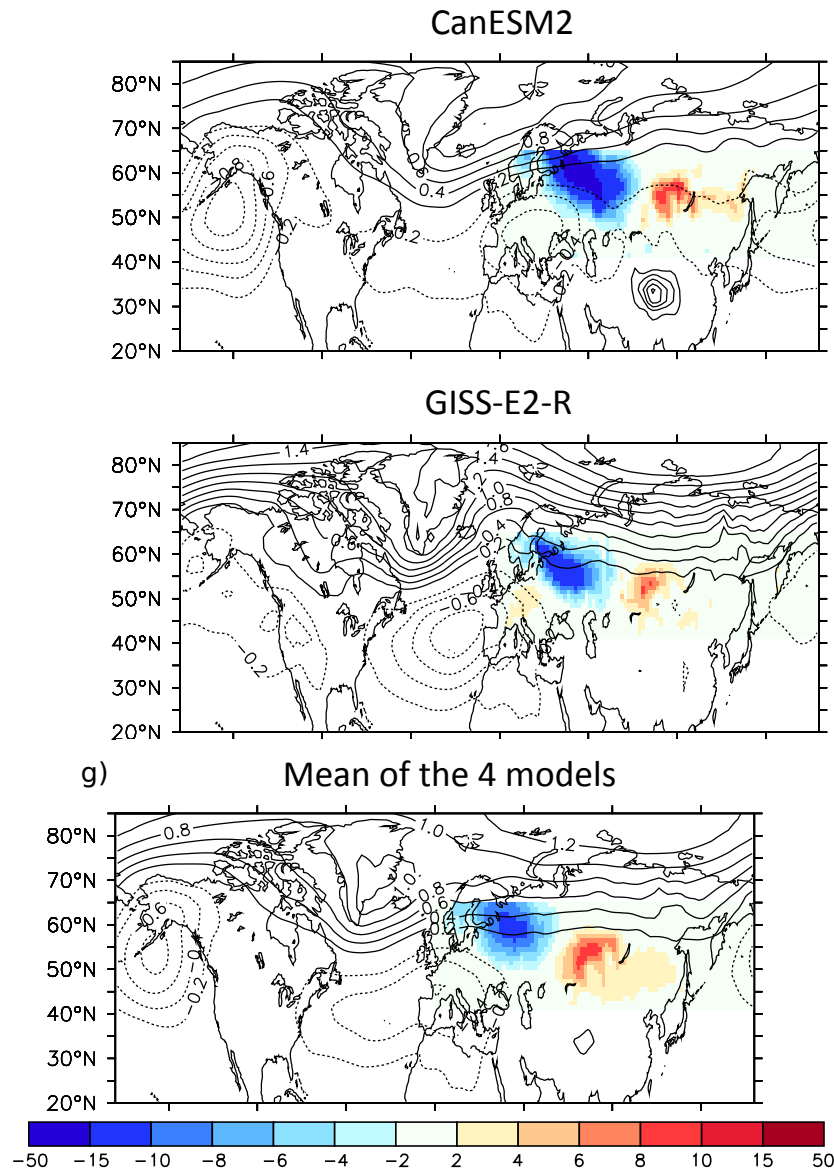


Gastineau et al., 2017, *J. Clim.*

- MCA statistics only show statistical significance with p-values $< 5\%$ for Snow in November and SLP in December/January
- The snow cover pattern that influence most the AO is a dipole,

Snow influence in CMIP5 models

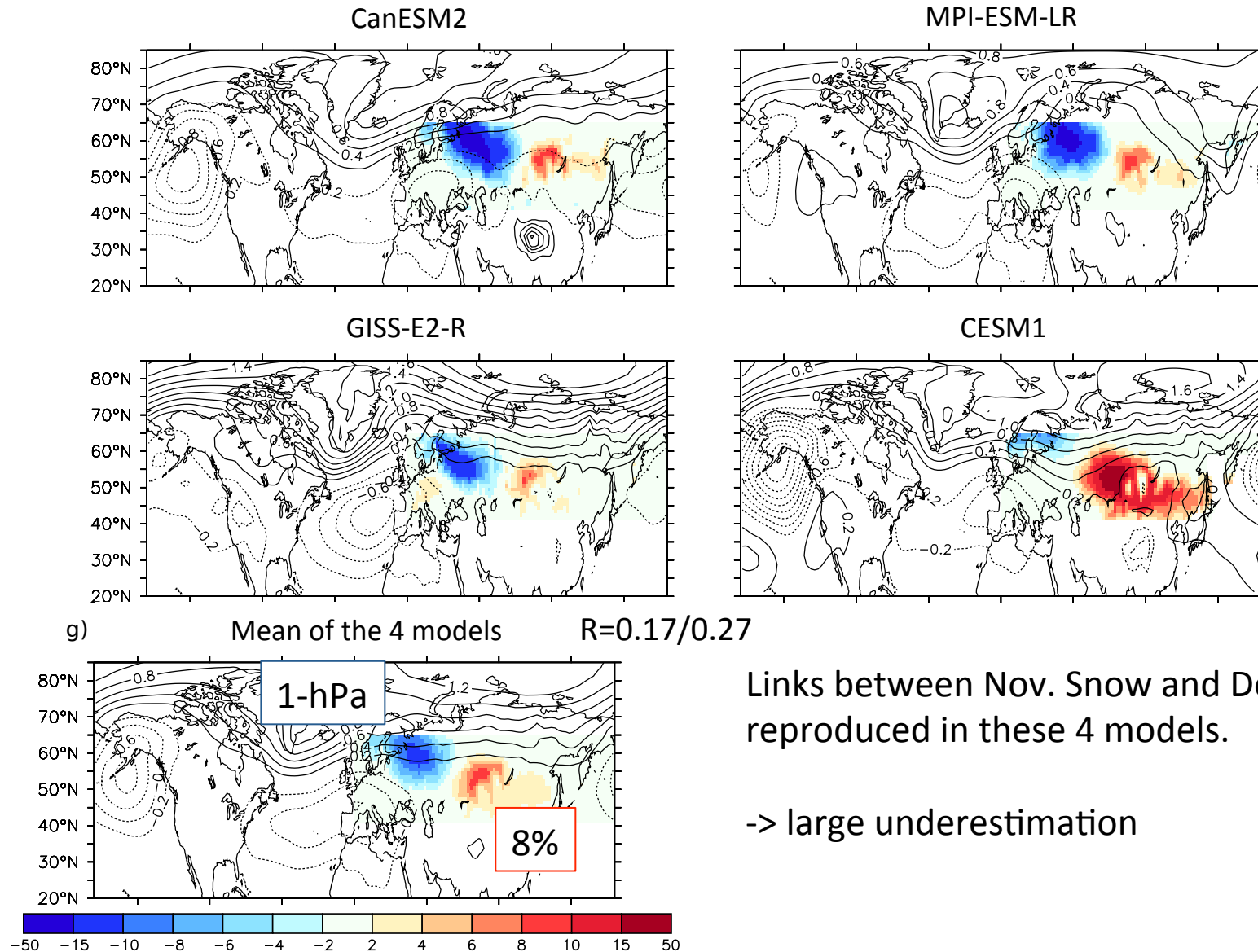
Homogeneous Nov. snow (colors, in %) and heterogeneous Dec SLP (contours, in hPa)



Links between Nov. Snow and Dec. SLP reproduced in these 4 models.

