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EXCELENCIA SEVERO OCHOA

Arctic Climate Spatio-temporal Modes of Variability as Sources of Predictability

Juan C. Acosta Navarro, Alasdair Hunter, Virginie Guemas, Pablo Ortega, Javier García-Serrano, Etienne Tourigny, Rubén Cruz, Francisco Doblas-Reyes

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Aims

- Apply a general method to study **interannual modes** of Arctic sea ice variability.
- Identify **sources of predictability** for Arctic sea ice.
- Provide a **framework** to evaluate the capacity of a given model to forecast Arctic sea ice in subseasonal to decadal scales.
- Show an example of how sea ice variability may affect mid-latitude climatic events.

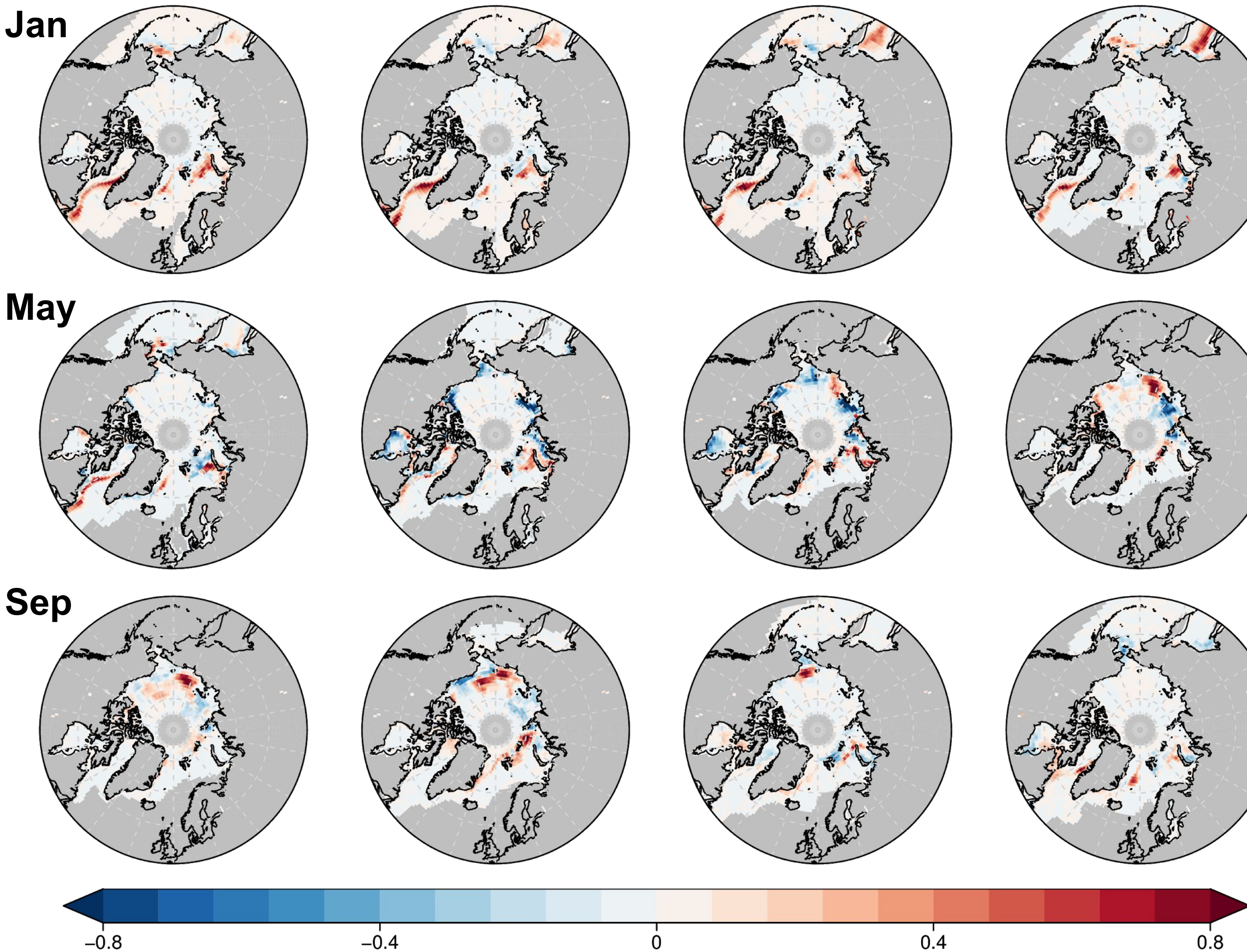
Motivation: Beyond Sea Ice Extent

- Pan-Arctic sea ice extent is an **important Arctic climate metric**, but has a limited **applicability** as a forecast product.

- Ability to predict the **spatial variability** can have several **practical** applications:
  - Low SIC autumn **Barents-Kara** ---> possible extreme **cold events in winter** in E. Asia (Kug et al., 2016, Tang et al. 2013).

  - Valuable information for the **shipping industry**:
    e.g: https://blogs.helmholtz.de/polarpredictionmatters.

Monthly SIC variance multiplied by persistence (detrended series)



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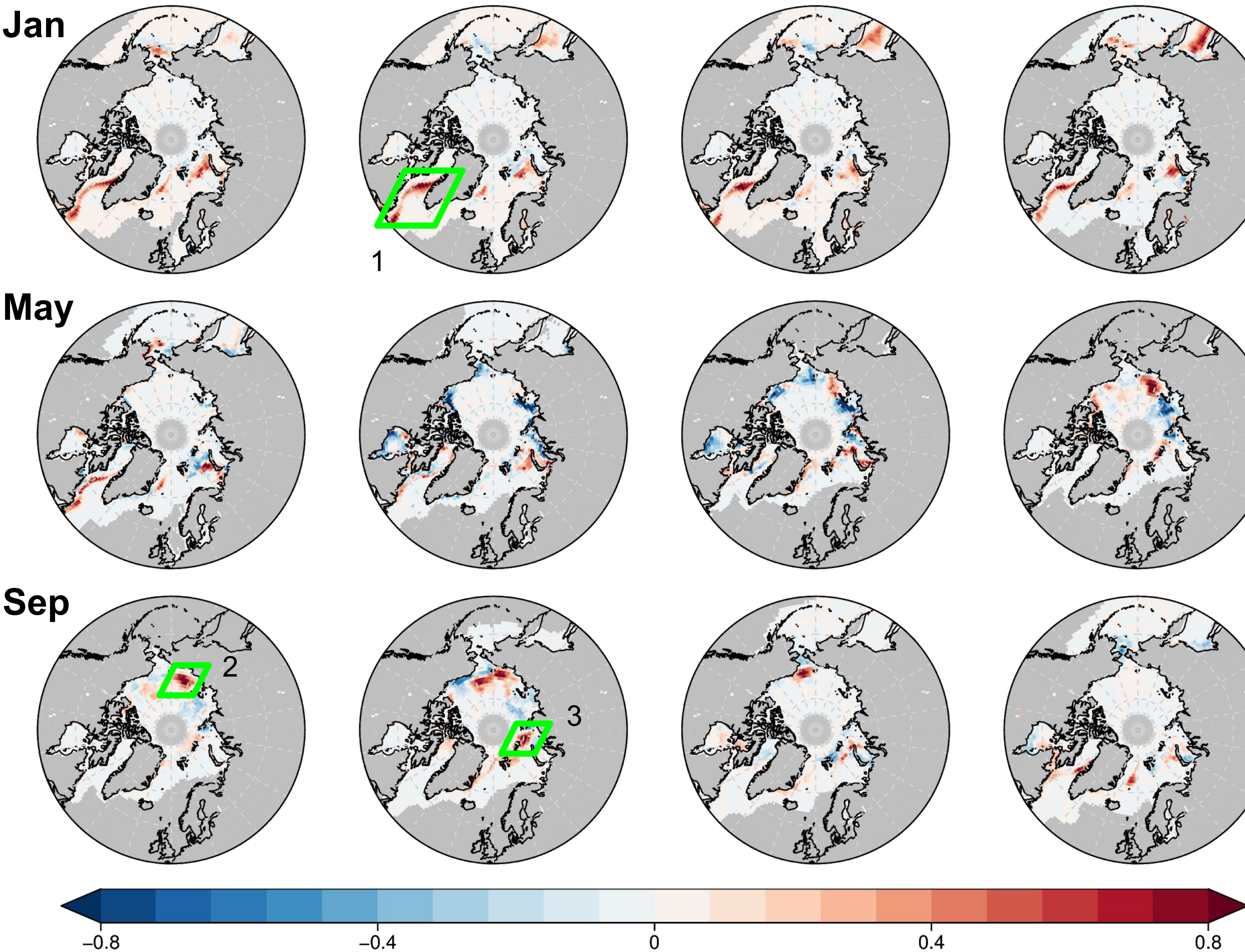


Methods part 1

Data: **38 years** (1979-2016) of continuous observations of monthly **Sea Ice Concentration** (SIC) from NSIDC & monthly North Atlantic Oscillation Index (**NAOI**) from NCEP-NOAA (http://www.cpc.ncep.noaa.gov/) and SLP from ERA-Interim.

Steps performed on the time series at each gridbox:

1. **Monthly anomalies** calculated by subtracting the climatological seasonal cycle.

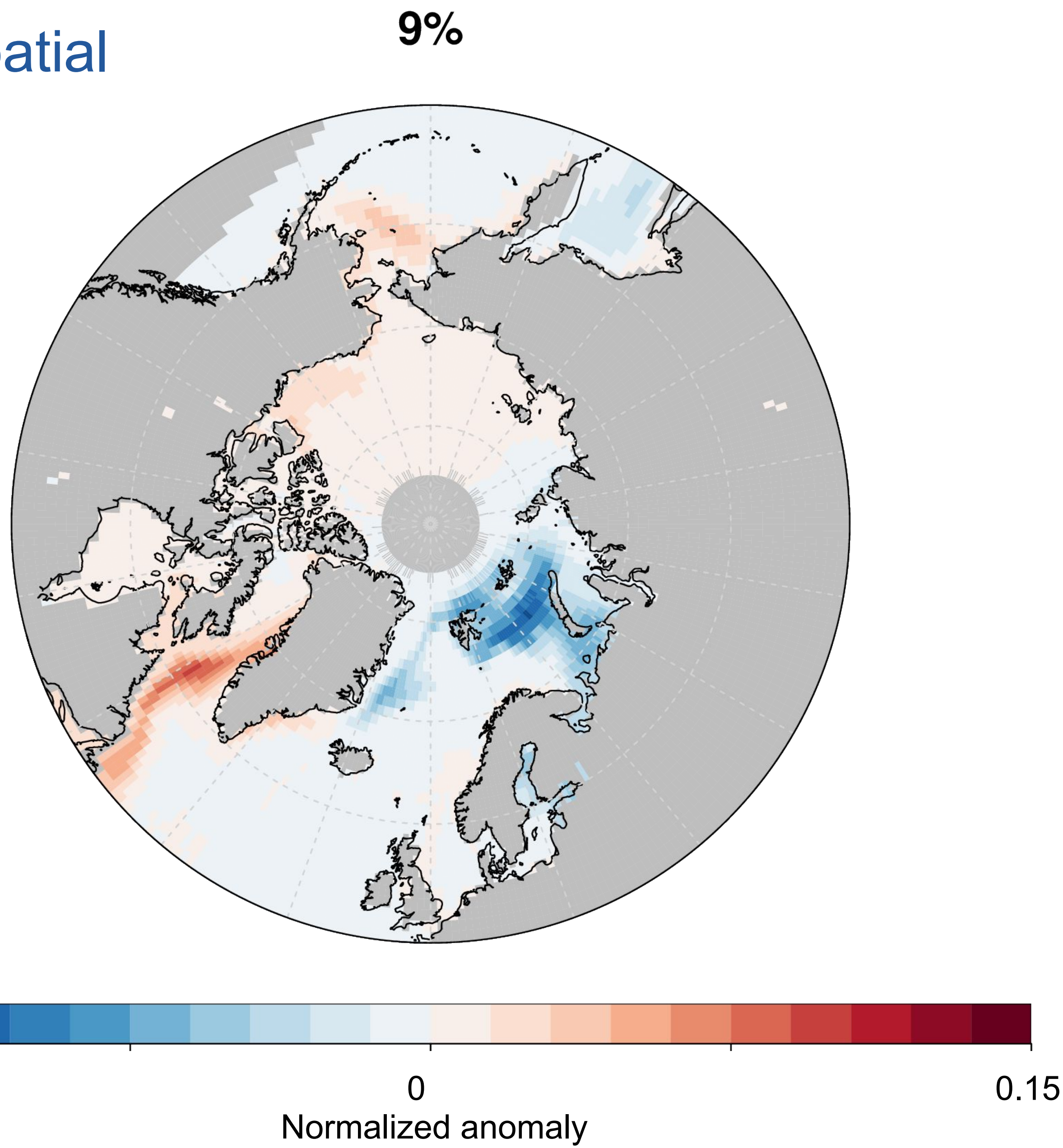
2. Detrending of series using **quadratic polynomial** fitting.

3. Area-weighted Empirical Orthogonal Functions (**EOFs**), **top twelve modes** calculated using the R package s2dverification (Manubens et al. 2018).

Associated **Principal Component** (PC) time series.

