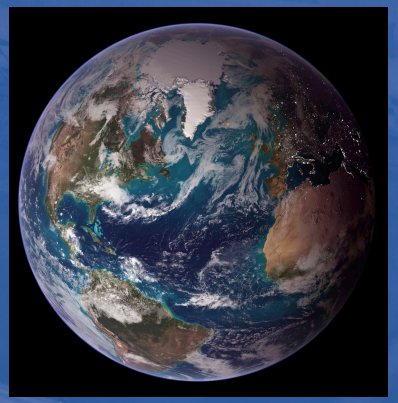
www.bsc.es

Earth Sciences Department



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Variability and prediction of the NH sea ice thickness clusters

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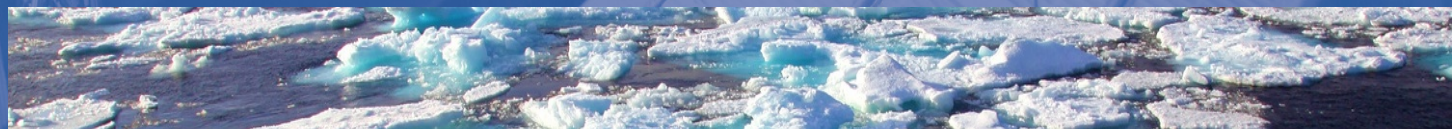
Université catholique de Louvain,
TECLIM, Louvain-la-Neuve, Belgium
24 February, 2016



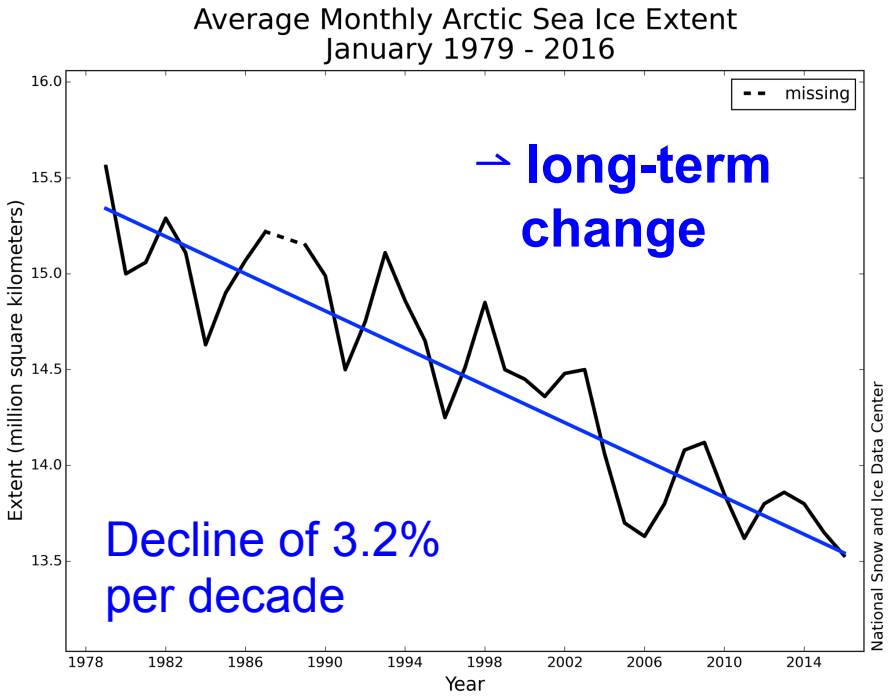
Motivation and aim

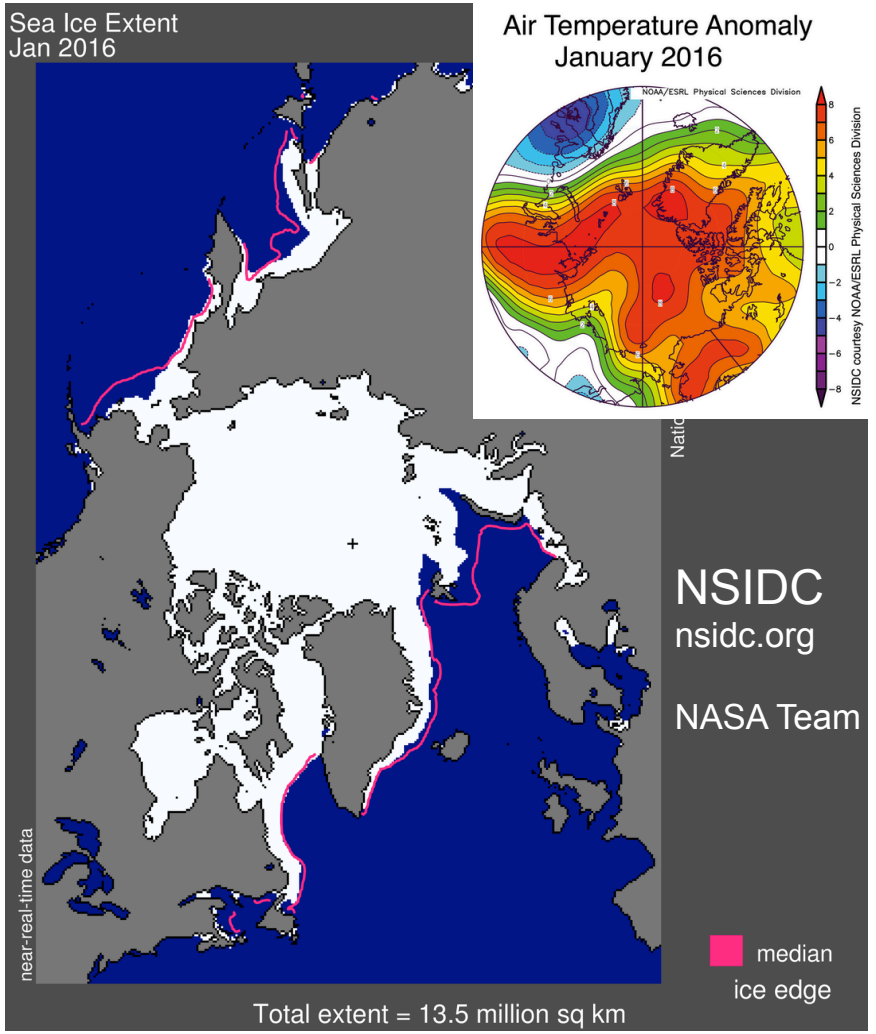
.. from climate perspective *"we live in interesting time"* ..