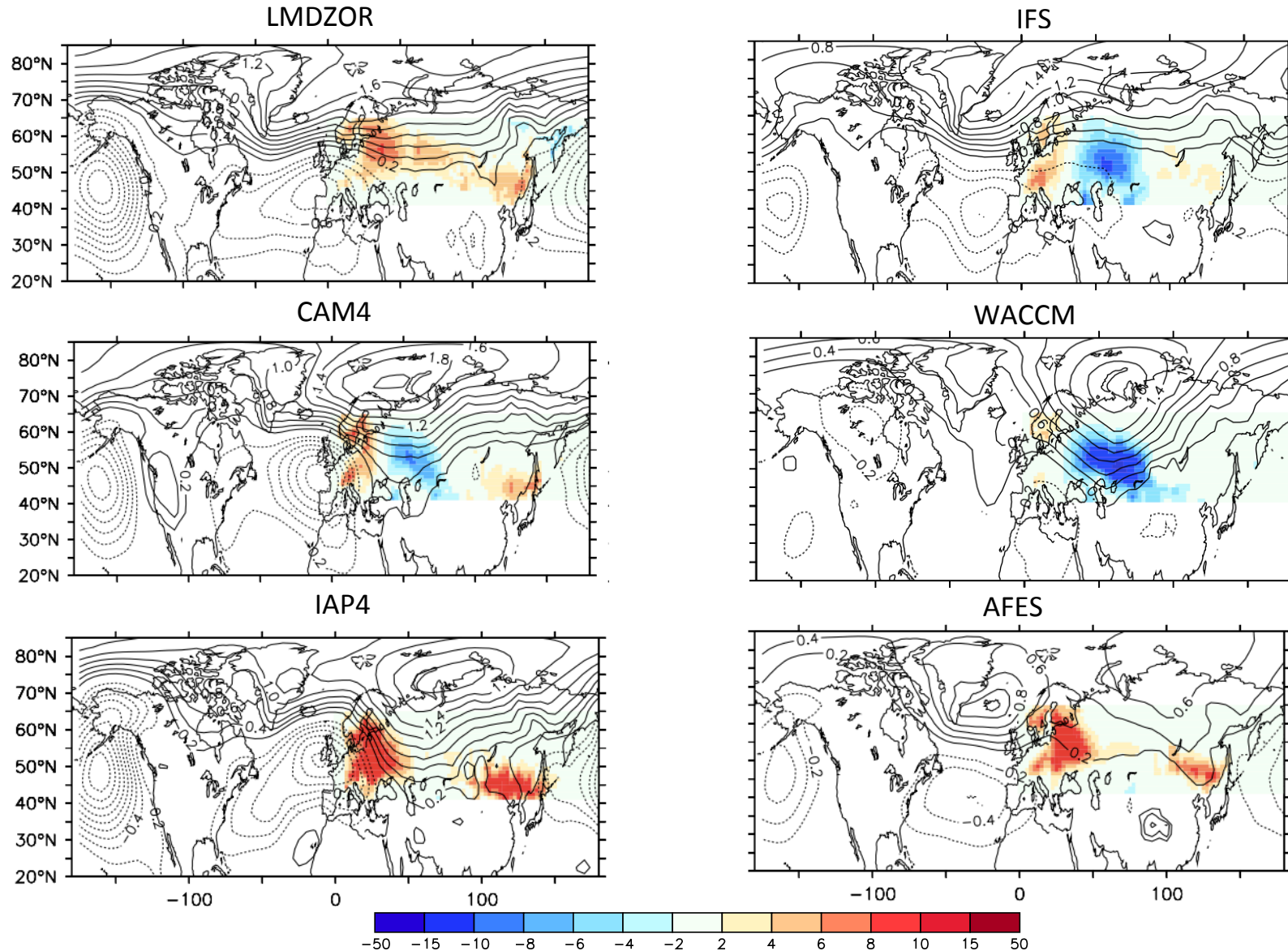
Snow influence in CMIP5 models

Homogeneous Nov. snow (colors, in %) and heterogeneous Dec SLP (contours, in hPa)



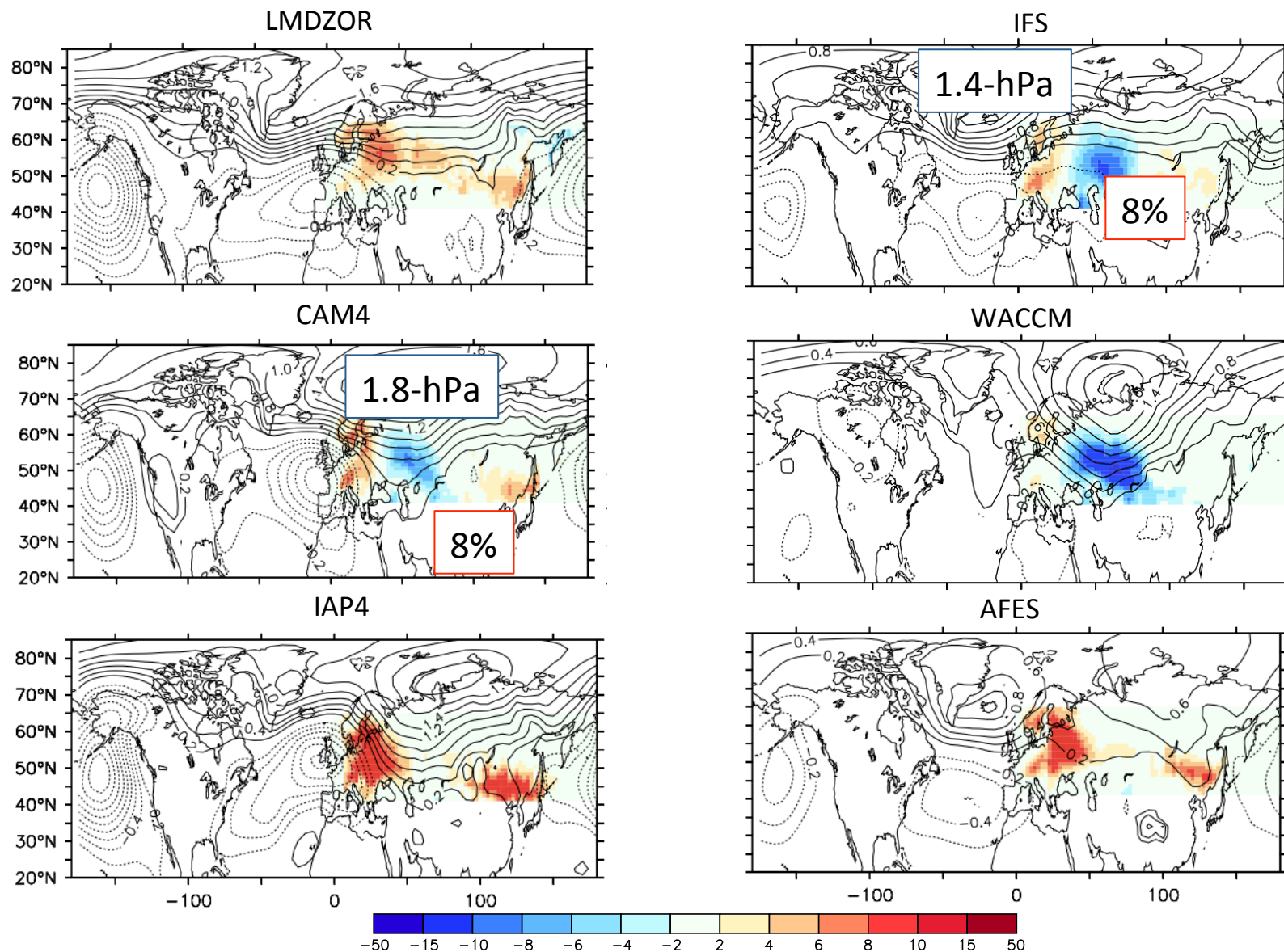
Snow influence in SST-SIC-EXP GREENICE

Homogeneous Nov. snow (colors, in %) and heterogeneous Dec SLP (contours, in hPa)