Dominant sea ice mode

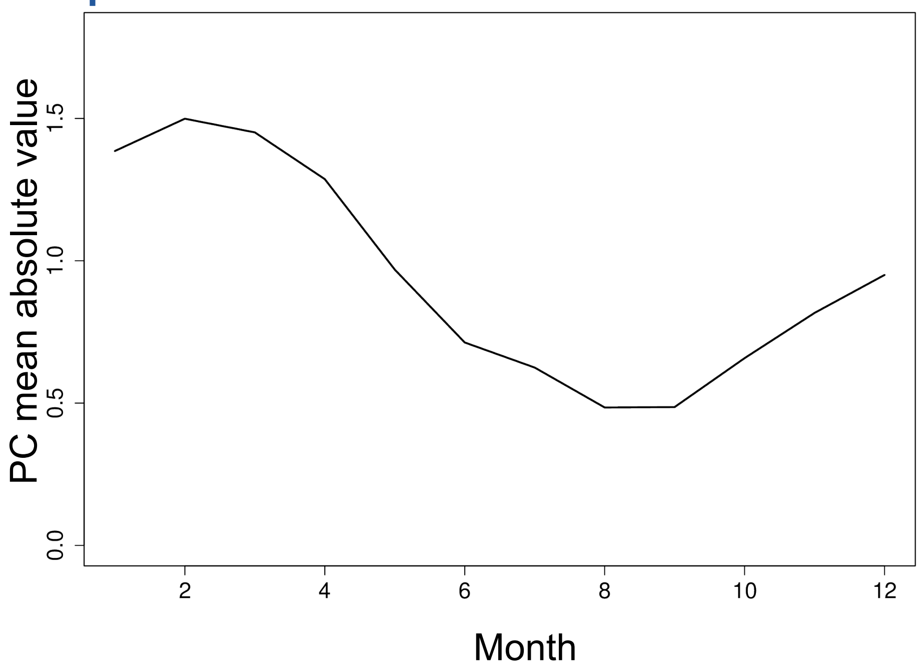
First SIC mode: spatial pattern

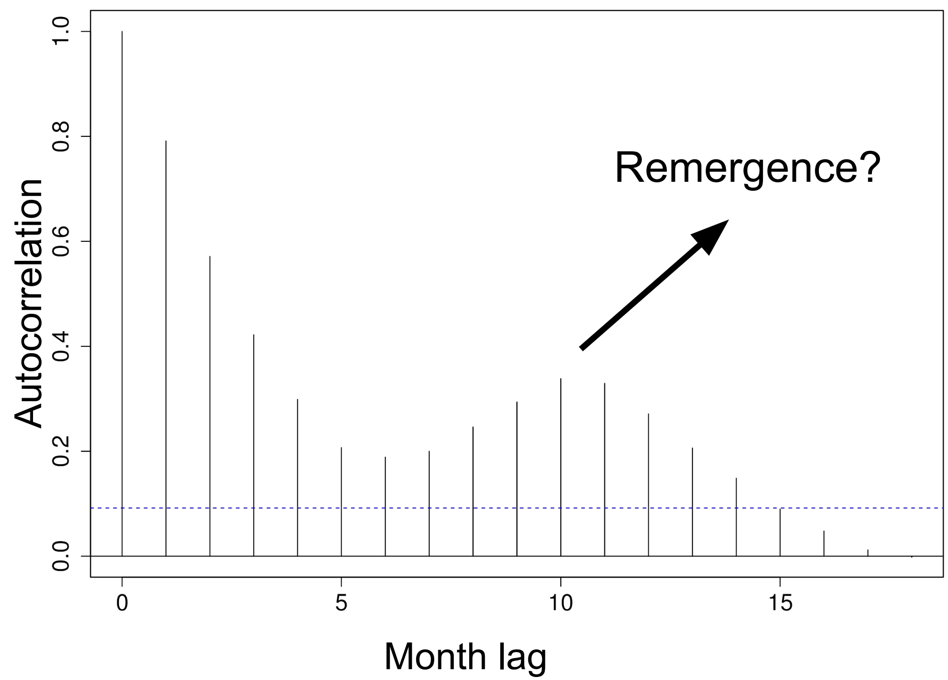


See e.g.: Deser et al. 2000-2004, 2007

Dominant sea ice mode

First SIC mode: seasonality & persistence

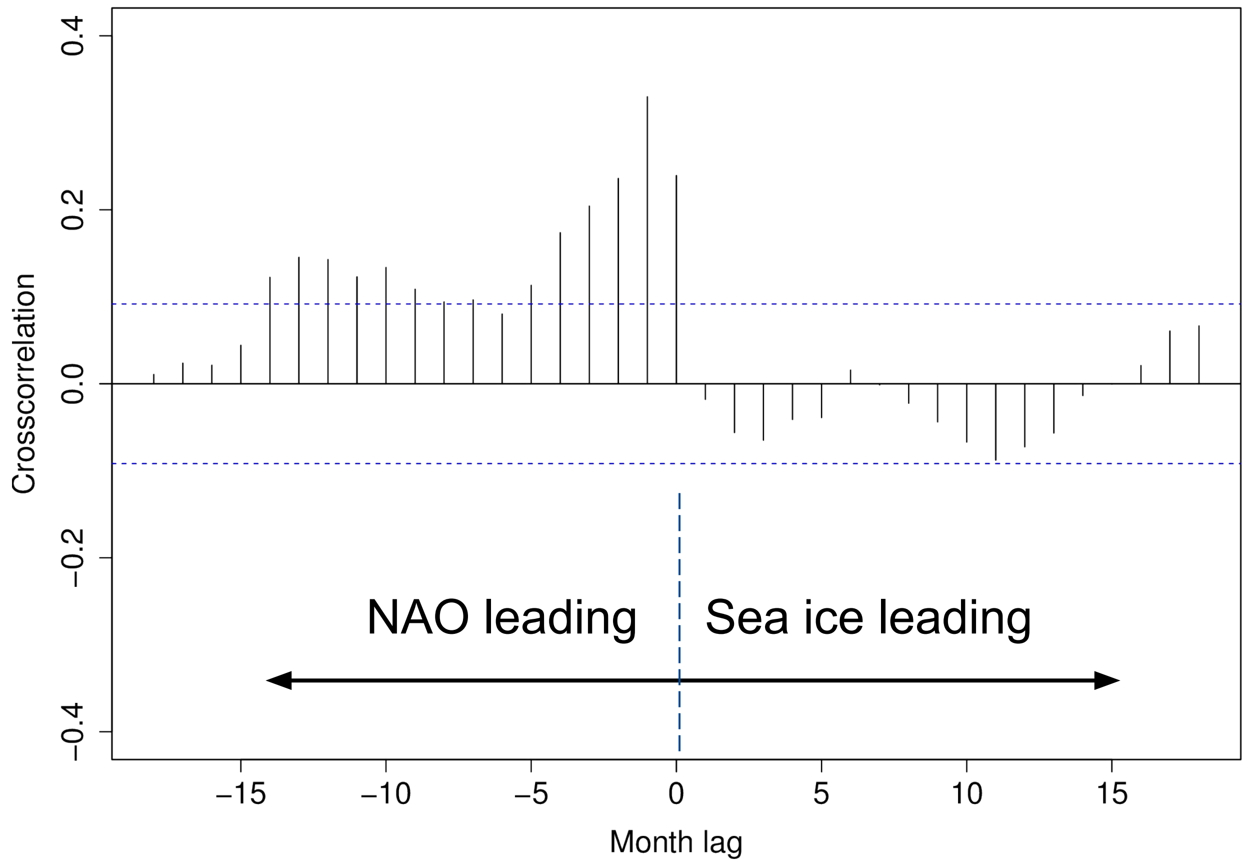




- Typical mode of variability during winter (Max. in Feb.).
- Persistency decays (~4-5 months).
- Possible reemergence in the following winter.

NAO leads dominant sea ice mode

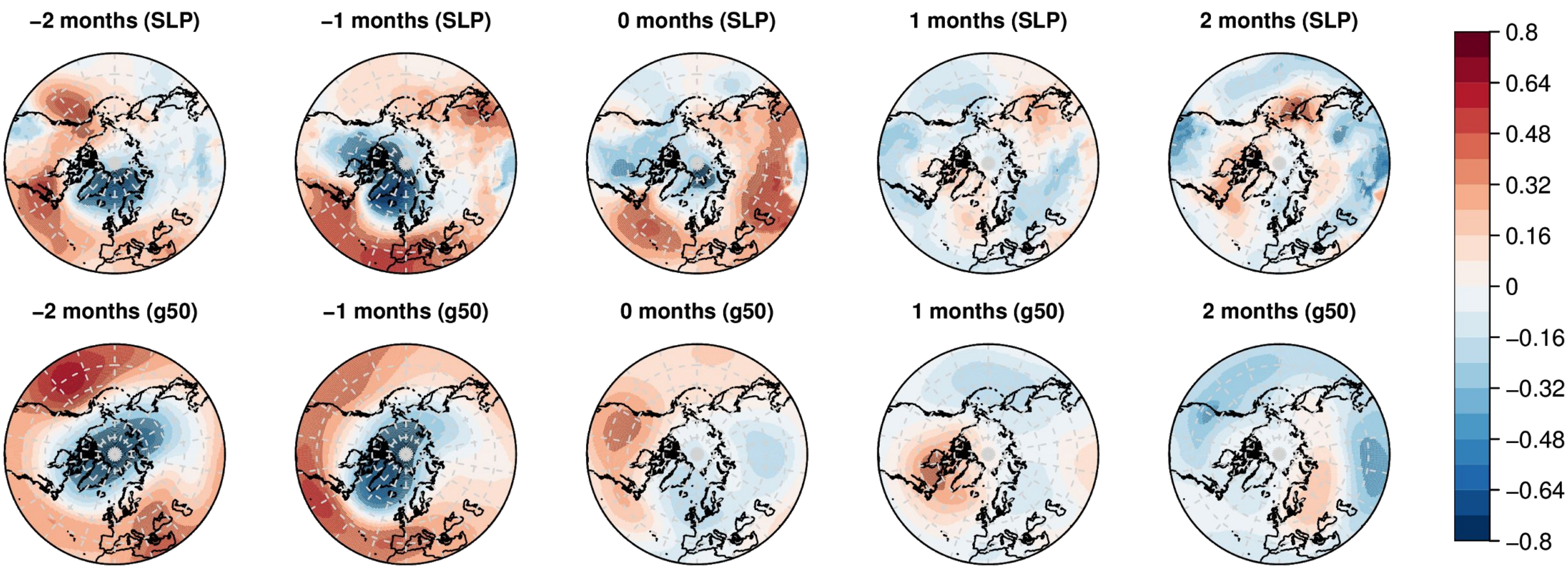
Crosscorrelation between North Atlantic Oscillation Index (NAOI) & First SIC mode



- NAOI **precedes** 1st PC of sea ice concentration.
- Maximum correlation (r = 0.33) with **one month** lag.

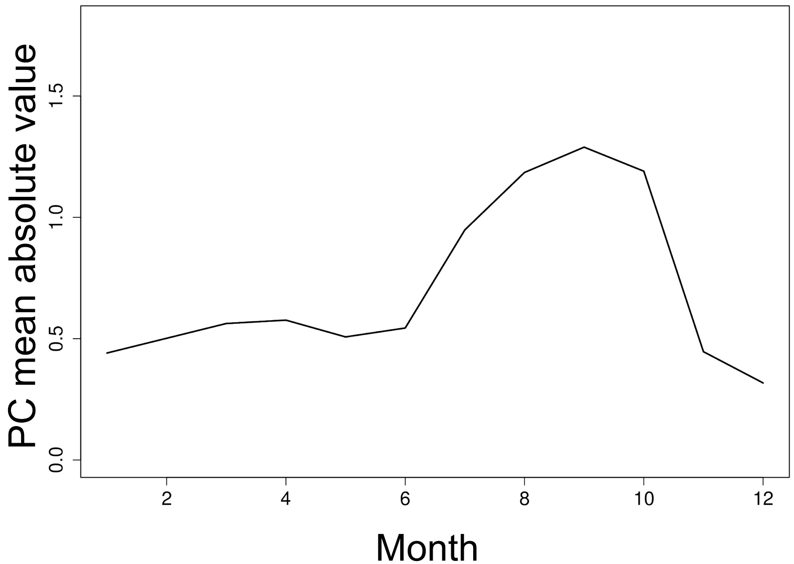
NAO leads dominant sea ice mode

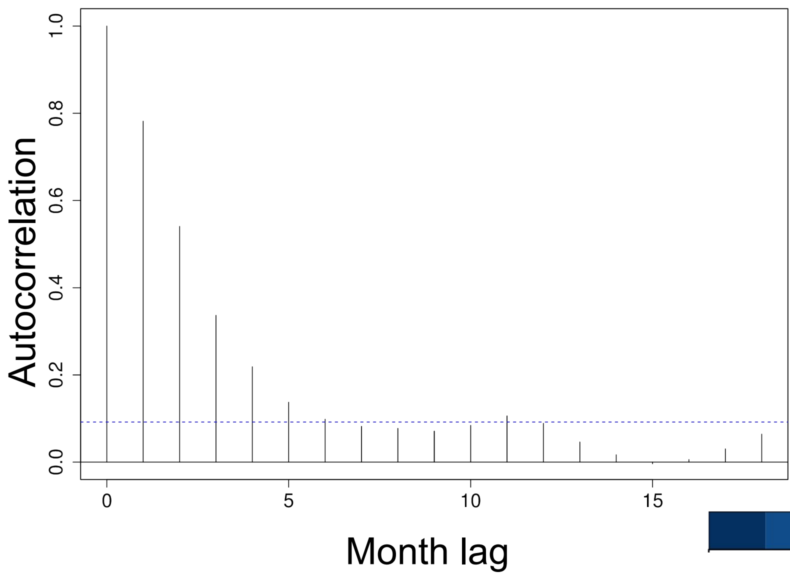
Crosscorrelation between anomalous sea level pressure (50 hPa geopotential height) & First SIC mode