.. to further understanding and prediction of the Arctic system

Arctic variability and change

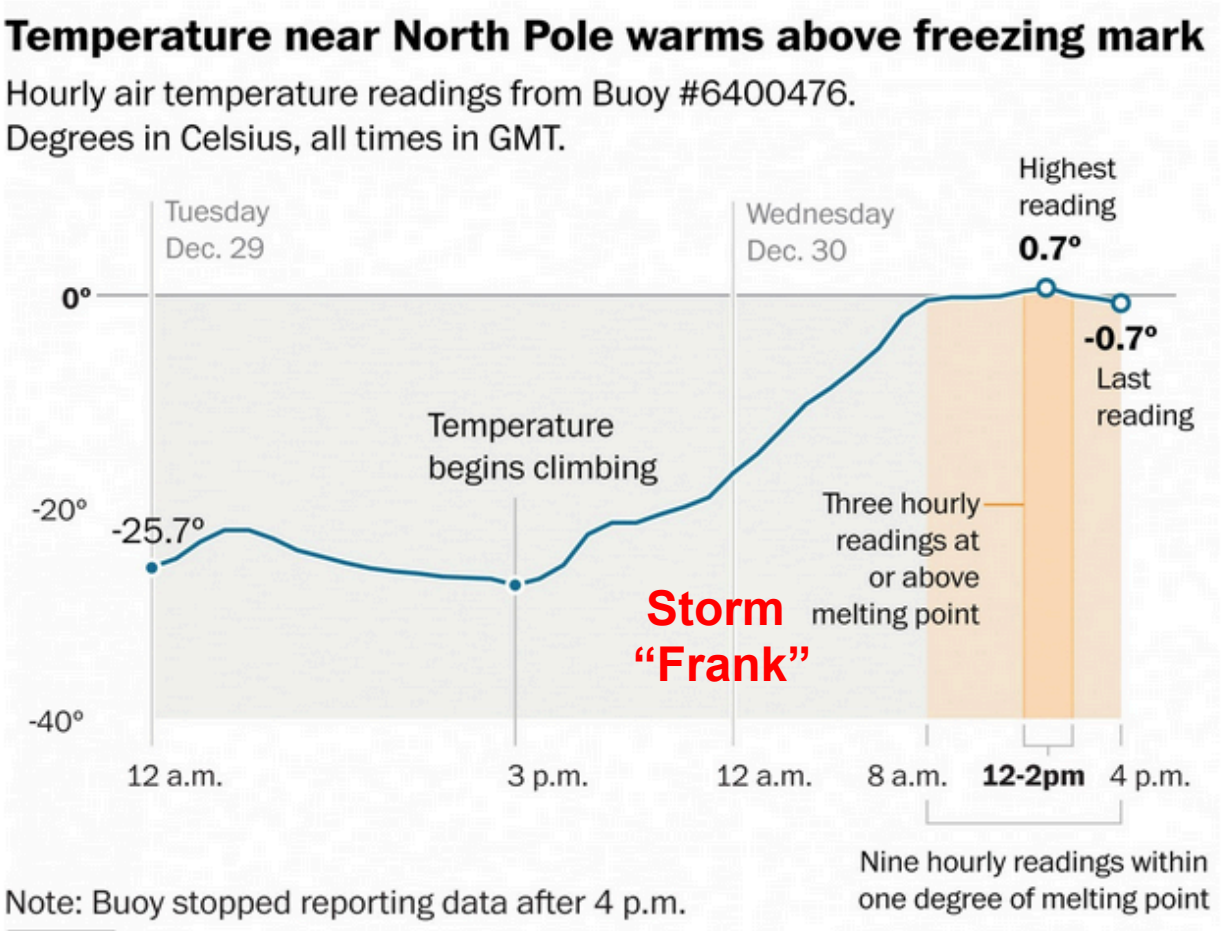
- **The lowest NH January SIE in the satellite record (since 1979)**
  - → unusually high SAT
  - → persistent negative AO phase





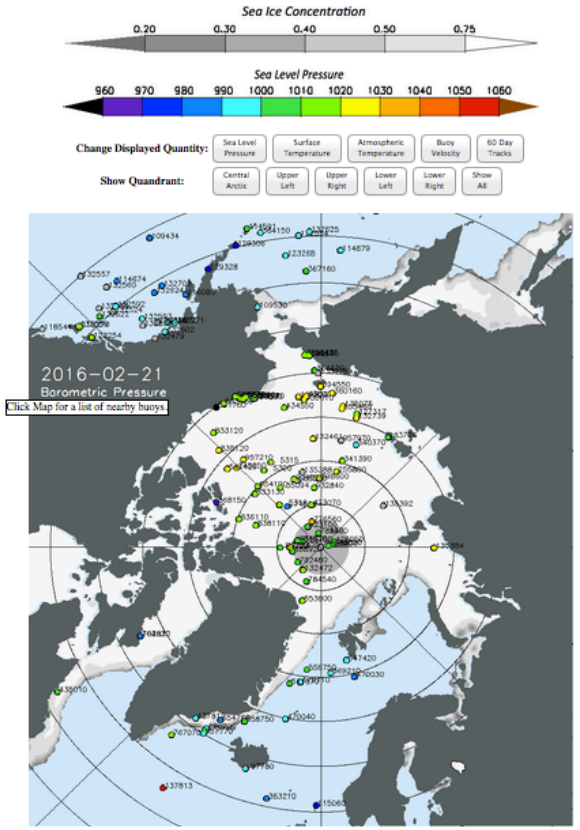
Arctic variability and change

→ short-term variability



International Arctic Buoy Program

iabp.apl.washington.edu

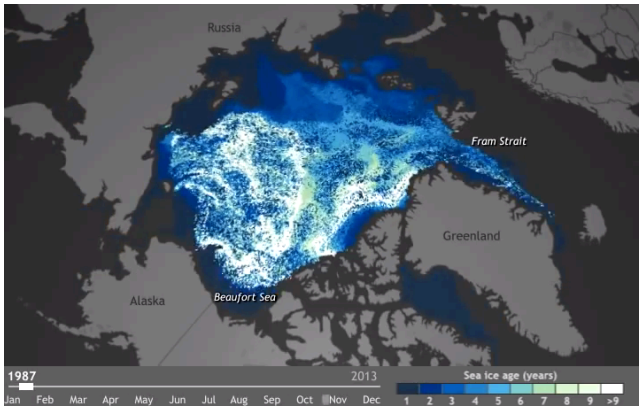


Arctic variability and change

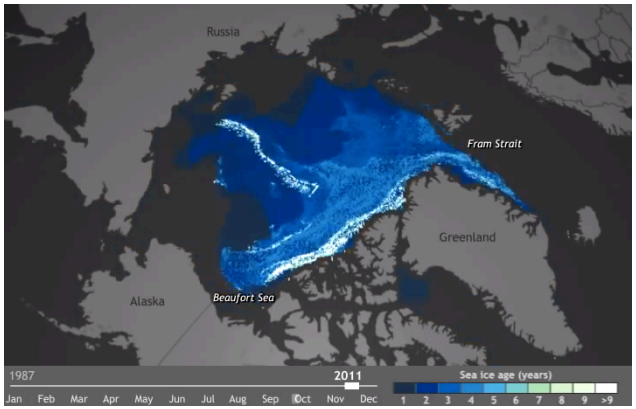
NH sea ice cover has experienced a long-term decline superimposed on a strong internal variability