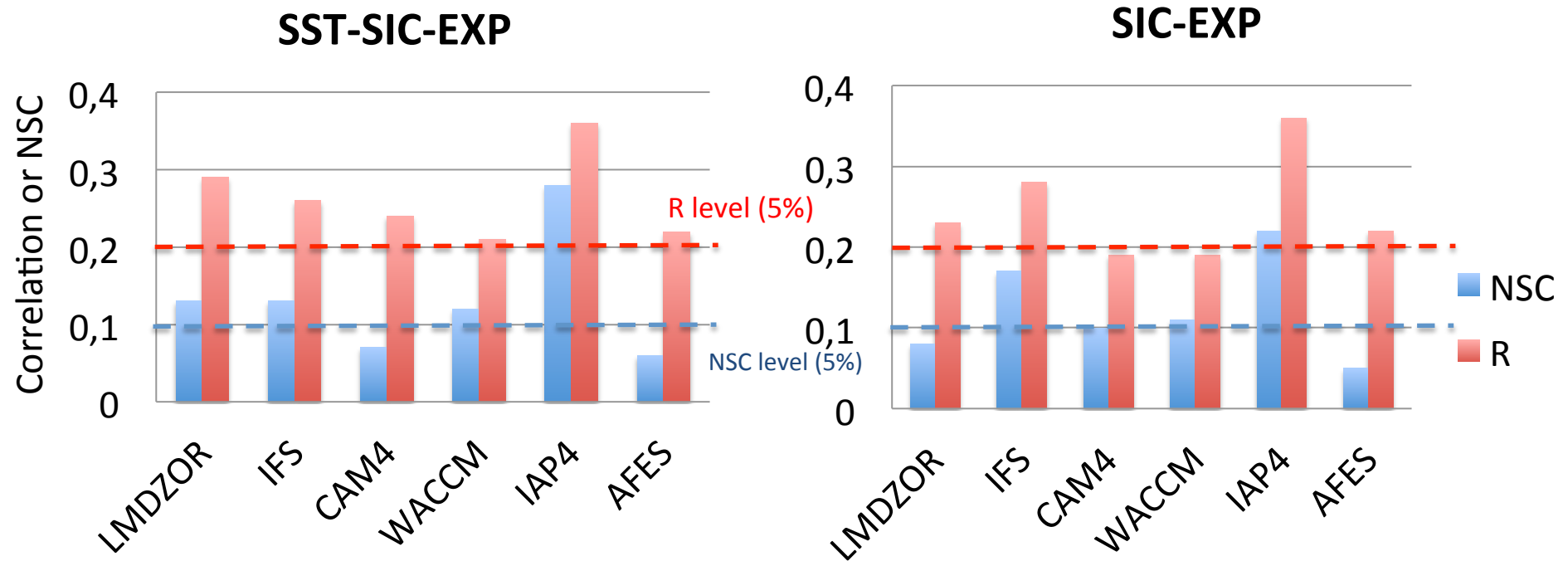


Snow influence in SST-SIC-EXP GREENICE

Homogeneous Nov. snow (colors, in %) and heterogeneous Dec SLP (contours, in hPa)



Statistics of MCA modes in GREENICE simulations



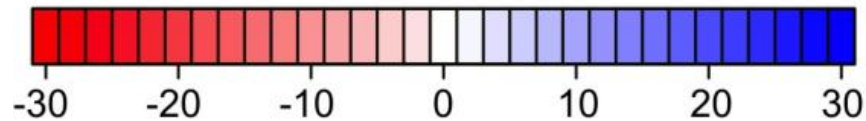
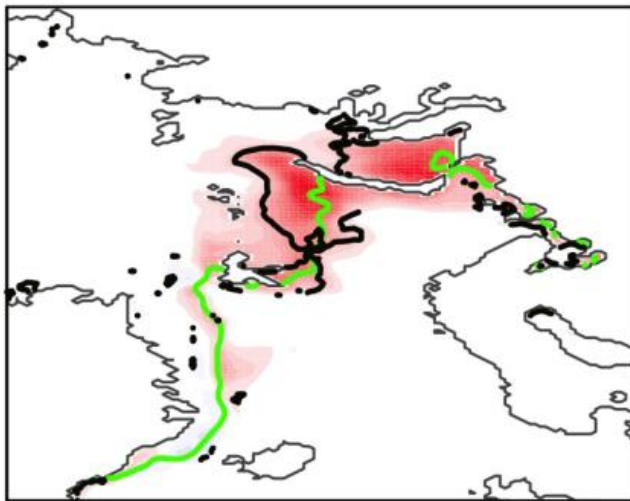
Summary :

- The November snow cover anomalies lead significant SLP anomalies in December in most models. But the snow dipole is not the dominant mode.
- SST-SIC-EXP and SIC-EXP show similar covariability patterns.

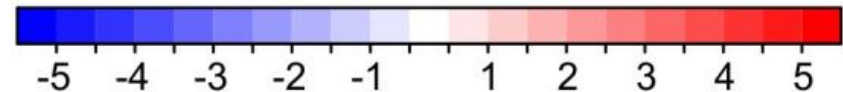
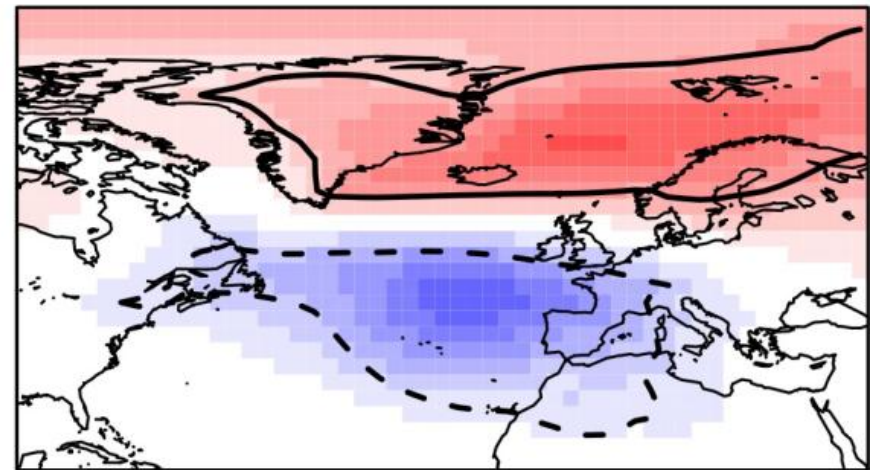
III. Interannual Sea Ice influence

- MCA between sea-ice cover in Barents-Kara Sea and SLP

Sea ice cover anomaly Nov. (%)



SLP in DJF (hPa)