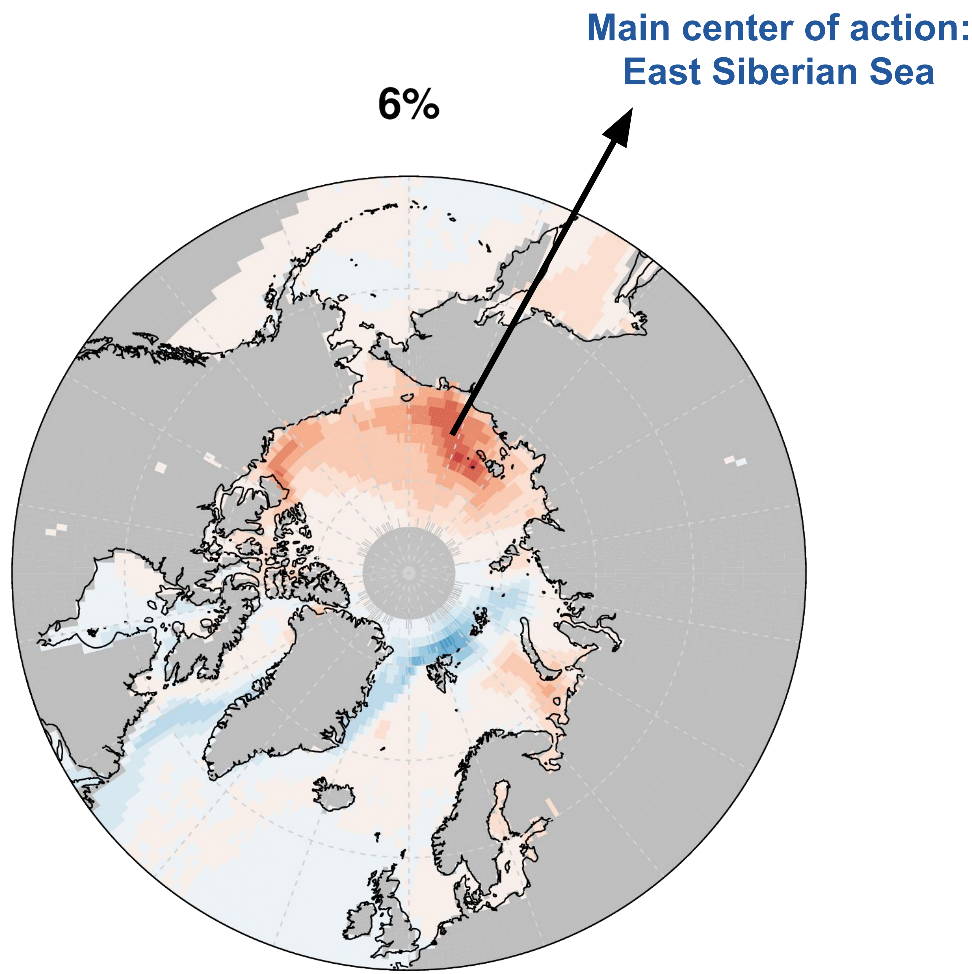


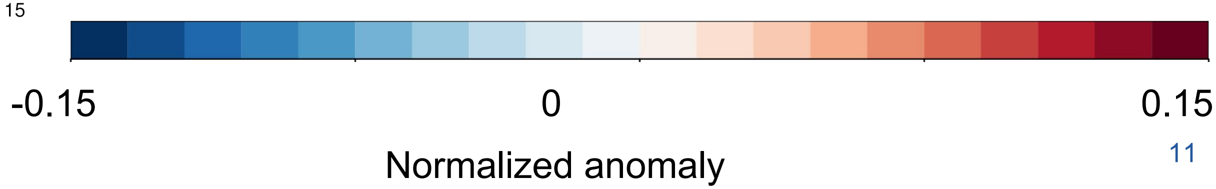
Sea ice lags | Sea ice leads

Results: Second mode

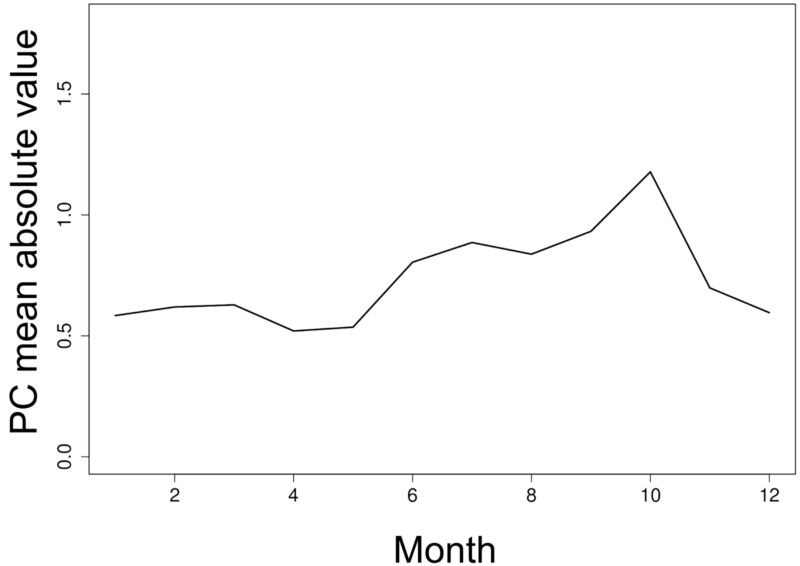


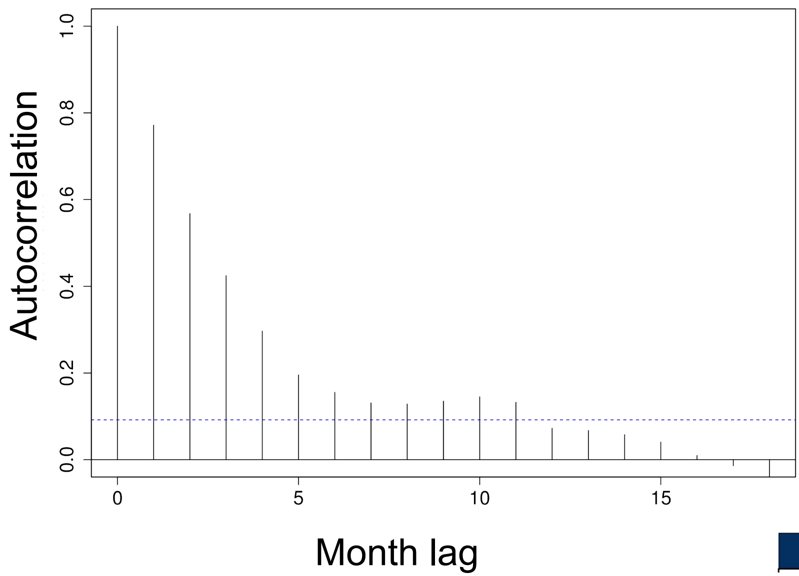


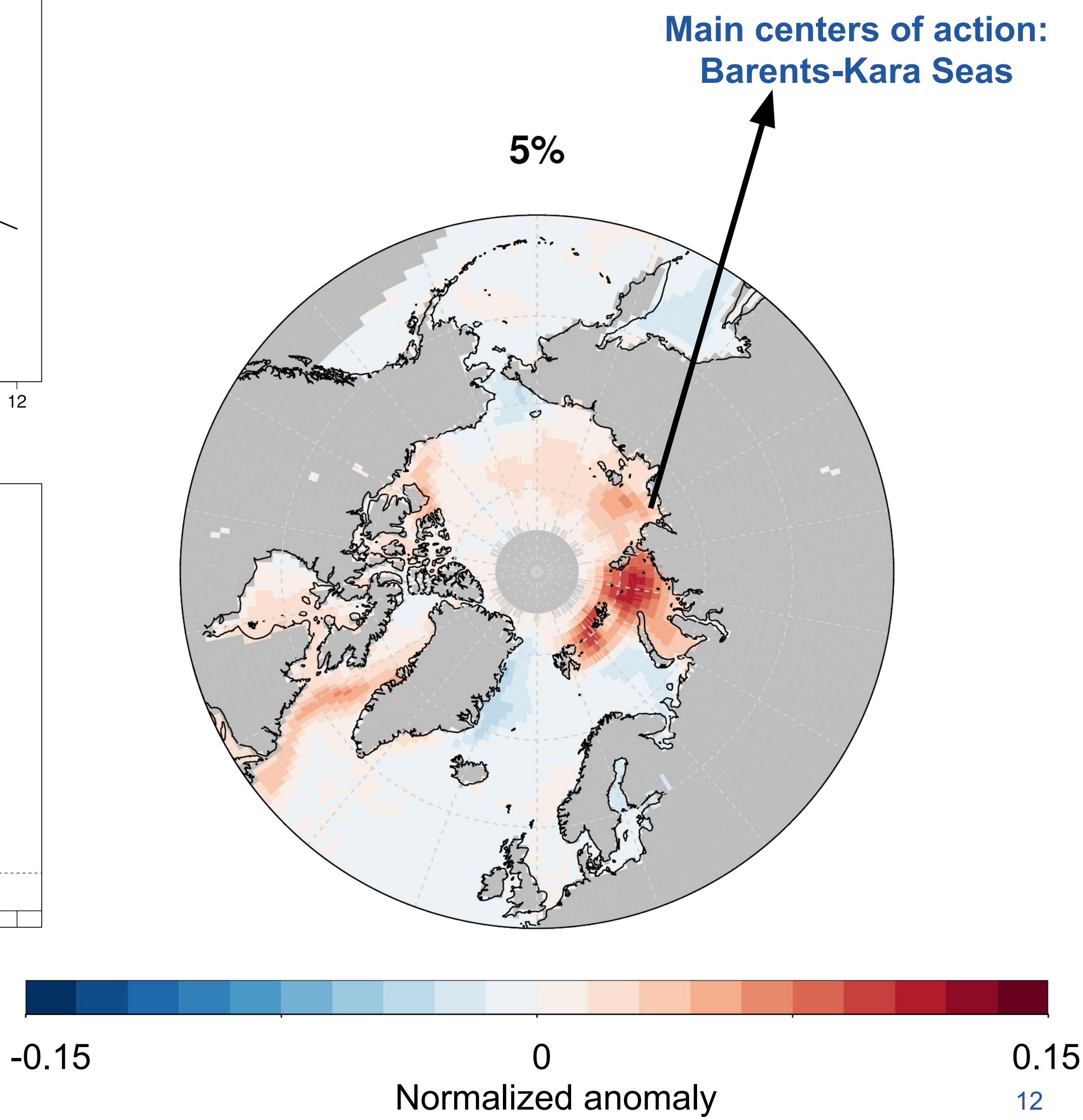




Results: Third mode



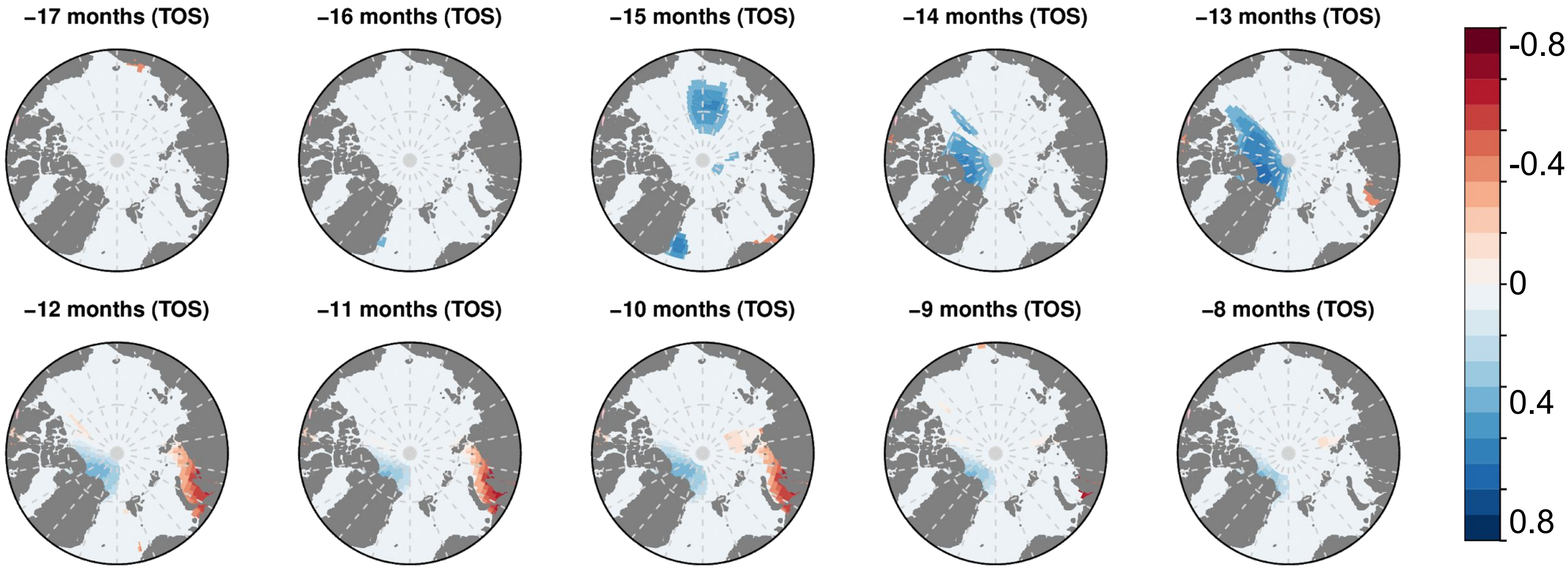




See e.g.: Yang and Yuan, 2014

Ocean surface temperature as potential source of predictability in Barents-Kara

Main centers of action: Barents-Kara Seas



Note inverted color scale

Methods part 2

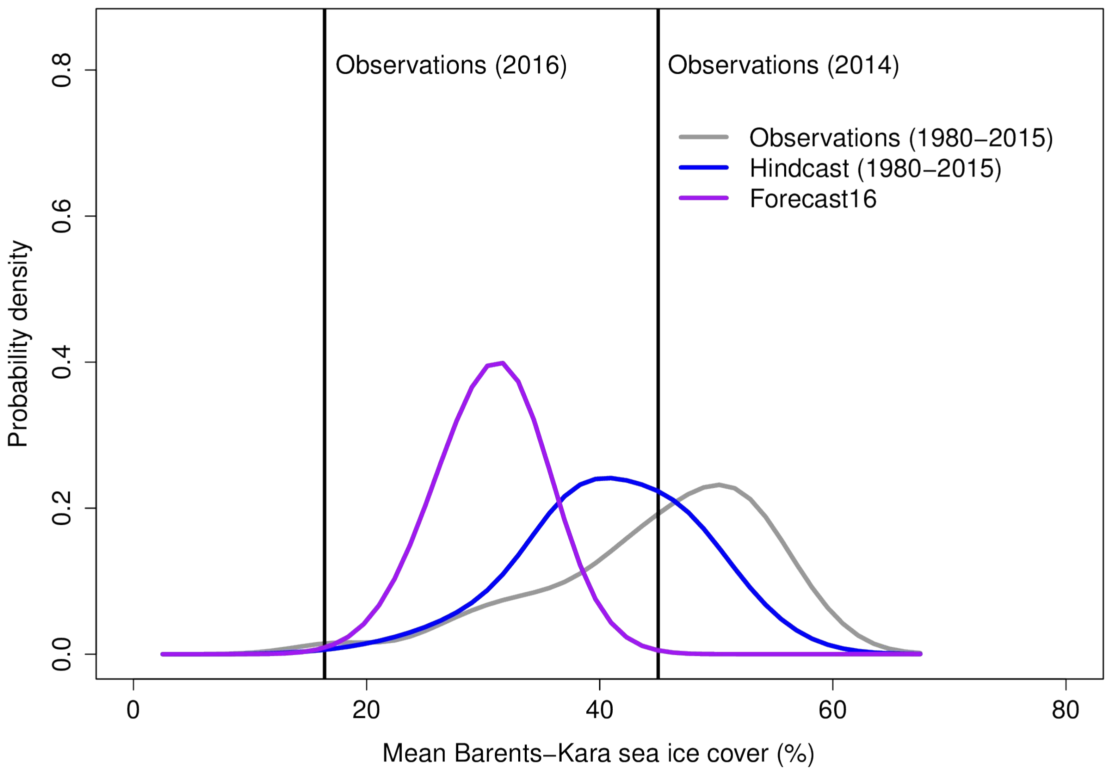
- Use the **EC-Earth 3.2 system** to forecast retrospectively a low precipitation event in Europe (December 2016).