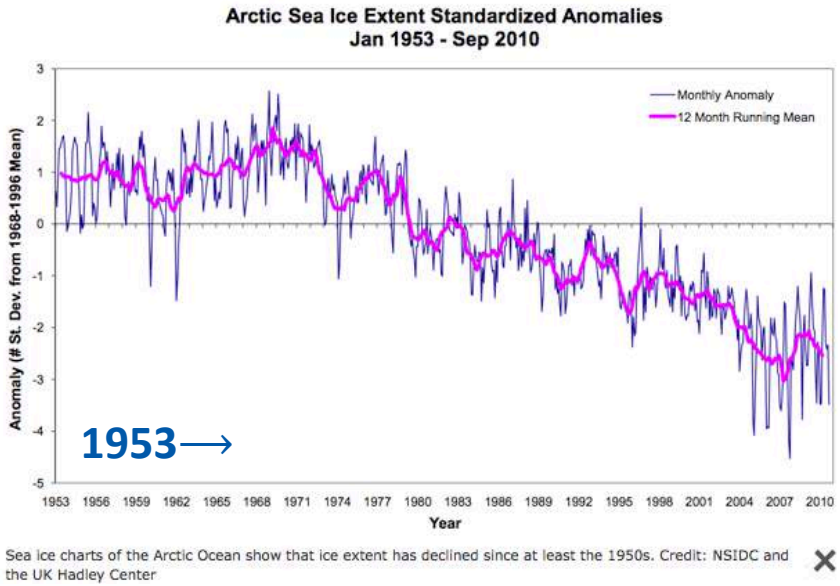
Sea ice age

1987



2011





Sea ice charts of the Arctic Ocean show that ice extent has declined since at least the 1950s. Credit: NSIDC and the UK Hadley Center

1) identify physically relatable patterns/modes of the NH sea ice variability on seasonal to interannual time scales disentangled from a long-term climate change and **2) explore their predictability with a dynamical system (CGMC)**

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Representation of internal variability modes

Unsupervised learning methods

Principal component analysis (PCA) produces a low-dimensional representation of the data that summarizes key properties

→ lin. decomposition in a set of uncorrelated (orthogonal) principal components or modes that successively maximize the variance captured

→ its limitations: symmetry between pos. and neg. phases, suppresses nonlinearity by using a lin. covariance matrix, PCA modes do not necessary represent physical modes, …

Clustering methods partition data into groups or clusters based on their distance – they can be hierarchical or non-hierarchical

→ aims to simultaneously minimize the distance between members of a given cluster/mode and maximize the distance between the centers of the clusters

→ without orthogonality or linearity constraints inherent in PCA

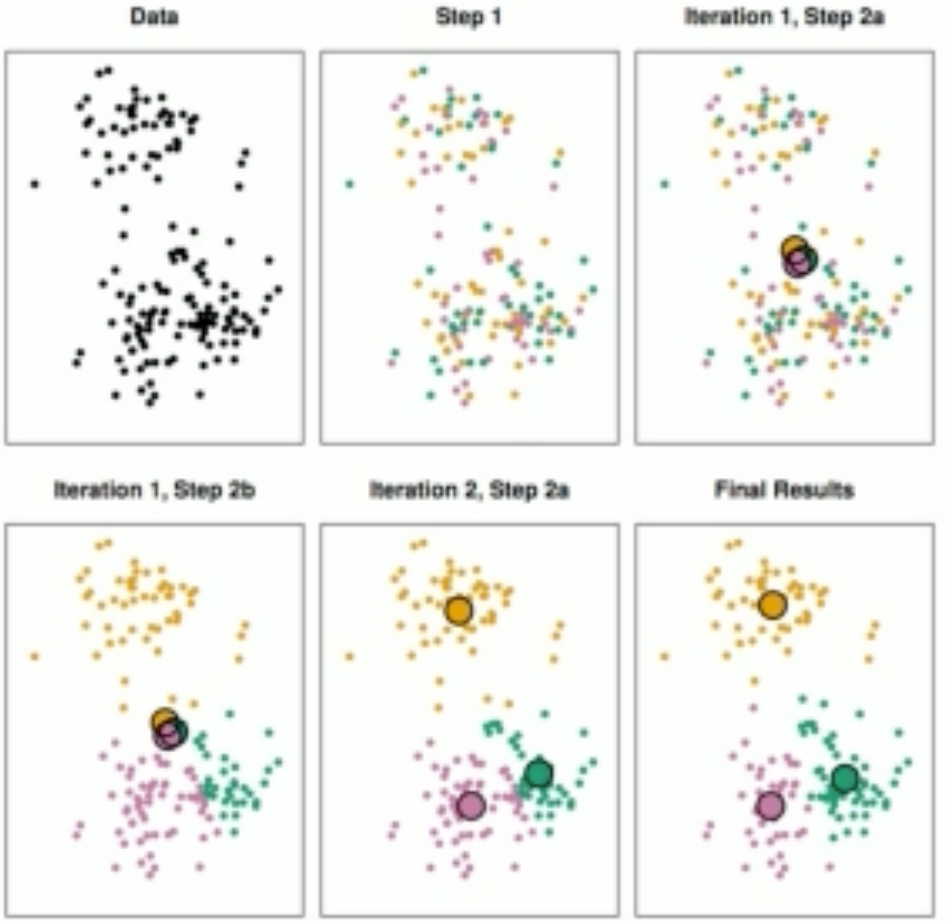
K-means cluster analysis

K-means method is non-hierarchical clustering analysis that allows reassignment of members between different clusters (not possible in hierarchical clustering):

→ **optimal number of clusters K** (typically determined via hierarchical approach) **has to be specified in advance**

→ **produces** representation of the spatial and temporal variability with **K patterns of cluster centers and time series of cluster occurrences**

E.g. iterative procedure for K=3 with data(x_1,x_2,t)