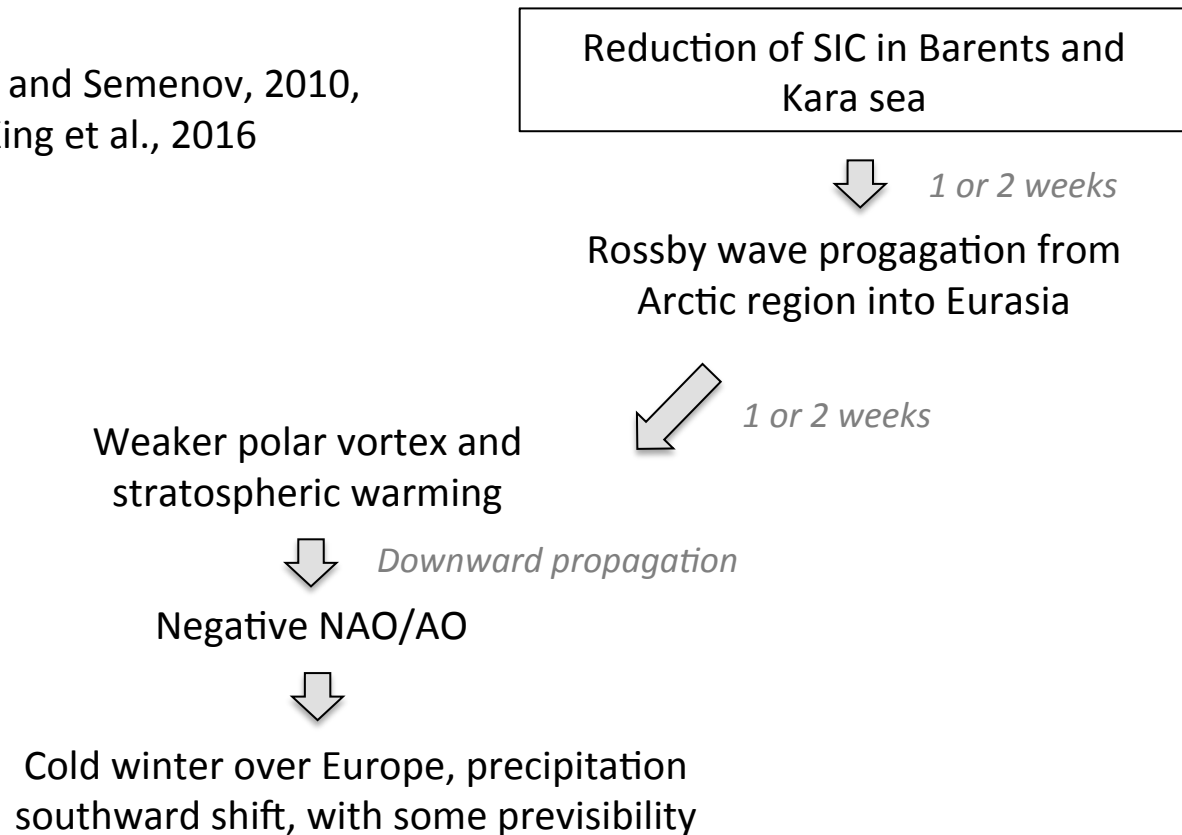


MCA mode 1 - SC = $1.02 \%^2 \text{ hPa}^2$ (3%) $R = 0.59$ (18%) SCF = 74.9% (8%)

García-Serrano et al. (2015, *J.Clim.*)

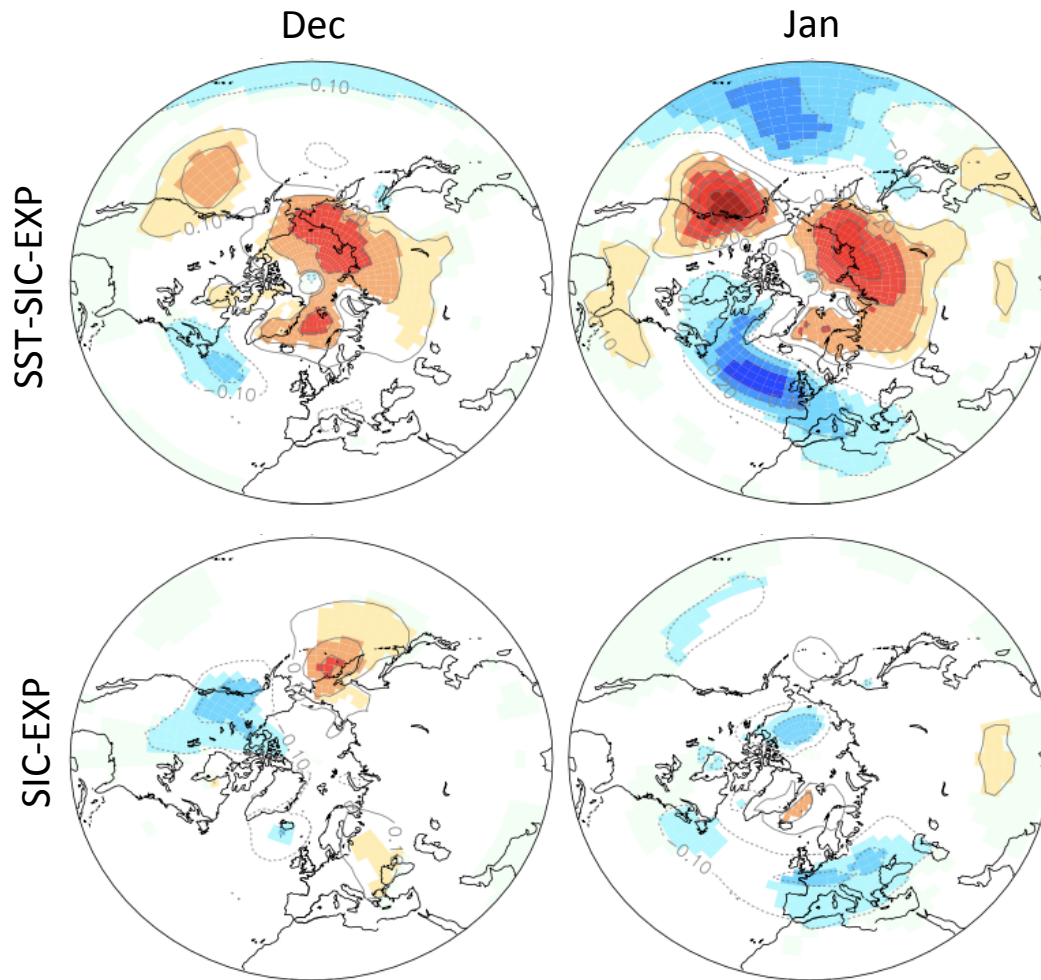
Processes related to Arctic surface state influence

Honda et al., 2009; Petoukov and Semenov, 2010,
Garcia-Serrano et al., 2015; King et al., 2016



Influence of sea ice Barents/Kara

Regression of SLP (hPa) onto SIC B/K in GREENICE



- Regression of SLP in each member, then averaged across members and models.
- Only weak impacts of SIC B/K

Conclusion

- Dipolar snow cover anomalies are found to have a large influence in November.
- Some CMIP5 and GREENICE models simulate an influence of snow similar to that observed, but it is underestimated:
 - (1) due to insufficient strato./tropos. Coupling ?
 - (2) due to poor simulation internal atmospheric variability (SCA) ?
- The links between the snow cover and the sea-ice revealed a dominant influence of snow cover. The role of snow cover needs to be investigated with sensitivity experiments.
- The impacts of the polar warming amplification on weather extreme remains controversial... Needs to be further studied.

Perspective

Blue-Action H2020 project : coordinated atmospheric experiments with 8 models.