- EC-Earth 3.2 -> fully coupled **ocean-sea ice-atmosphere** model.

- **Hundred** member simulations initialized on November 1st 2016 using reanalysed state of ocean, atmosphere and sea ice.

- Parallel experiment using a 2014 (climatological) sea ice state to test the role of sea ice conditions on the precipitation event.

Case study: Forecast Nov-Dec 2016 with EC-Earth3.2 (100 members)



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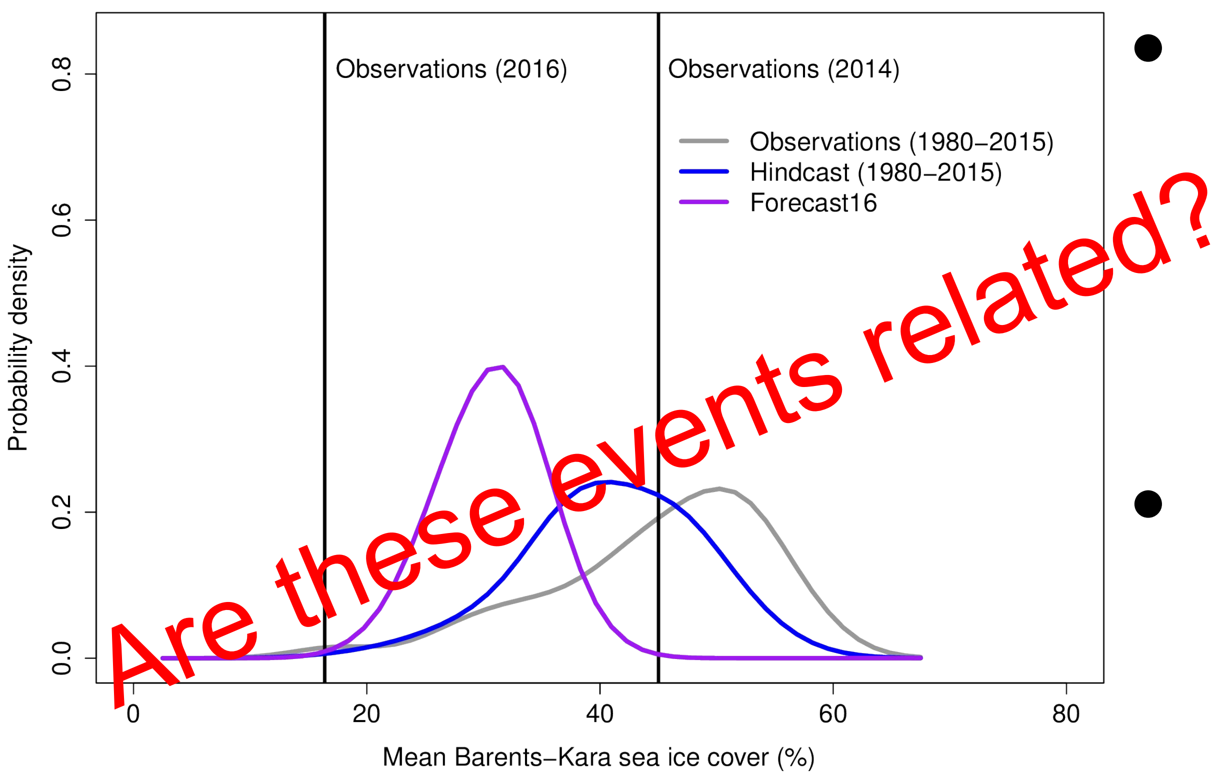

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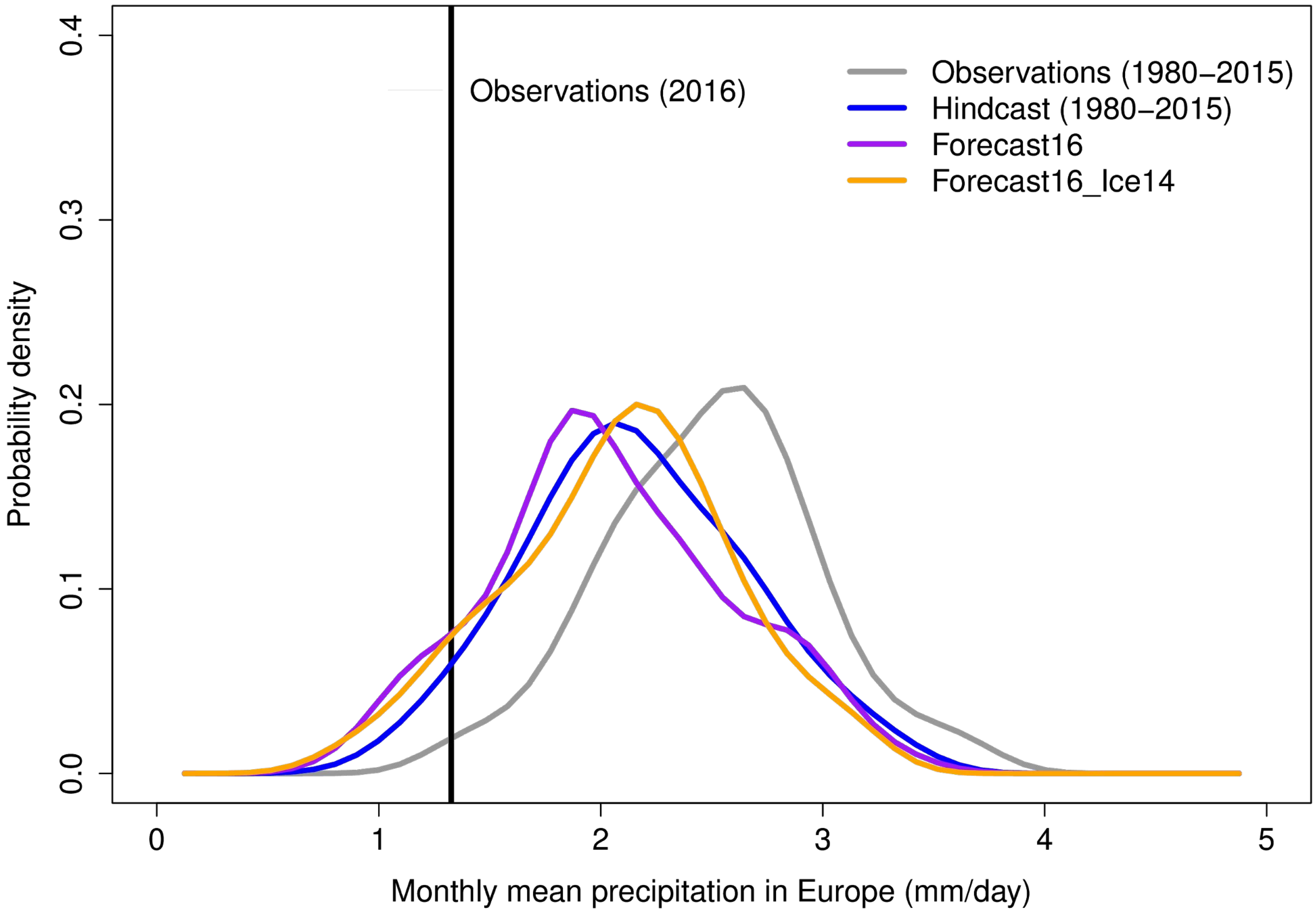
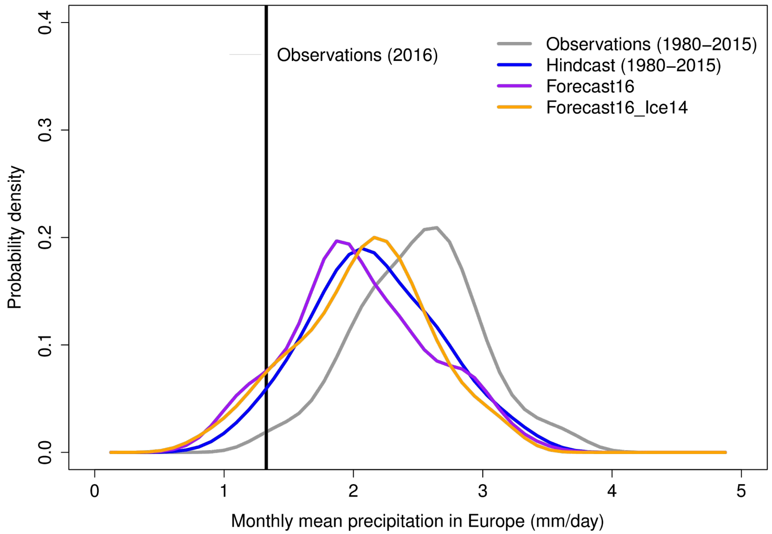
Sea ice initial conditions shift the dec. precipitation probability density function



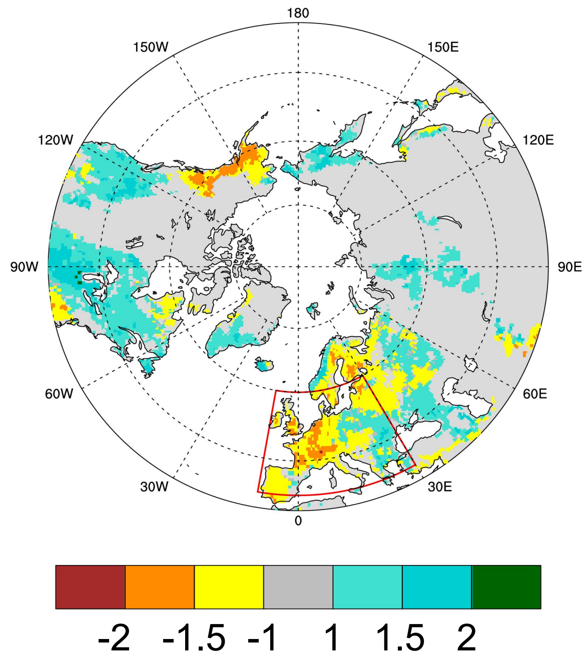
- In 100-member retrospective forecasts December 2016 the extreme low precipitation is better predicted using correct sea-ice initial conditions.

December precipitation odds ratio



Acosta Navarro et al. Submitted

Simulations initialized from correct 2016 sea-ice



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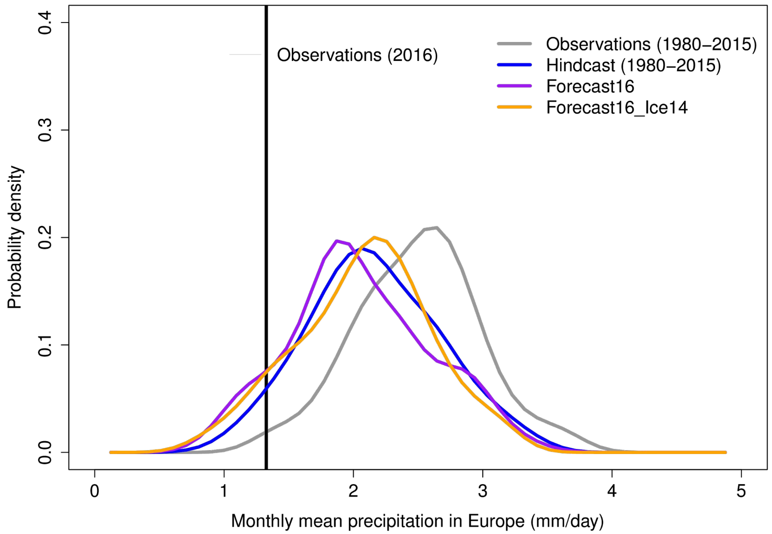

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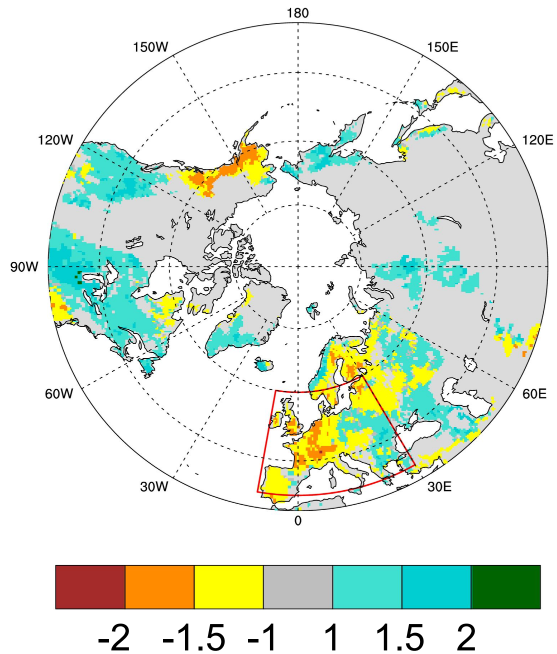
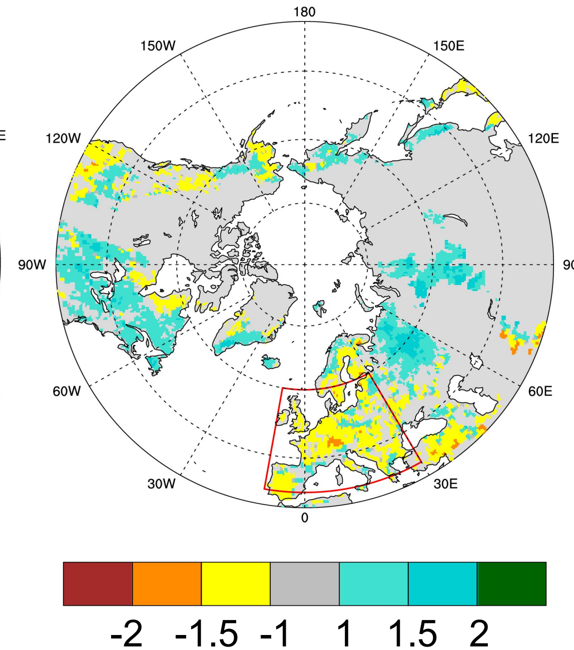


Simulations initialized from 2014 sea-ice



- In 100-member retrospective forecasts of Nov-Dec 2016 the extreme low precipitation is better predicted using correct sea-ice initial conditions.