Climate memory buffer of the sea ice system

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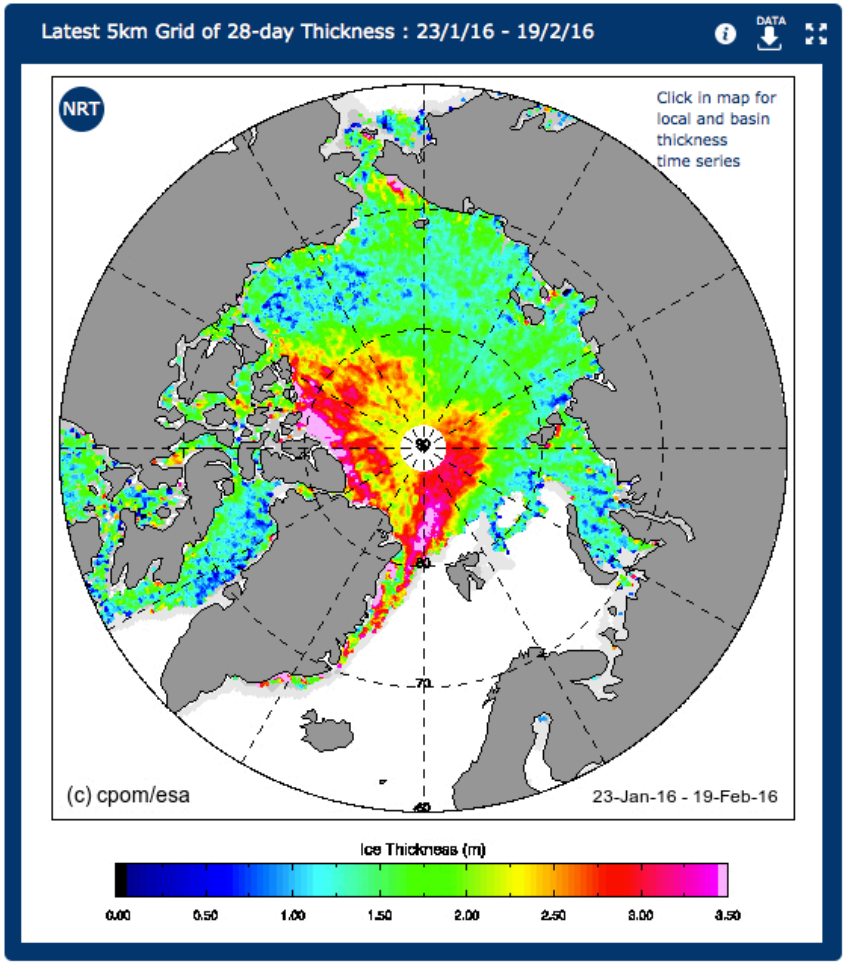
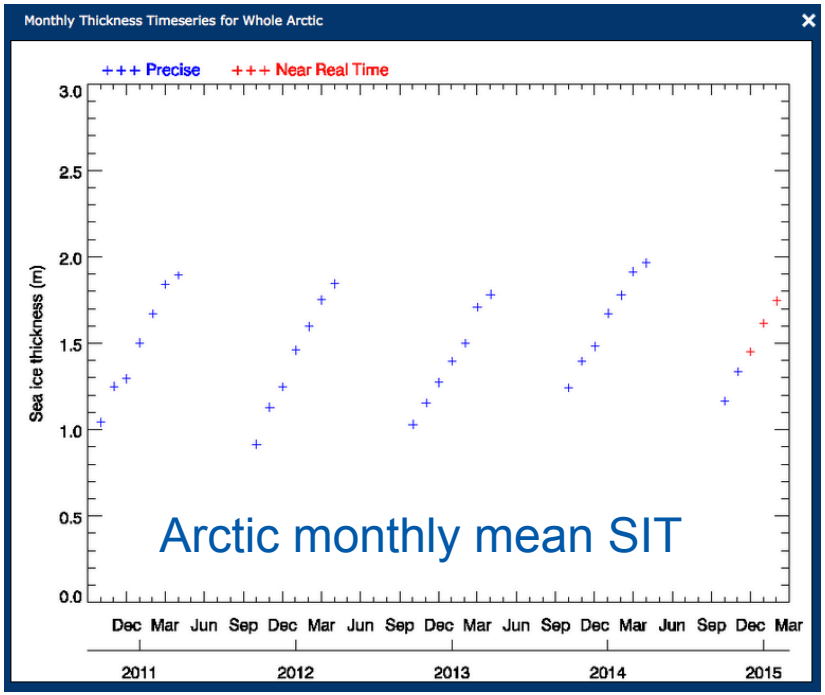
Sea ice thickness



→ focus on **sea ice thickness (SIT)** – likely a key medium for the sea ice system memory on longer time scales

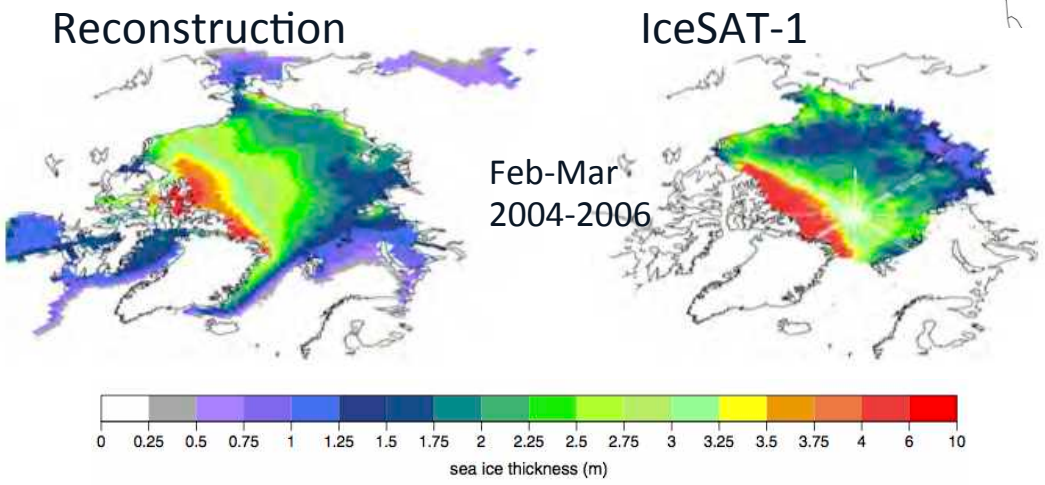


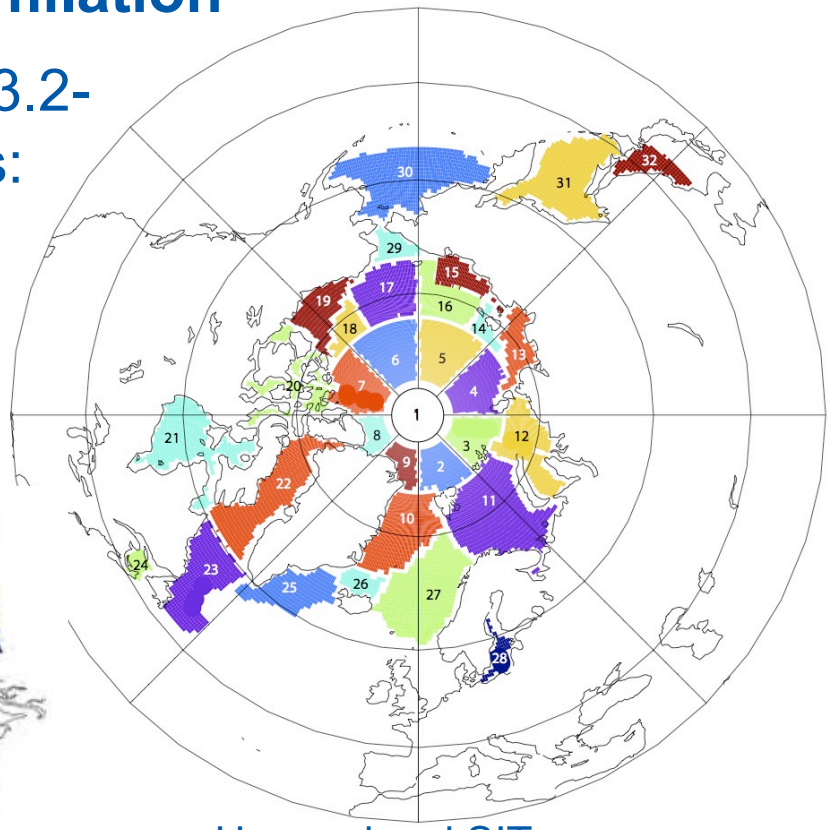
CryoSat-2 www.cpom.ucl.ac.uk/csopr/seaice.html