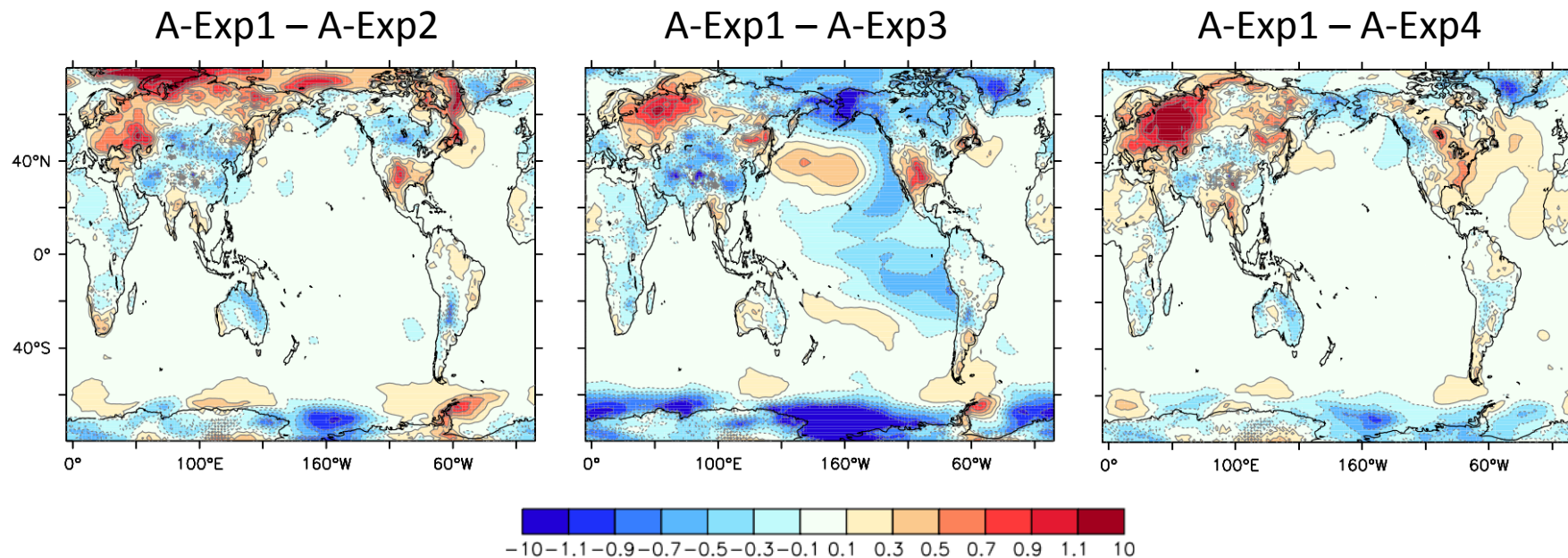
EXP1 : vary SST, vary SIC

EXP3 : vary SST with IPV removed, vary SIC

EXP2 : vary SST, clim SIC

EXP4 : vary SST with AMV removed, vary SIC

Difference T2m (in K) 1998-2014 minus 1980-1994



Proof of concept - > experimental protocol allows to reveal the separated effects of sea ice, IPV and AMV onto the Arctic region.



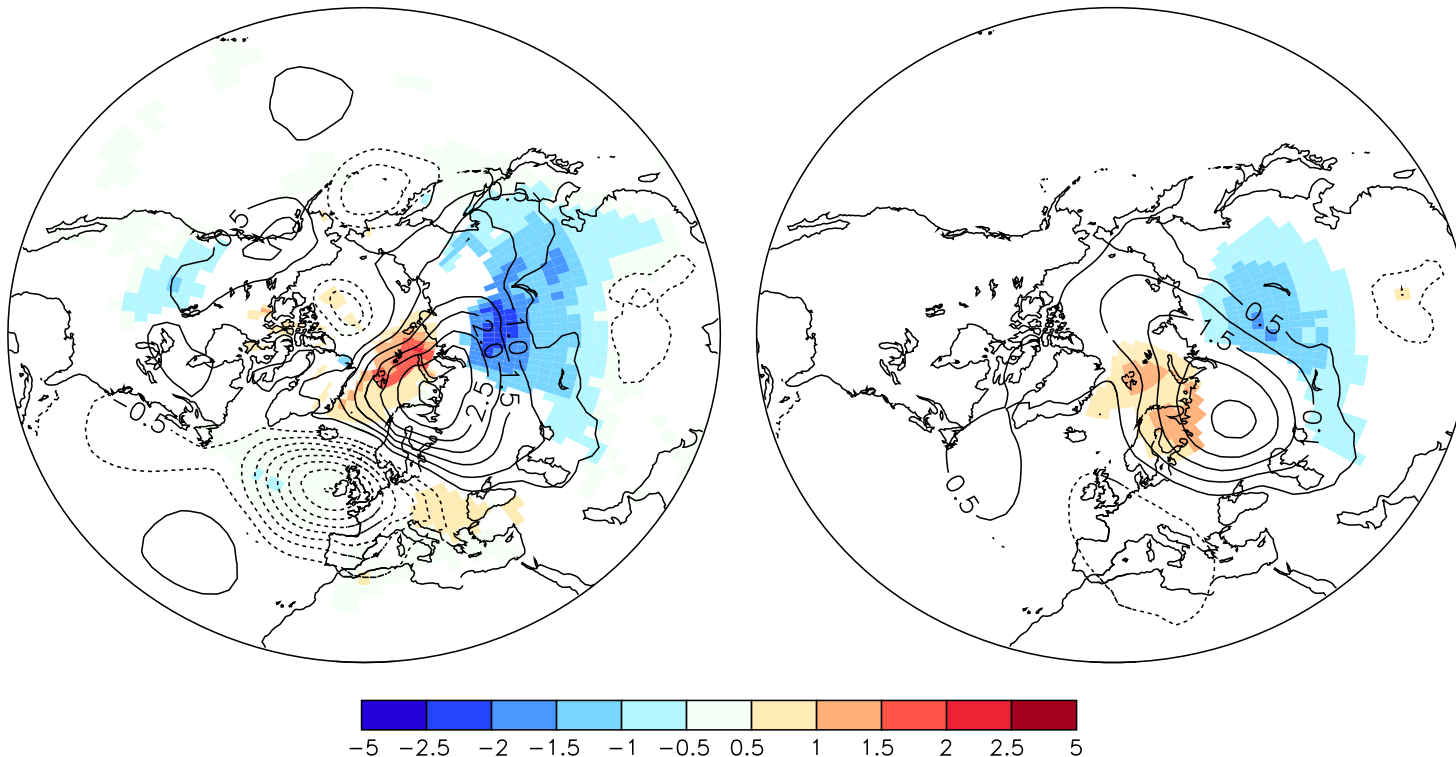
The research leading to these results has received funding from the H2020 project Blue-Action, under grant agreement n.727852. www.blue-action.eu/

Origin of snow dipolar anomalies

Air temperature at 2m (in K, color) and SLP (in hPa, contour) in Nov., regression onto MCA snow time series