Recap

- **First EOF (mode)** explains **9%** of Arctic SIC **variability**, typical of **winter**, persistence loss after **5-6 months** with possible remergence in following winter & is often preceded by NAO.

- **Second EOF (mode)** explains **6%** of Arctic SIC **variability**, typical of **summer**, persistence of **~5 months**.

- **Third EOF (mode)** explains **5%** of Arctic SIC **variability**, typical of late **summer early autumn**, low persistence of **~3 months.** Sea surface temperature (ocean heat content 0-300m) as a potential source of predictability.

Recap

- Low **Barents & Kara** sea ice cover during autumn may increase the likelihood of low precipitation in Europe the following month(s).

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Thank you!

For further information please contact **jacosta@bsc.es**

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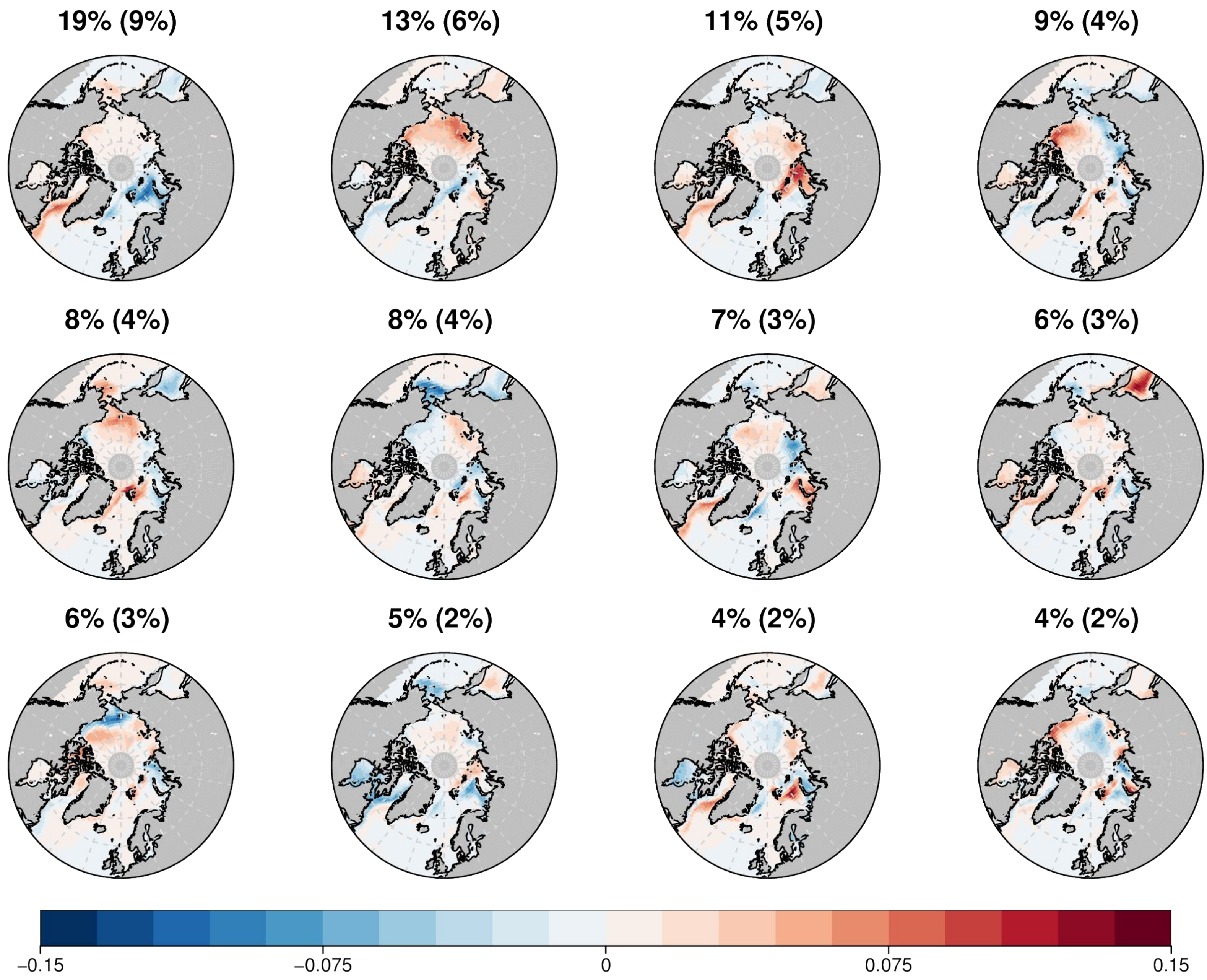
Extra slides



Case study: Forecast Fall-Winter 2016 with EC-Earth3.2 (100 members)

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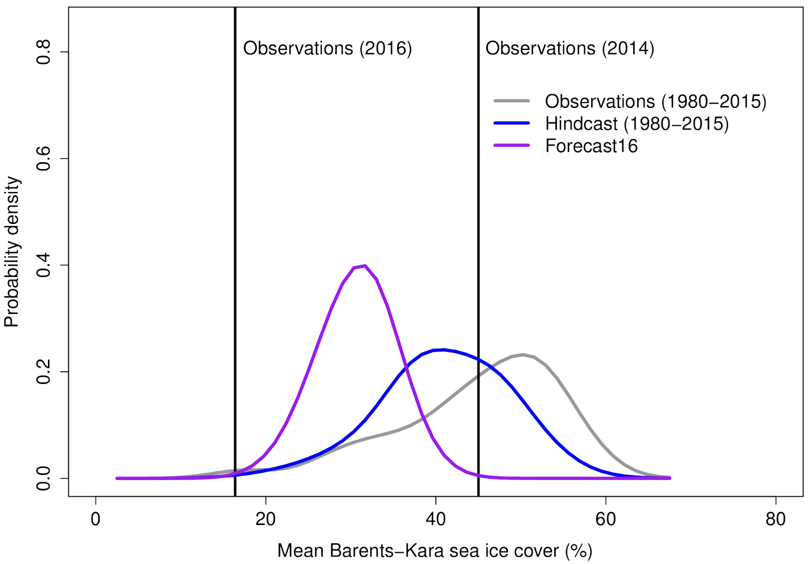

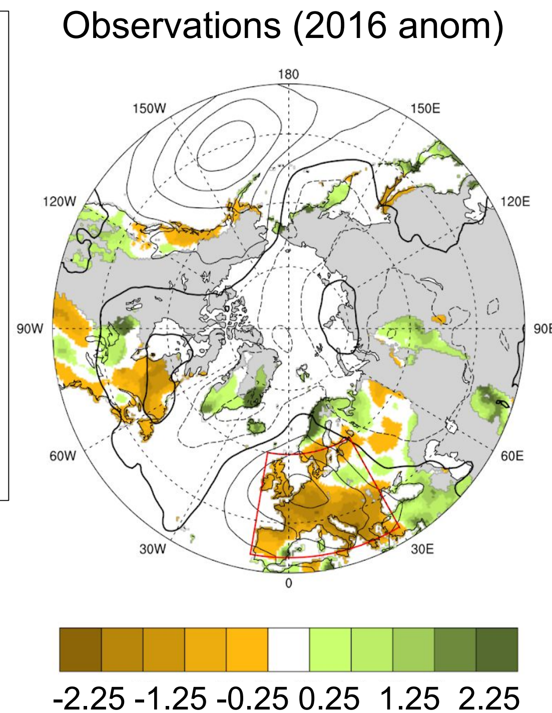

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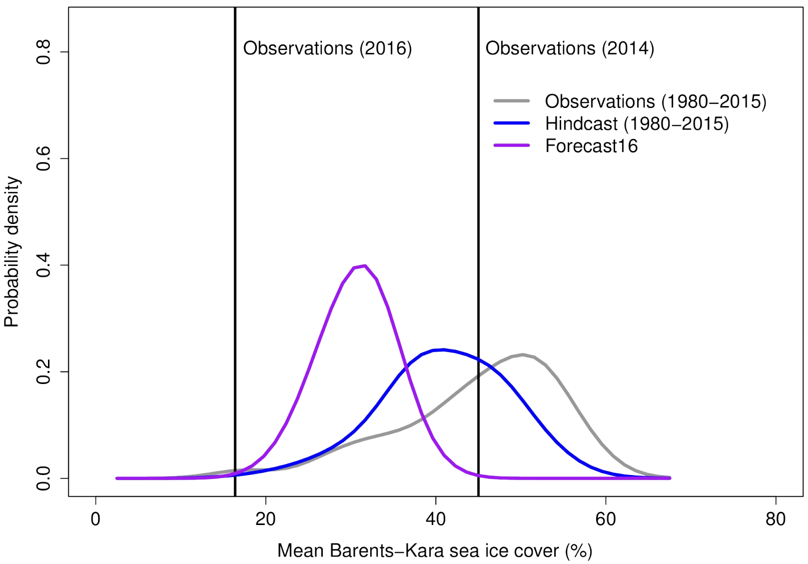

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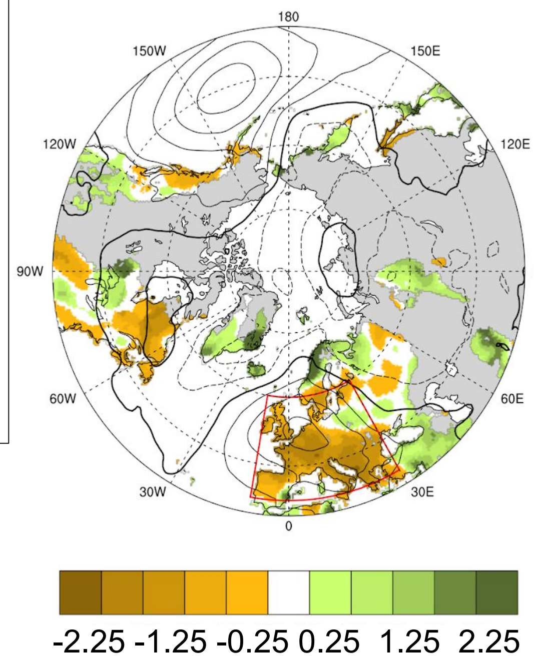
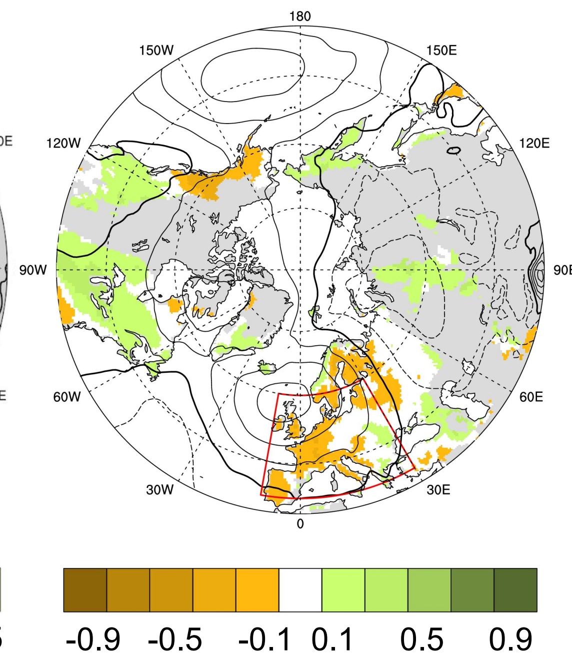
Observations (2016 anom)



Model (2016 anom)



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- Compare against other large scale climatic **indices**
  - Study other potential sources of predictability
  - Study physical mechanisms.

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- Cross-correlations between different PCs and extended EOF analysis ---> To evaluate **progression** of modes.

Next steps to gain understanding

- Compare against other large scale climatic **indices**
  - Study other potential sources of predictability
  - Study physical mechanisms.

- Cross-correlations between different PCs and extended EOF analysis ---> To evaluate **progression** of modes.

- Evaluate **models** performing similar analysis.

Next steps to refine analysis

- **Normalizing** adequately the monthly **variance** to have **fair** EOF comparison.