Sea ice reconstruction

Measuring **SIT** is a demanding task at any scale ⇒ use **reconstruction = GCM + data assimilation**

Combined two multi-member NEMO3.2-LIM2 reconstructions (surface forcings: DFS4.3 and ERA-Int, and ocean restoring: ORAS4) to get continuous **SIT** over the 1958-2013 period

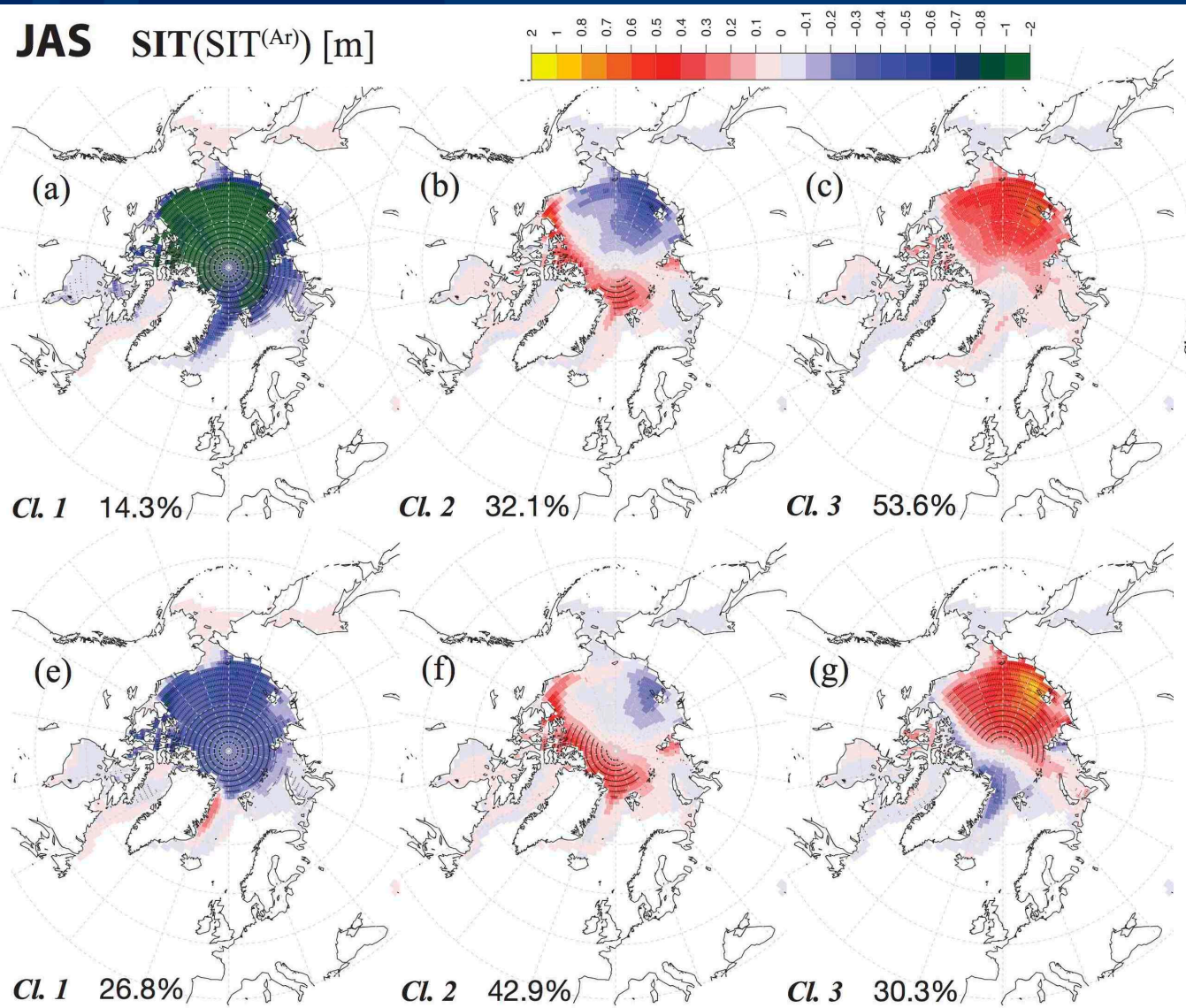




Use regional SIT averages:
~1000 → 32 degrees of freedom

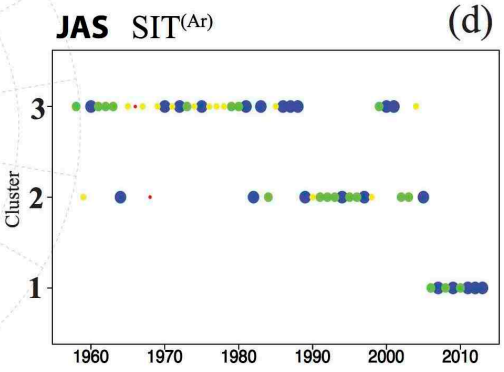
How to disentangle long-term climate change?