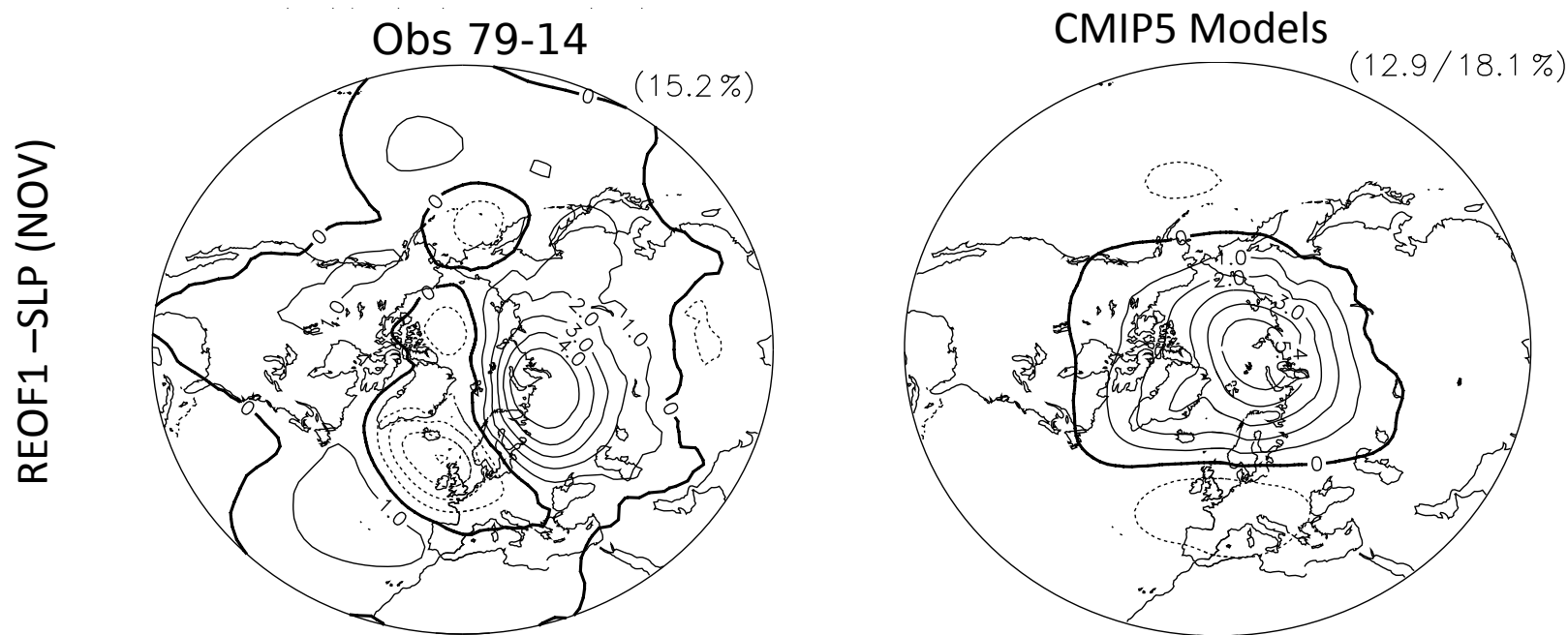
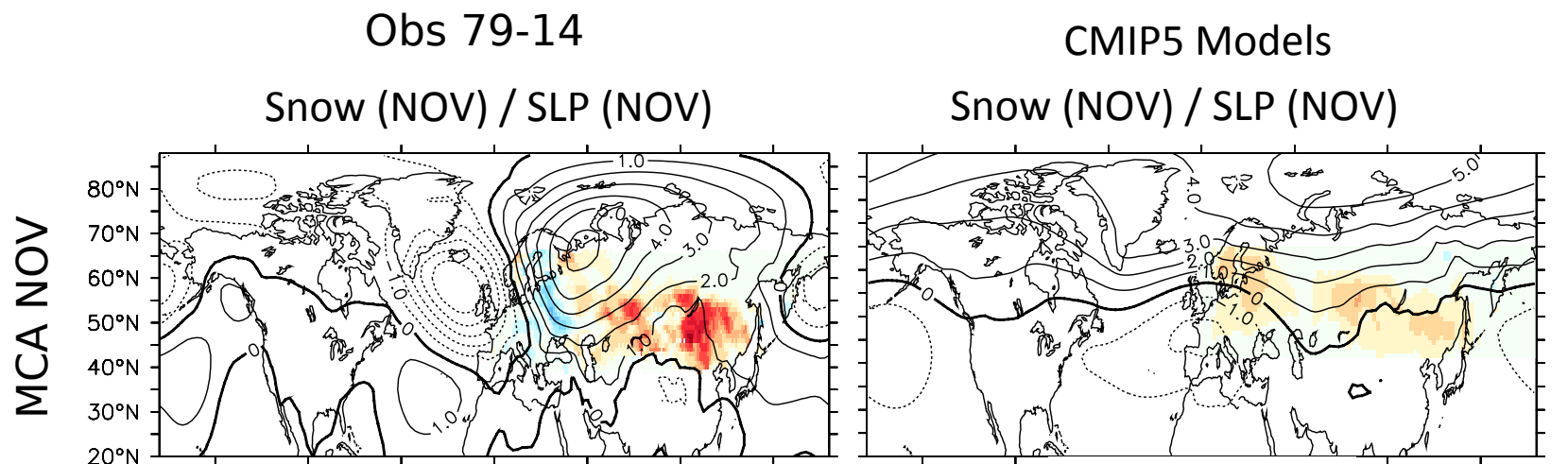
Obs. 79-14

CMIP5 Models



Atmospheric pattern :
- Scandinavian Pattern (SCA) – Bueh and Nakamura (2007),
- Eurasian pattern type 1 – Barnston and Livesey (1987),
- Russian pattern – Smoliak and Wallace (2015)