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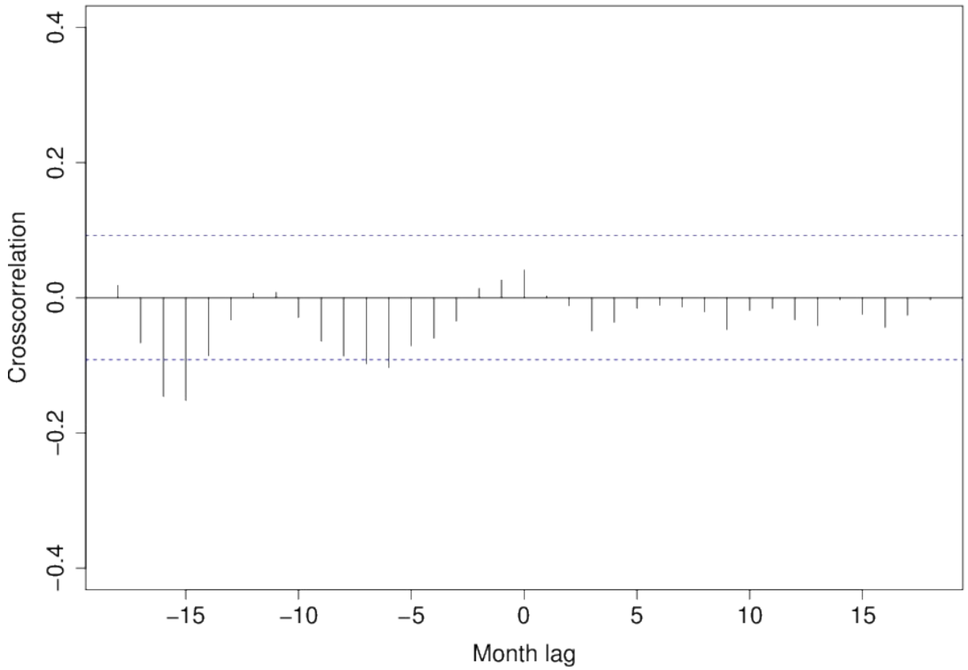
- **Normalizing** adequately the monthly **variance** to have **fair** EOF comparison.

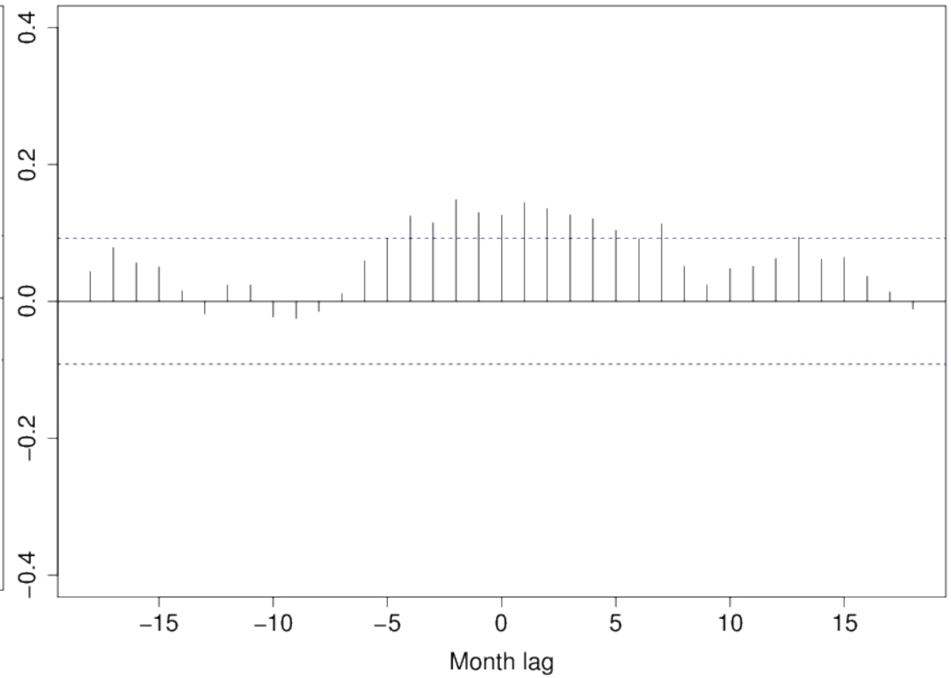
- Better estimates of **persistence** (e.g. simple anomaly persistence, e-folding decay time, refine significance levels).

- Take into account the **autocorrelation** in time series.

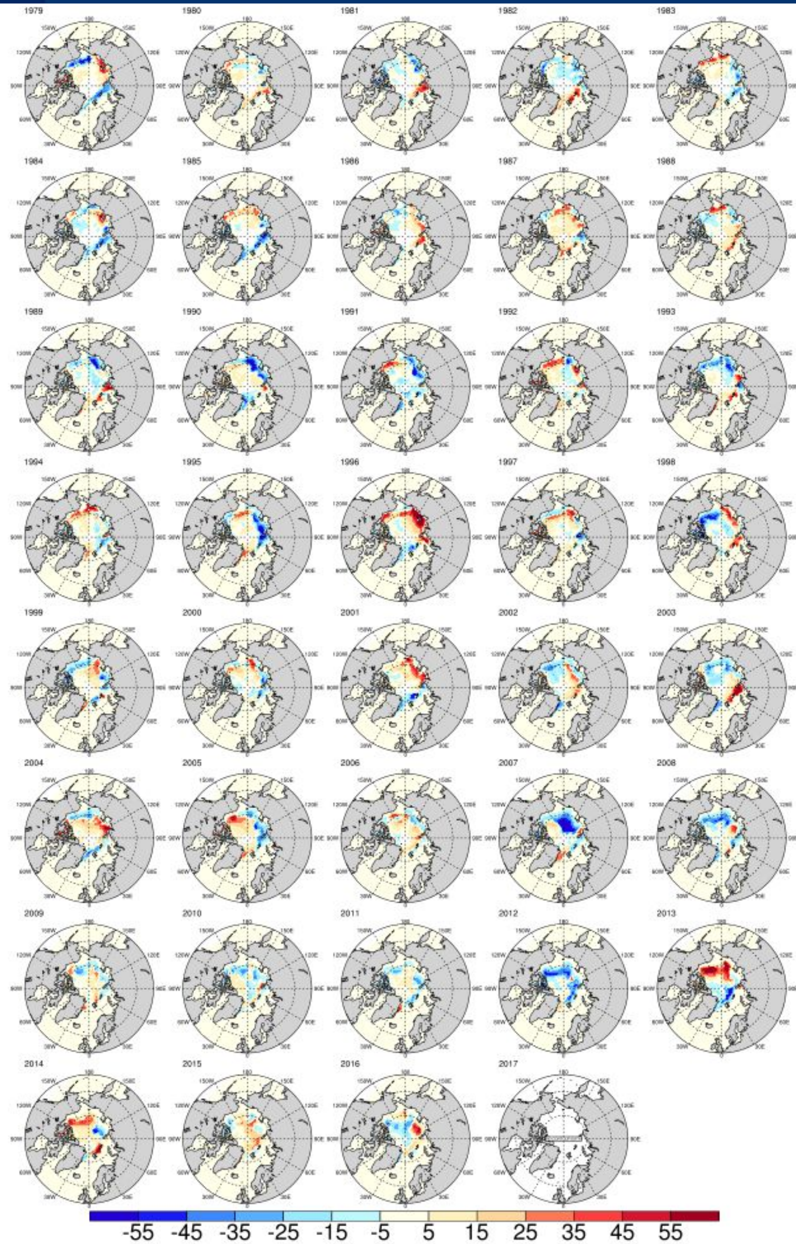
NAOI vs. PC2



NAOI vs. PC3



Extra slides



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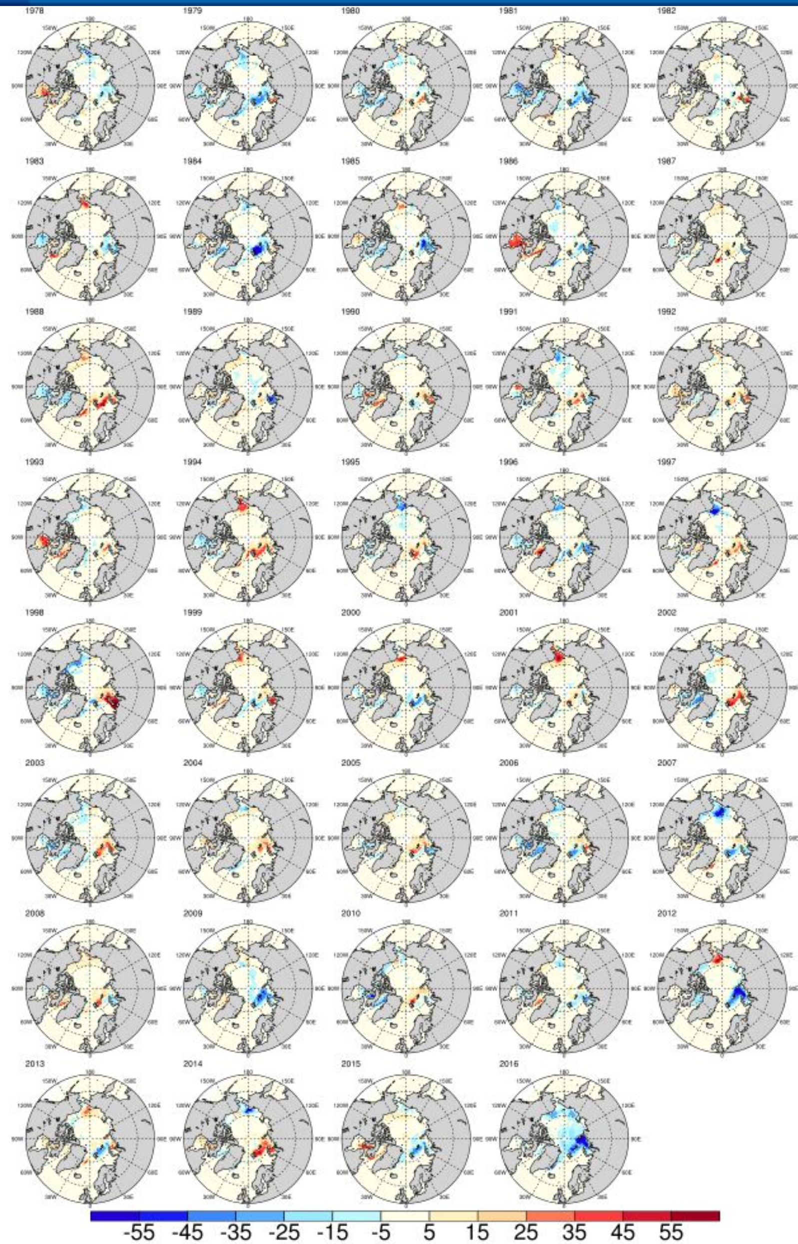


Extra slides

Methods

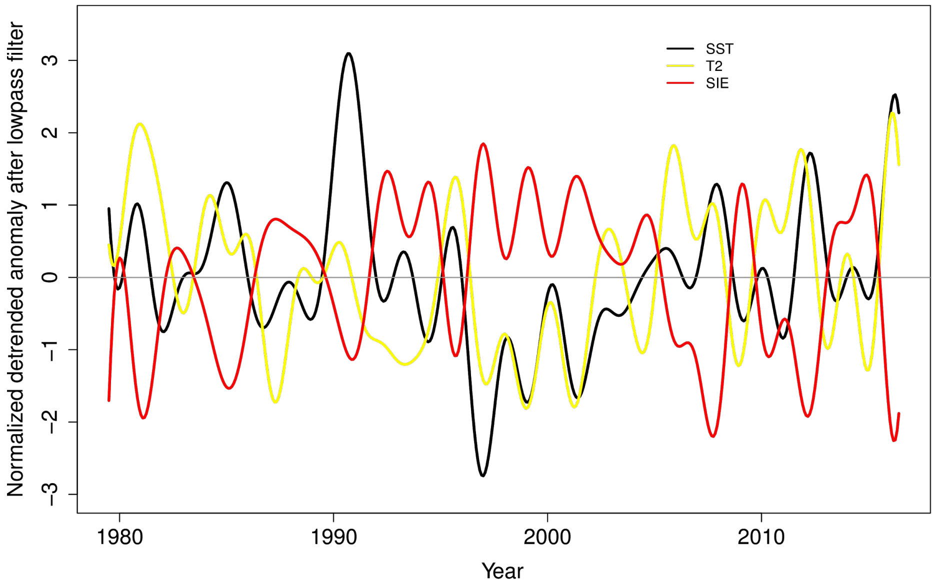
Advantages:

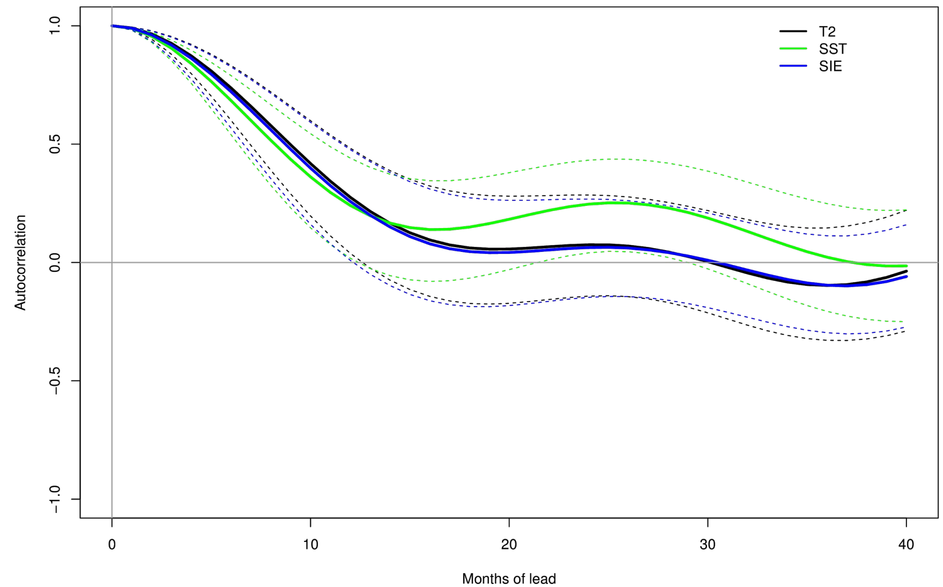
- Broad and general
- No a-priori assumptions made
-