Filtering out climate change

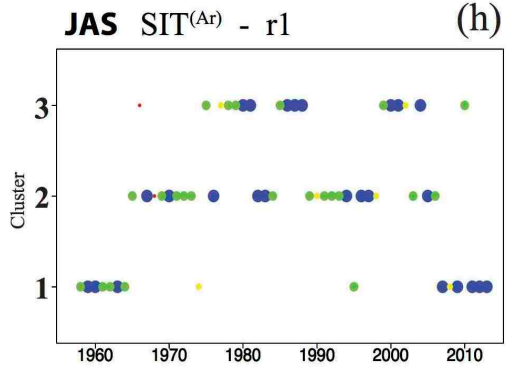


K=3

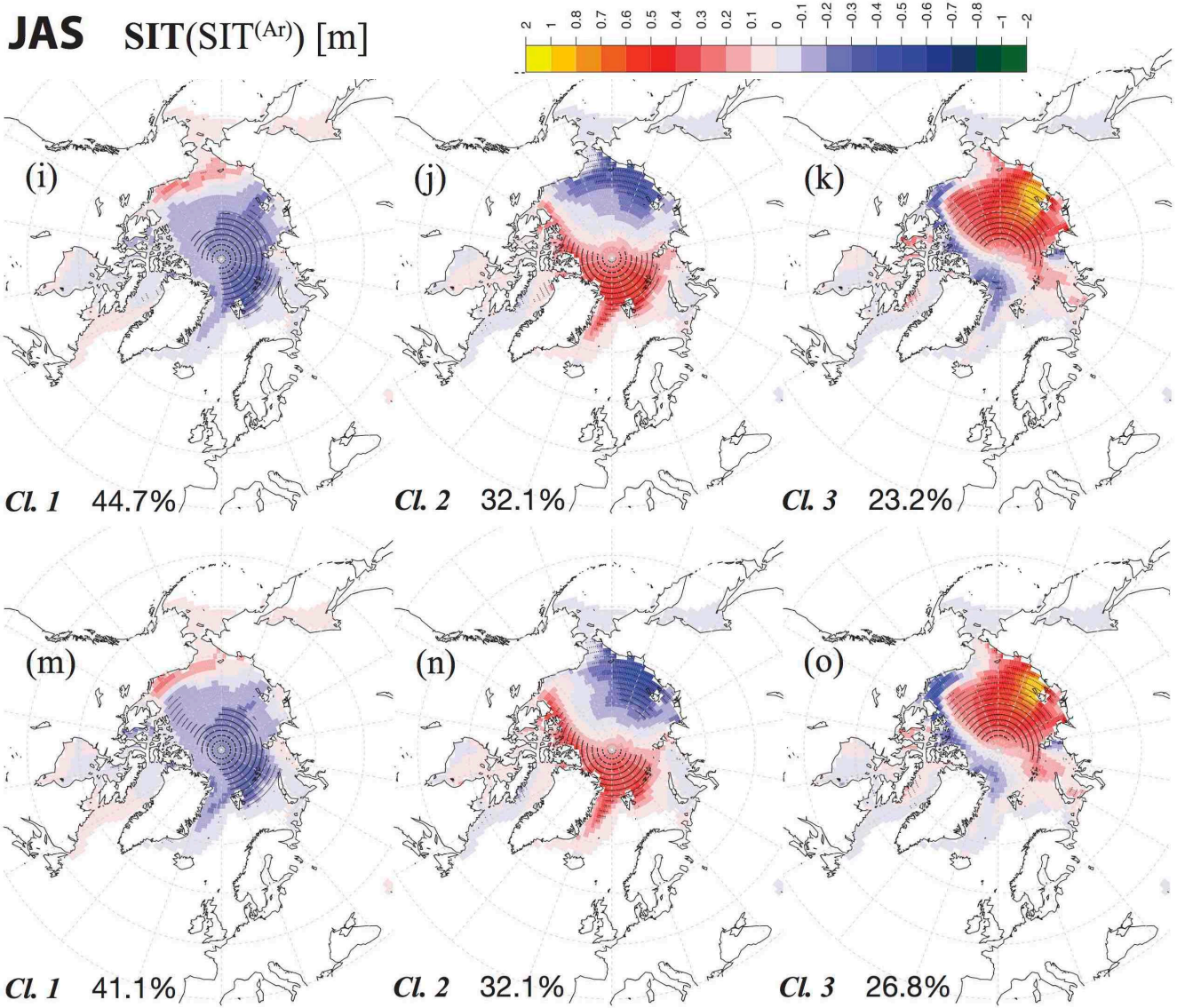
- 0th order residuals



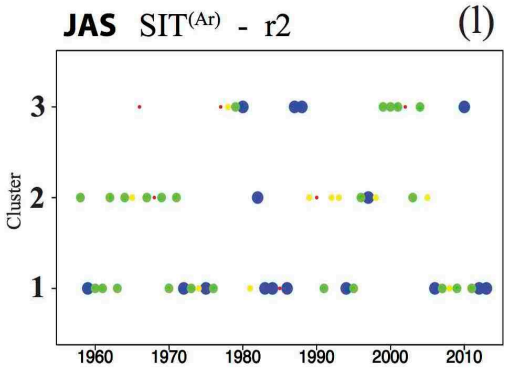
- 1st order residuals



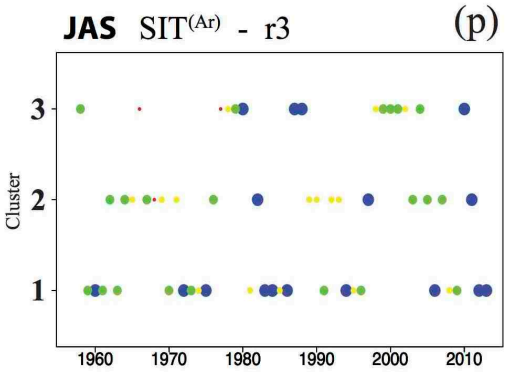
Filtering out climate change



- 2nd order residuals

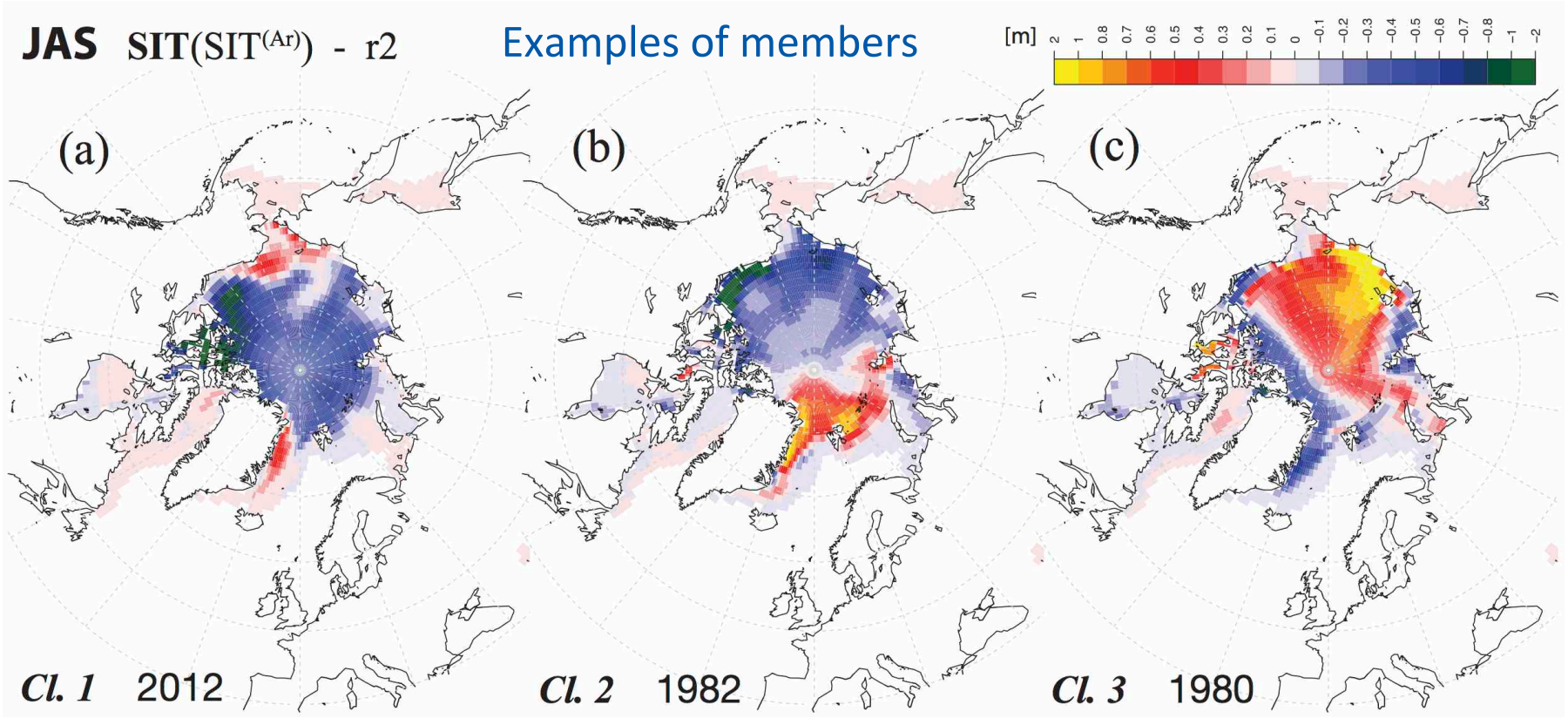


- 3rd order residuals



SIT cluster members