Atmospheric forcing of snow cover

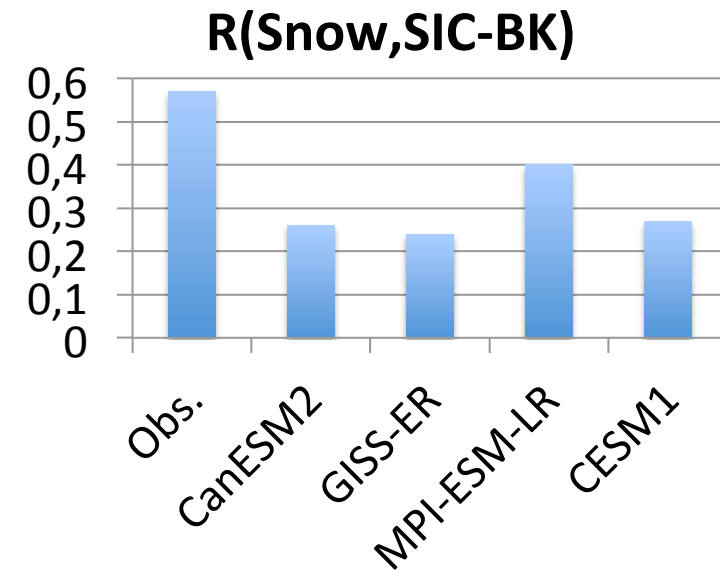
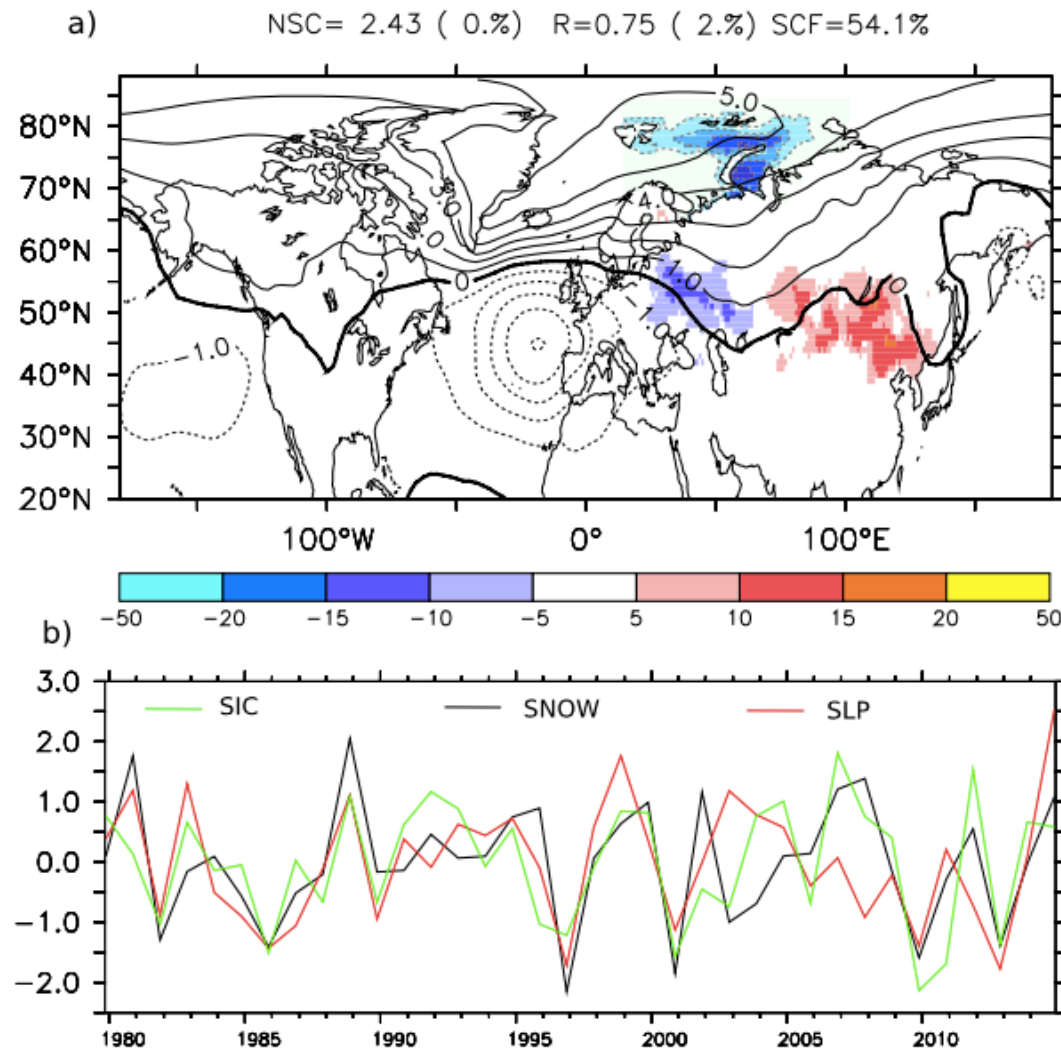


SCA pattern key for snow forcing

AO influence dominates in models

Analysis with (Snow+SIC) Nov/SLP Dec

Homogeneous Nov. Snow + SIC (colors, in %) and heterogeneous Dec SLP (contours, in hPa)

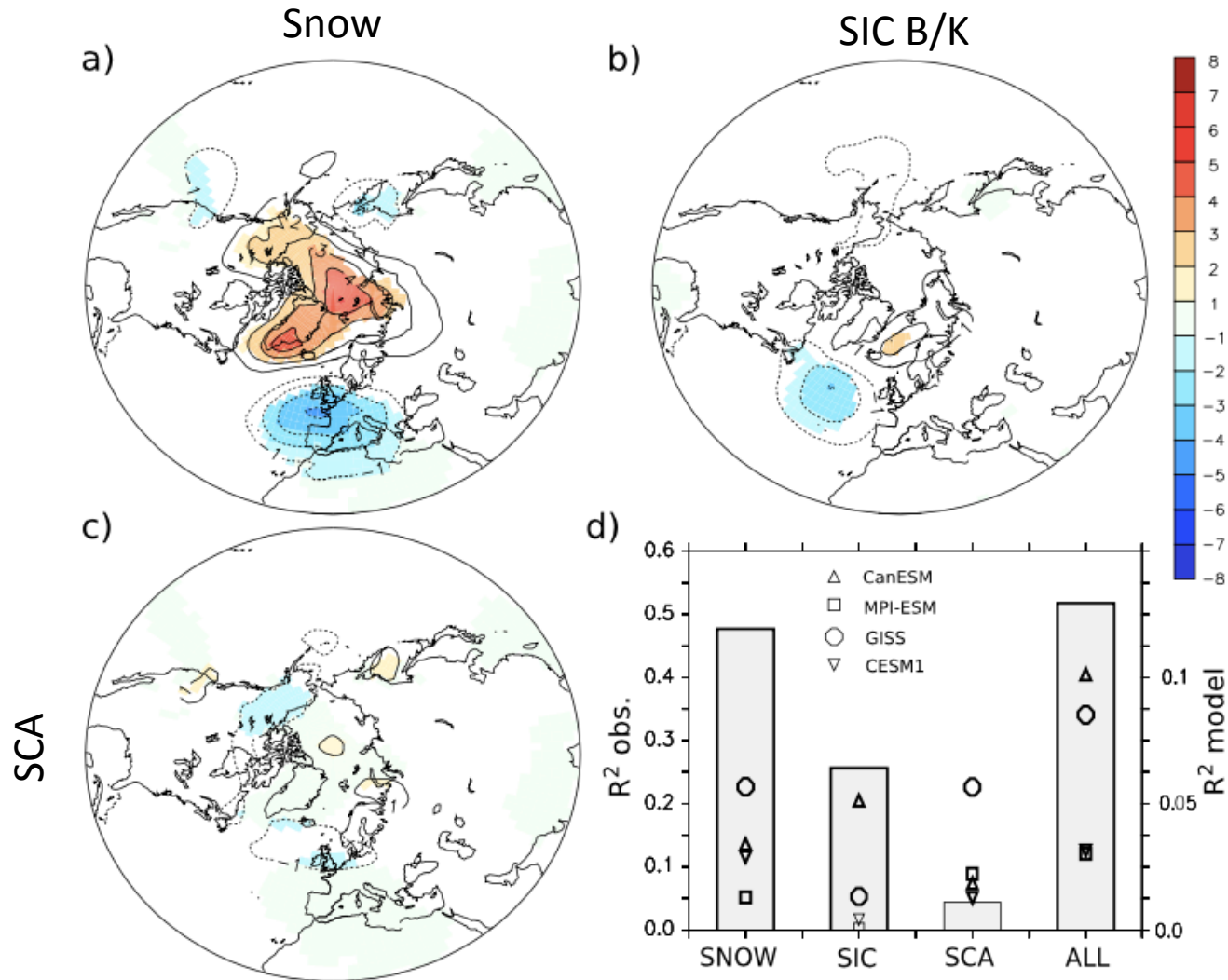


Conclusion : large association between snow and sea-ice that is underestimated in CMIP5 models