Limitations:

-

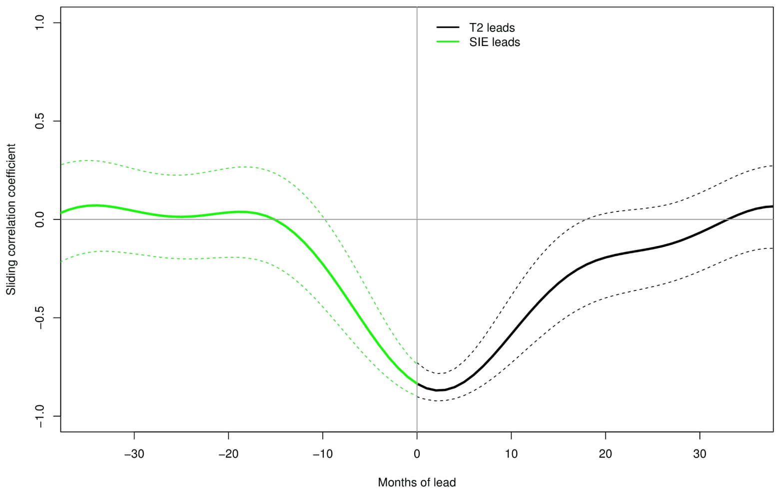
Pan-Arctic SST (HadSST), T2m (ERA-Int) and SIE (NSIDC)

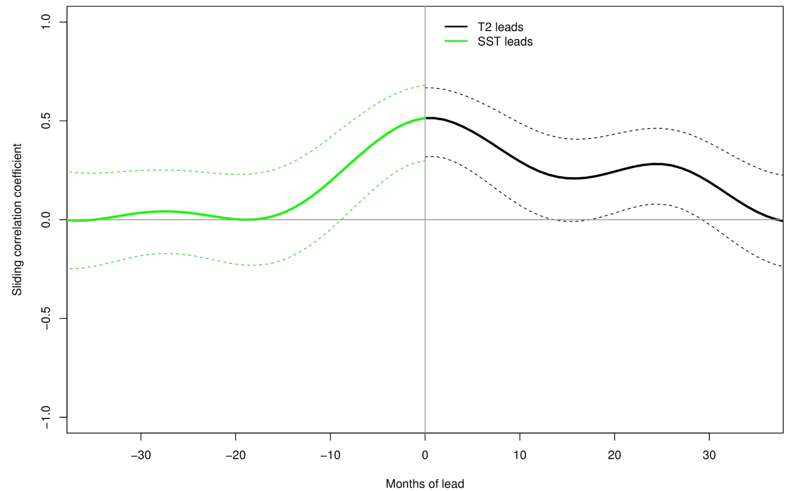


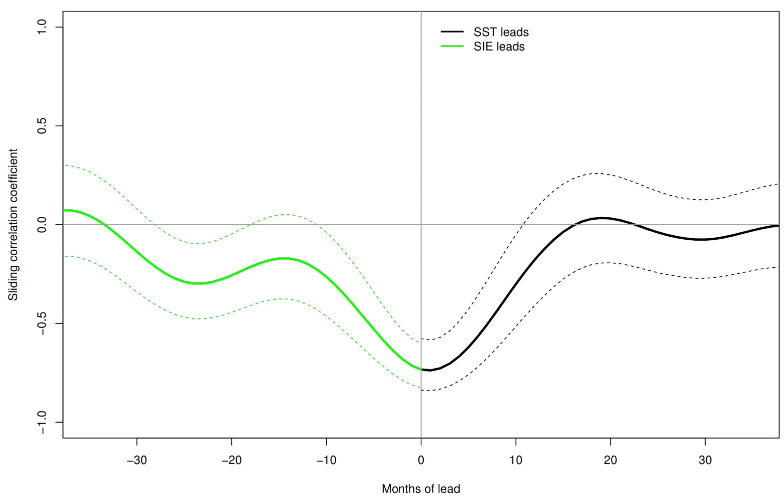


- Fast Fourier Transform low-pass filter allows only temporal variability of oscillations with period longer than 2 years.
- Linearly detrended after low-pass filter.

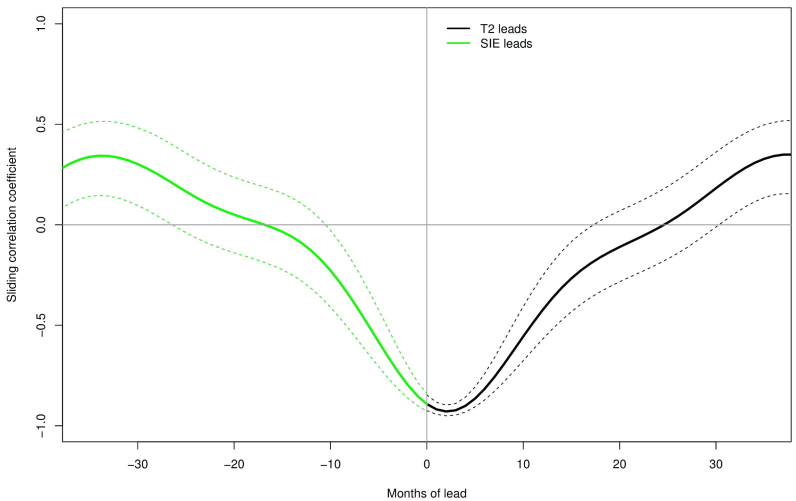
Lag-lead series (NH)

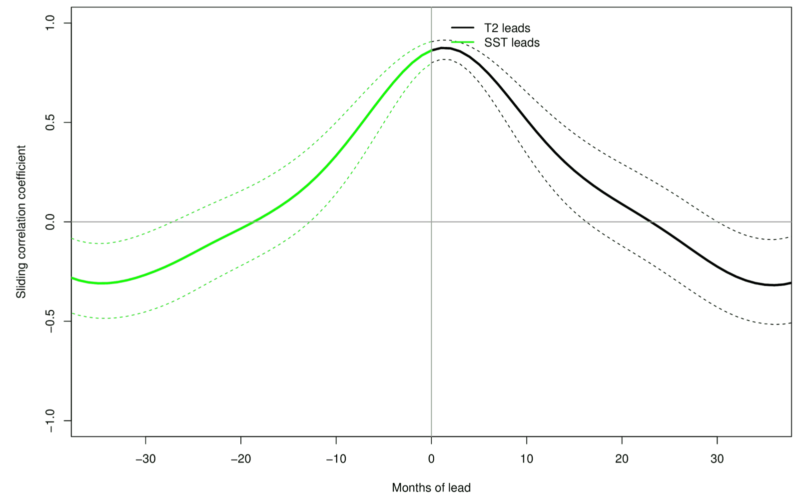


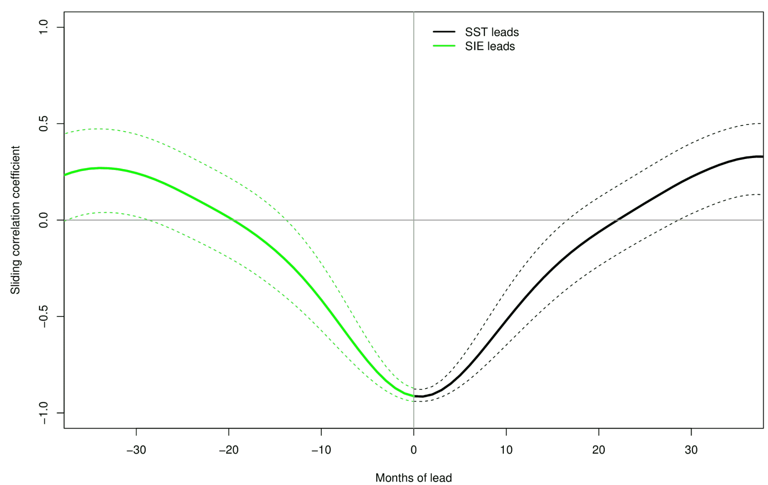




Lag-lead series (Barents & Kara seas)







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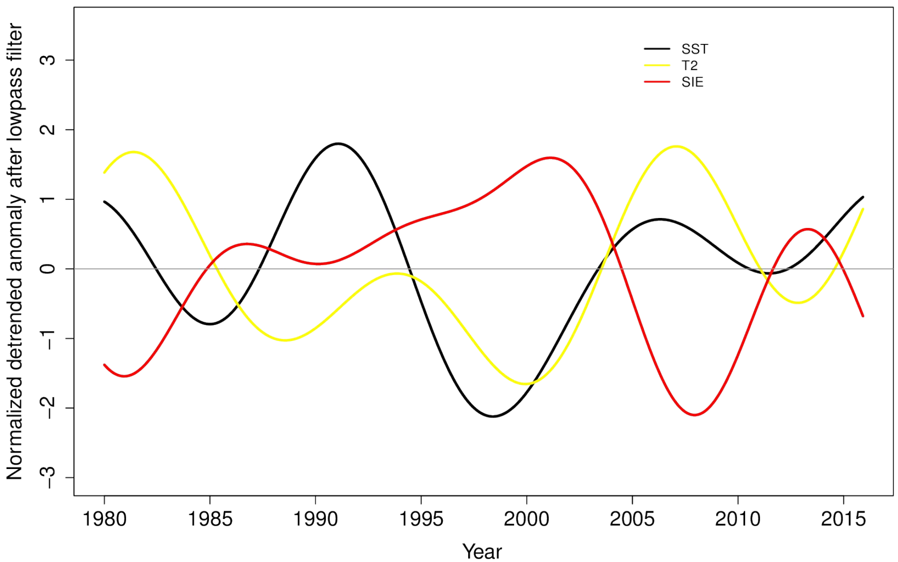

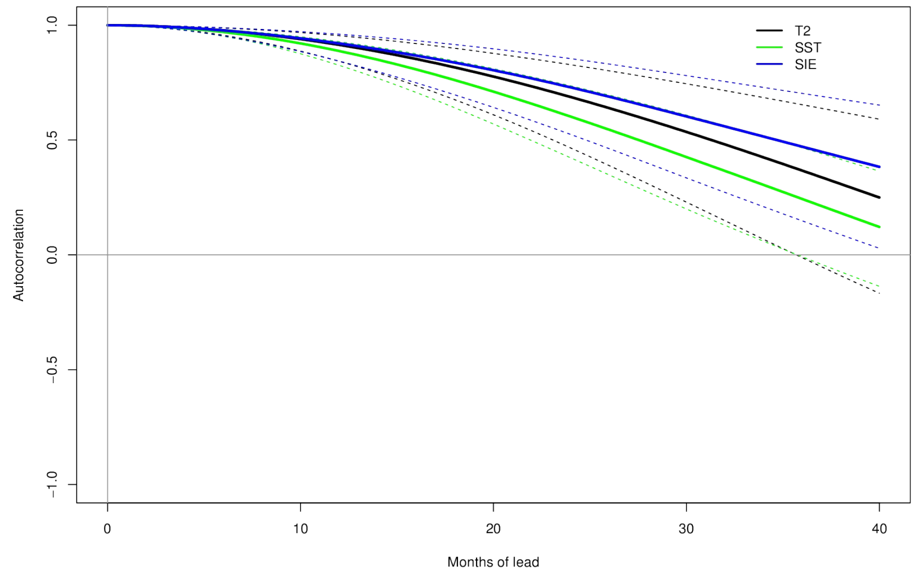

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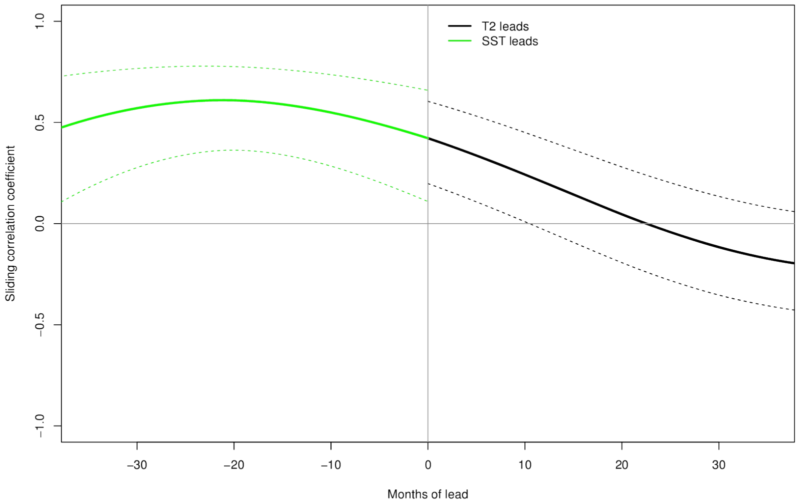
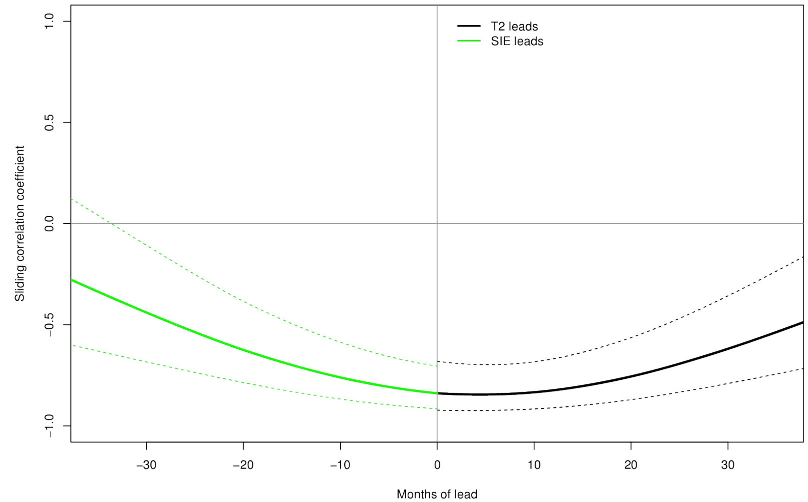
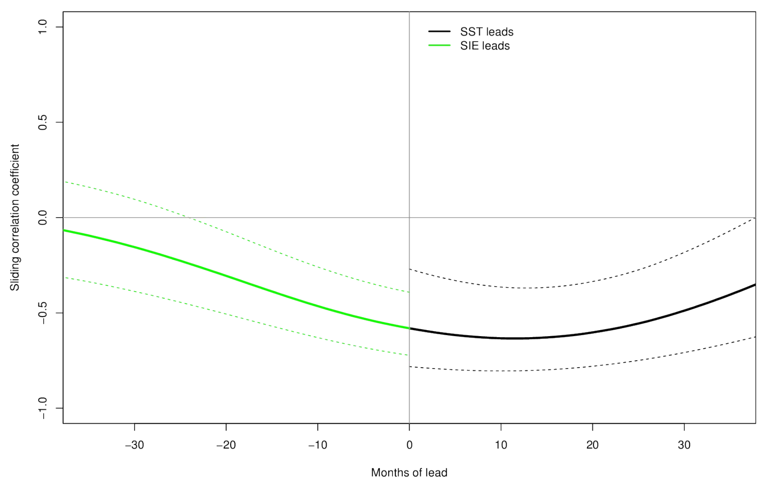
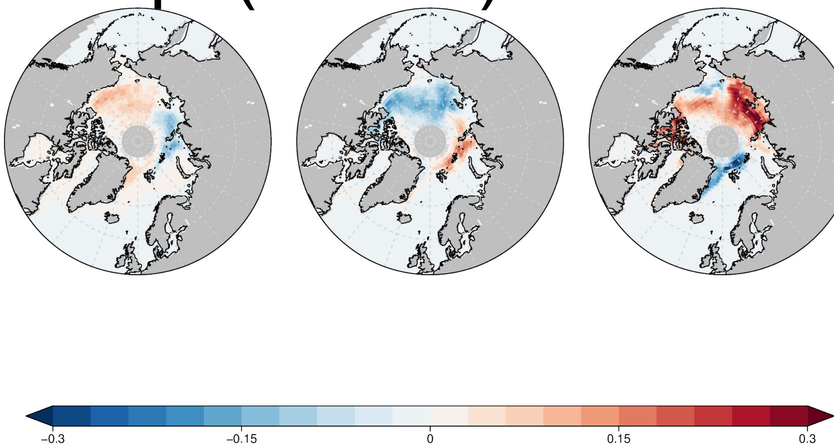