⇒ nonlinear forced response of the Arctic requires removing 2nd order polynomial approximation of the long-term climate change to determine robust SIT variability clusters

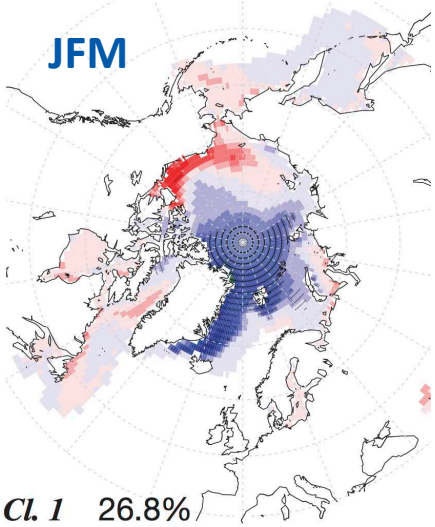


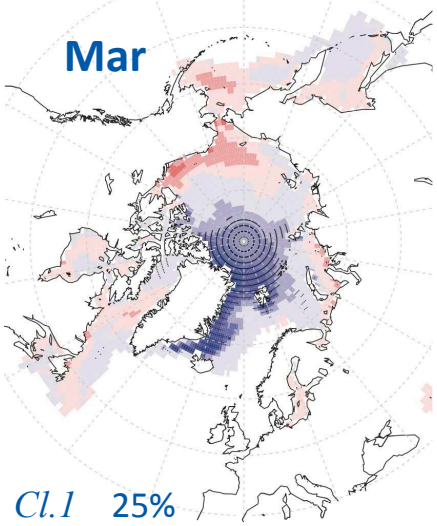
Structure of the NH SIT cluster centers

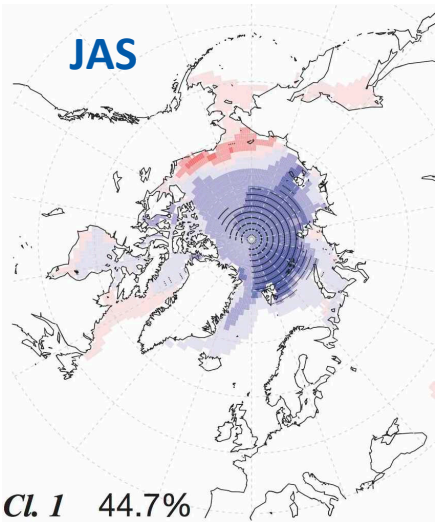
SIT cluster centers & SIC comp.

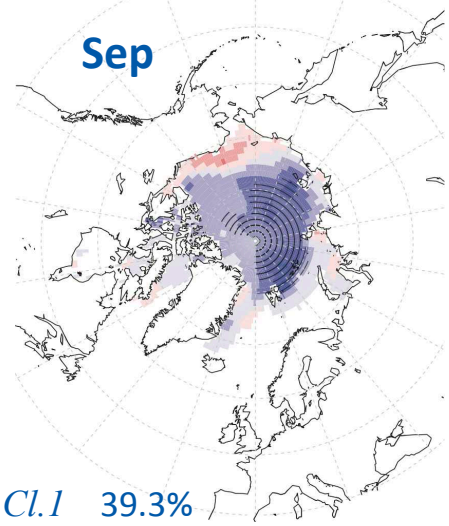
Cluster 1 = Central Arctic Thinning (**CAT**) mode