-> expected from SCA forcing

Regression analysis

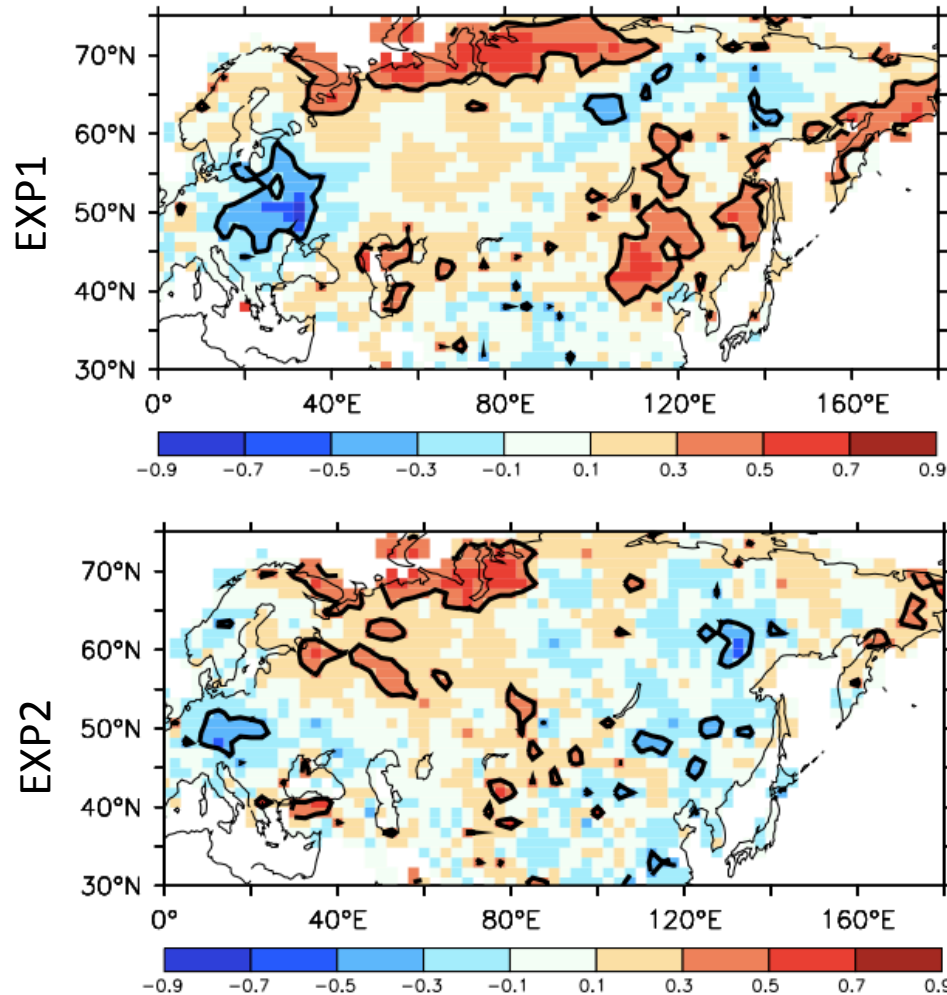
$$\text{Model : } \alpha (\text{Snow_Dipole}) + \beta (\text{SIC_BK}) + \gamma (\text{SCA}) = \text{SLP}$$



- Both in observation and the selected CMIP5 models snow is dominant
- SCA does explain a lot of variance in models

Influence of SIC and SST onto continental snow cover

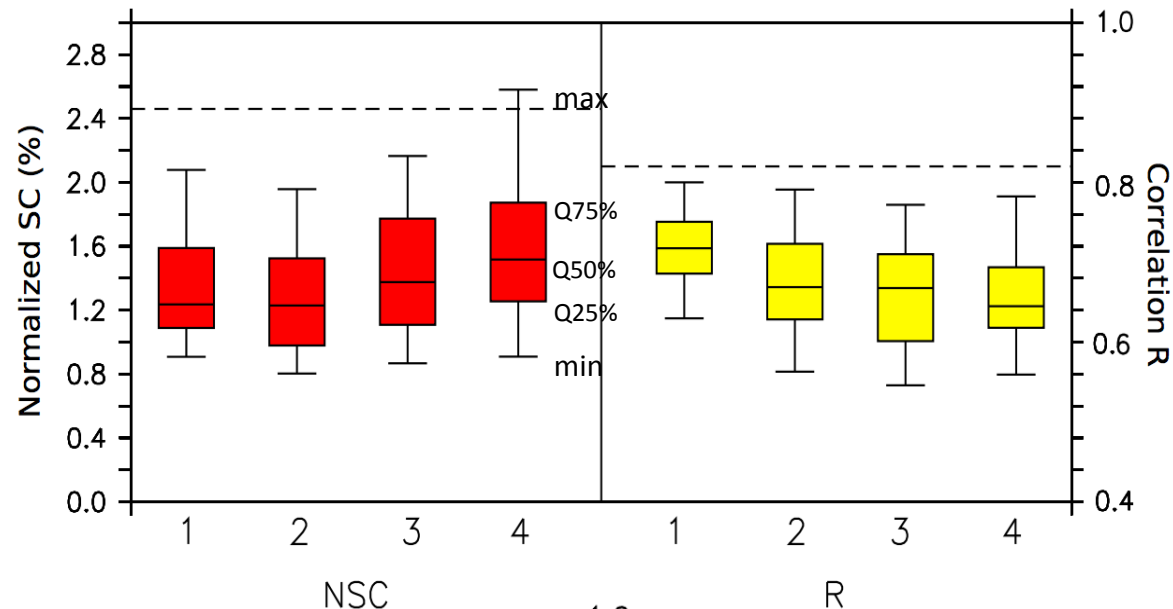
Correlation snow cover OBS vs GREENICE
Multi-model Mean



The correlation between model and observed snow cover show :

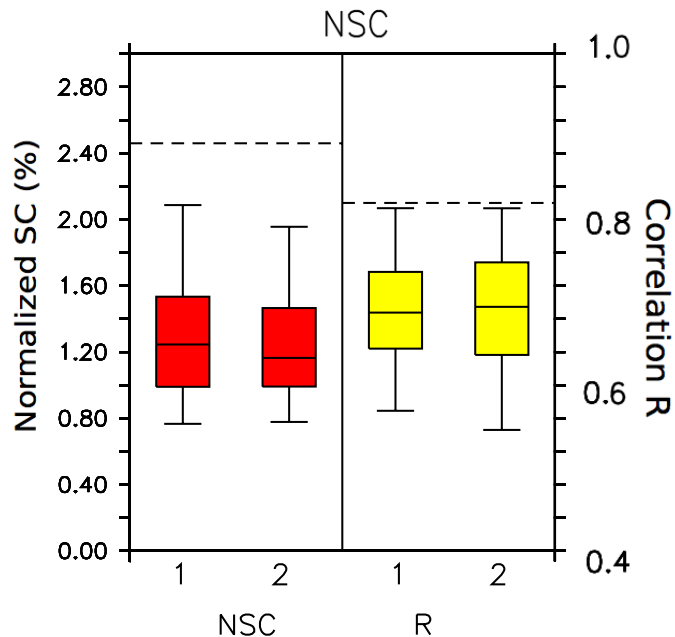
- Influence of SST anomalies onto snow cover large over eastern Siberia and Pacific sector.
- Influence of SIC anomalies onto snow cover limited to the surrounding of Barents and Kara Seas.

Internal atmospheric variability?



The CMIP5 control runs were divided into 36-yr periods.

Model :
 1. CanESM2
 2. MPI-ESM
 3. GISS-E2-R
 4. CESM1



Same analysis for all GREENICE simulations:

Ensemble :
 1. EXP1
 2. EXP2

Summary : internal atmospheric variability cannot explain the underestimation of R and NSC