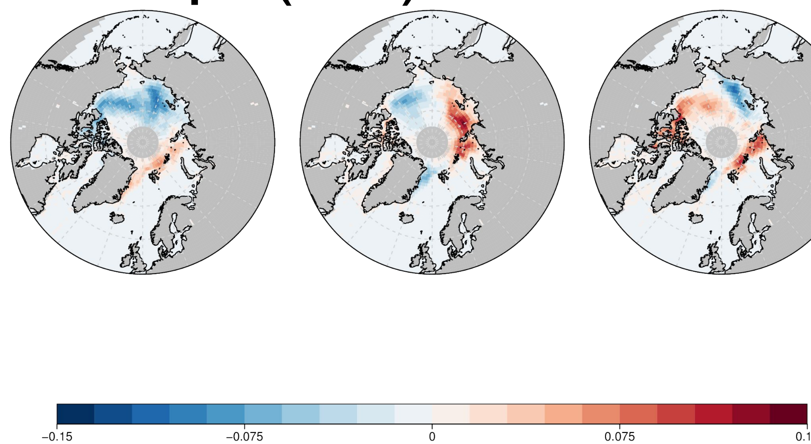
47% – 1.6 years   37% – 1.6 years   16% – 1 years

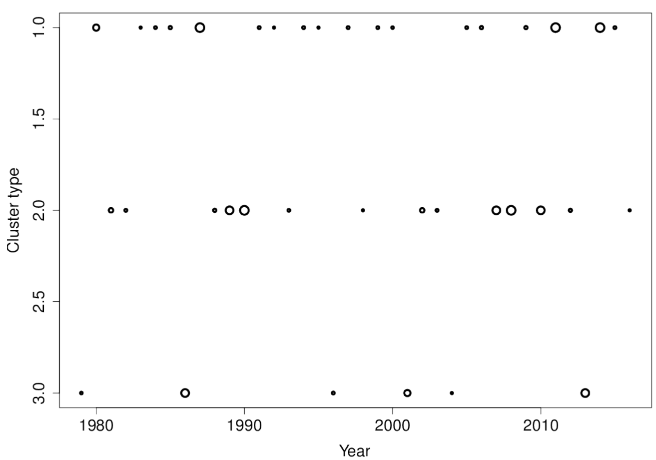
Sept (cluster)

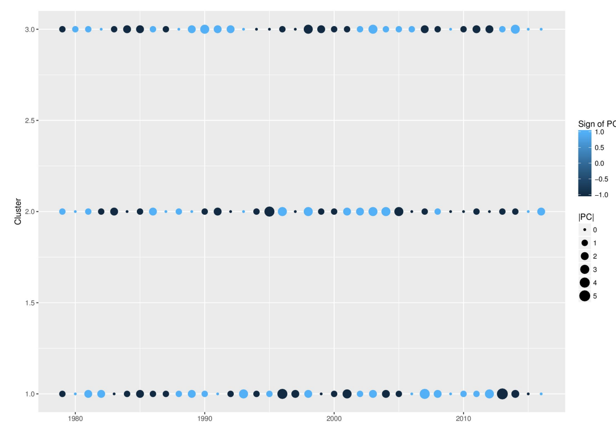


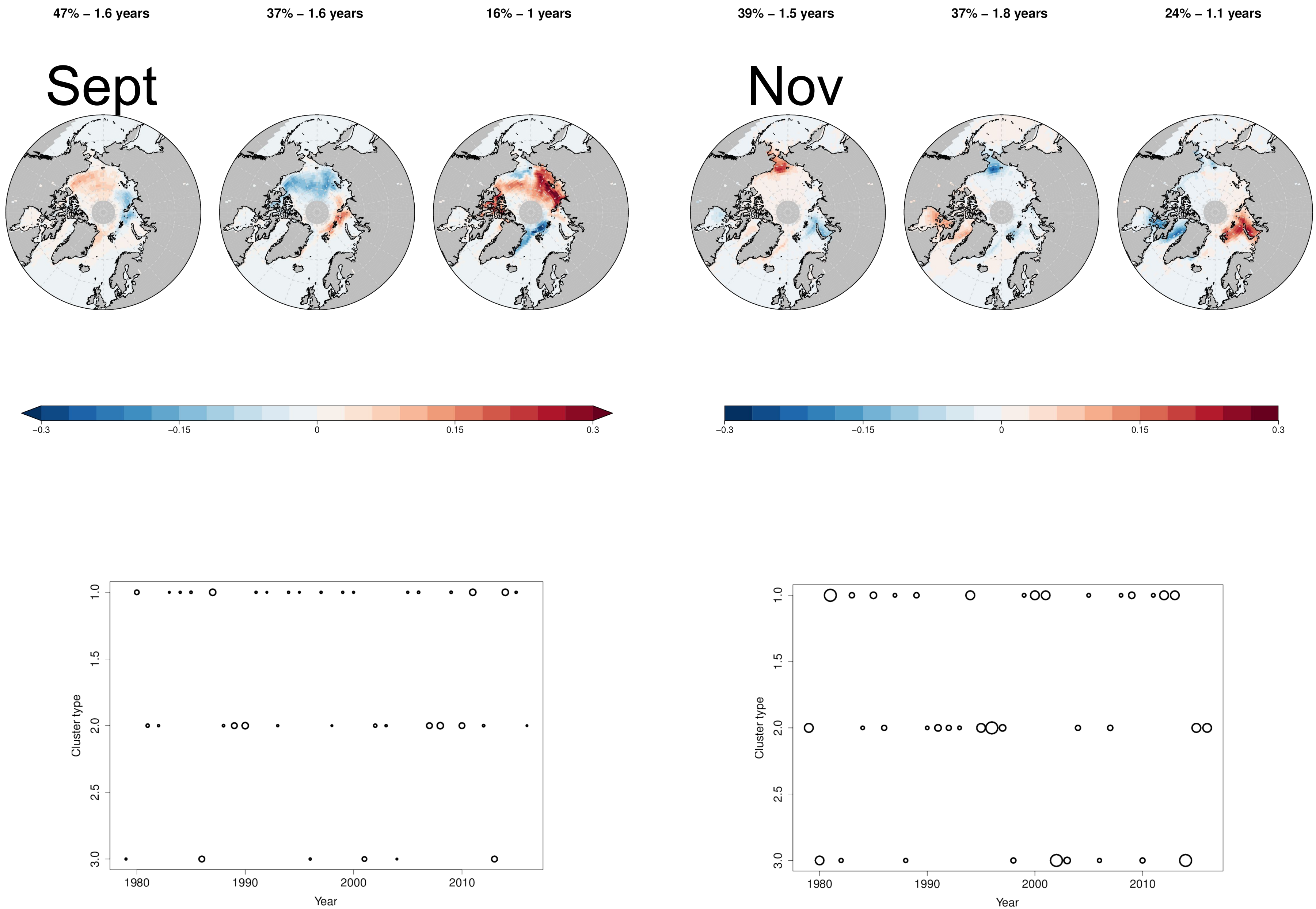
43% (17%)   32% (13%)   25% (10%)

Sept (PC)

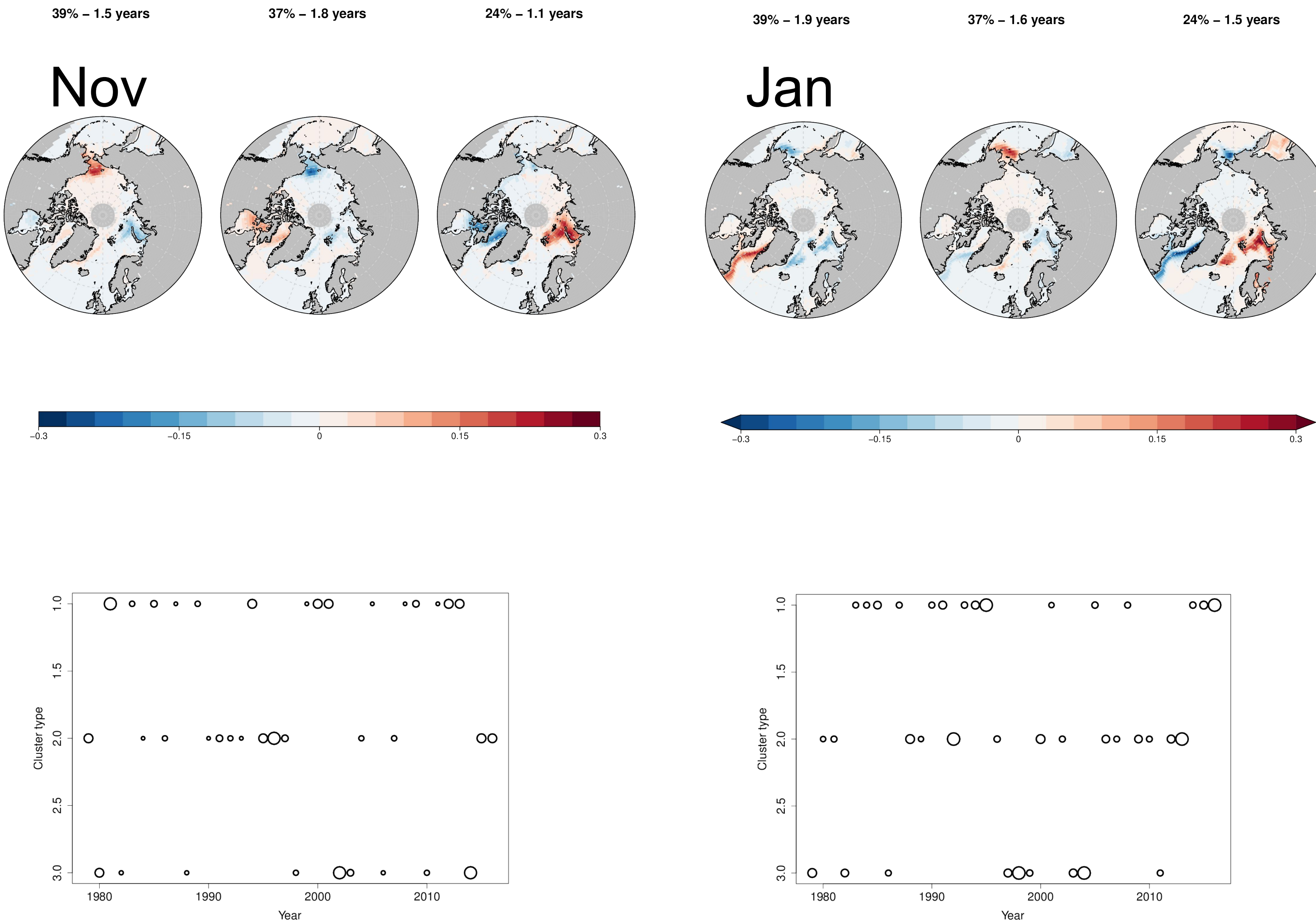








47% – 1.6 years
37% – 1.6 years
16% – 1 years
39% – 1.5 years
37% – 1.8 years
24% – 1.1 years
Sept
Nov
−0.3
−0.15
0
0.15
0.3
−0.3
−0.15
0
0.15
0.3
Cluster type
1.0
1.5
2.0
2.5
3.0
1980
1990
2000
2010
Year
Cluster type
1.0
1.5
2.0
2.5
3.0
1980
1990
2000
2010
Year


39% – 1.5 years
37% – 1.8 years
24% – 1.1 years
39% – 1.9 years
37% – 1.6 years
24% – 1.5 years
Nov
Jan
−0.3
−0.15
0
0.15
0.3
Cluster type
1.0
1.5
2.0
2.5
3.0
1980
1990
2000
2010
Year