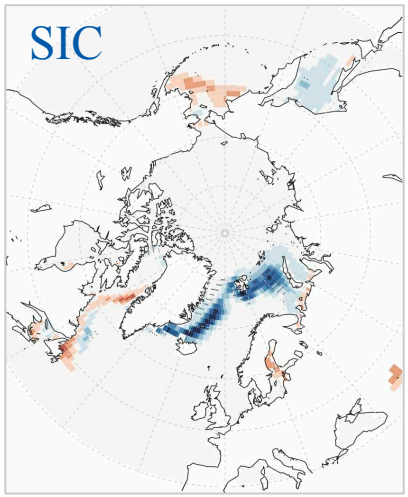
SIT(SIT$^{(Ar)}$) - r2

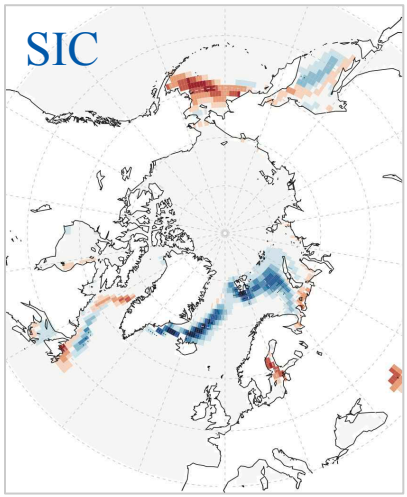


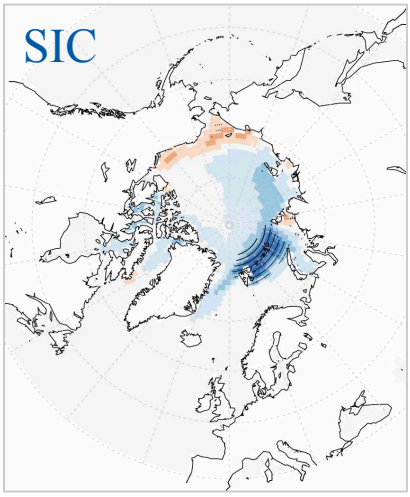


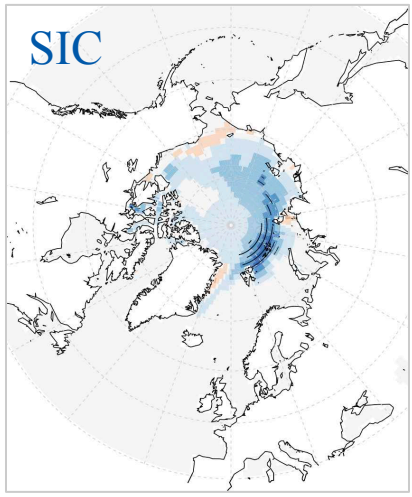












framed by SIT clusters

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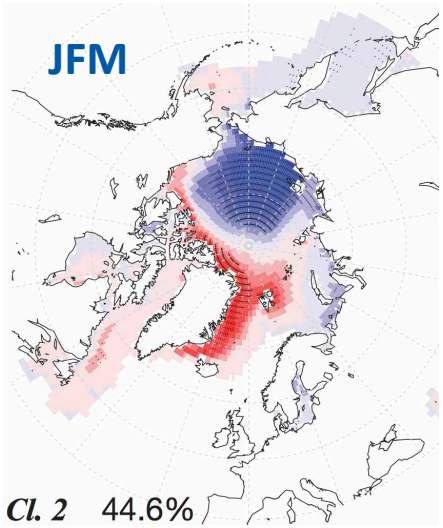
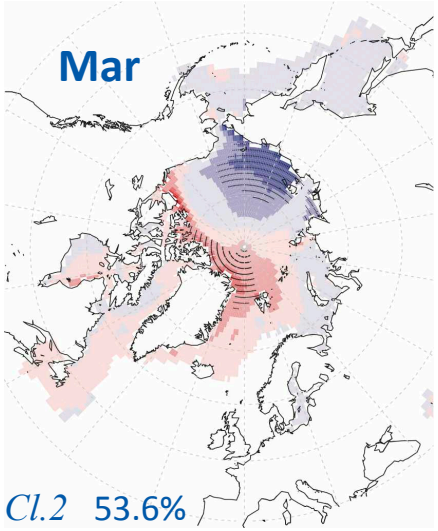
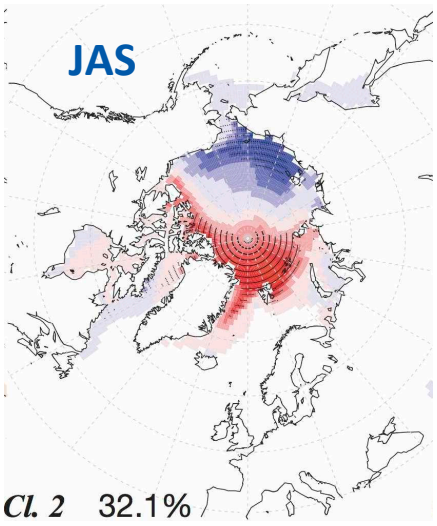
SIT cluster centers & SIC comp.

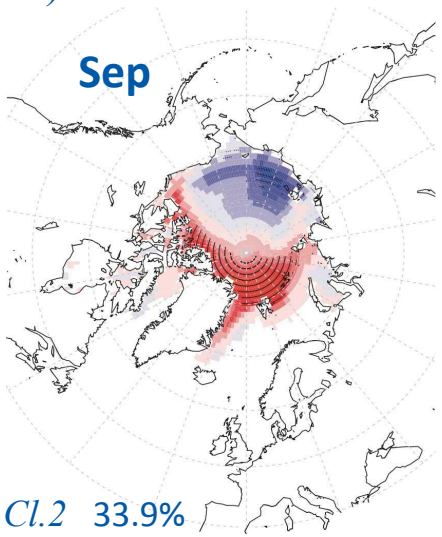
Cluster 2 = Atlantic Pacific Dipole (**APD**) mode

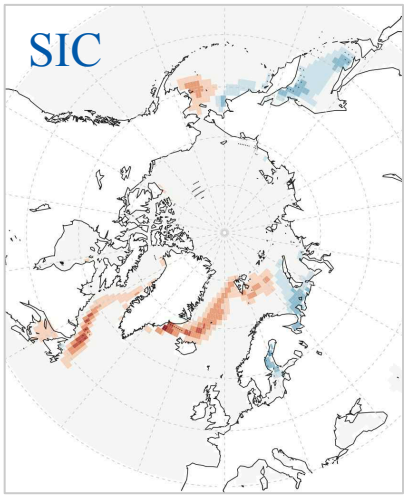
SIT(SIT$^{(Ar)}$) - r2

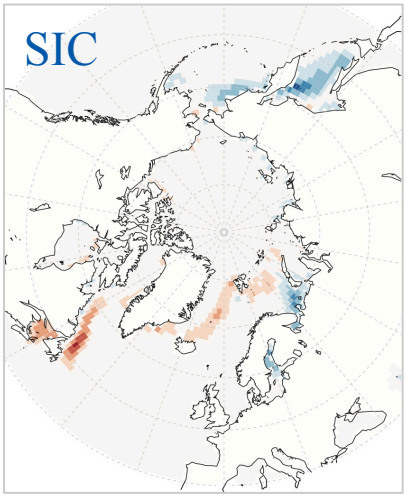


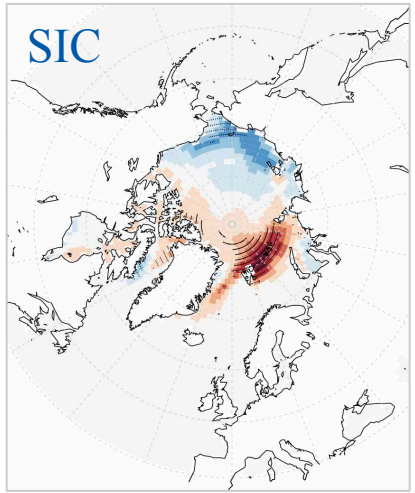


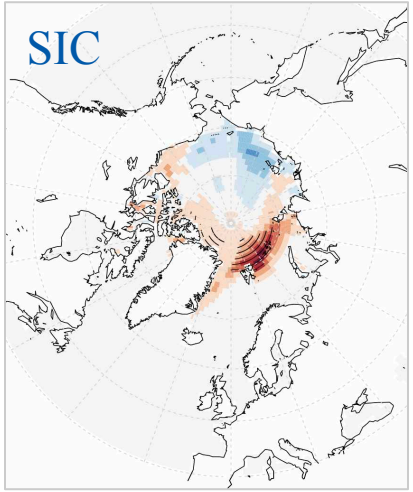












framed by SIT clusters

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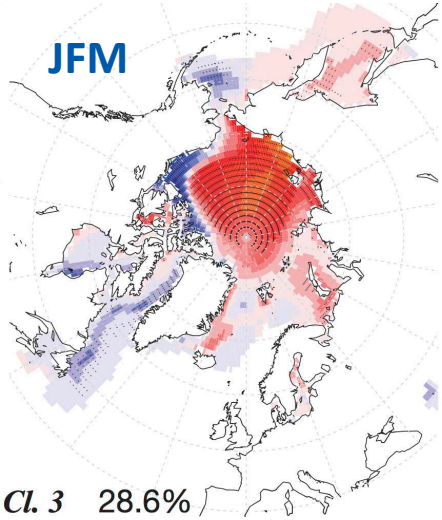
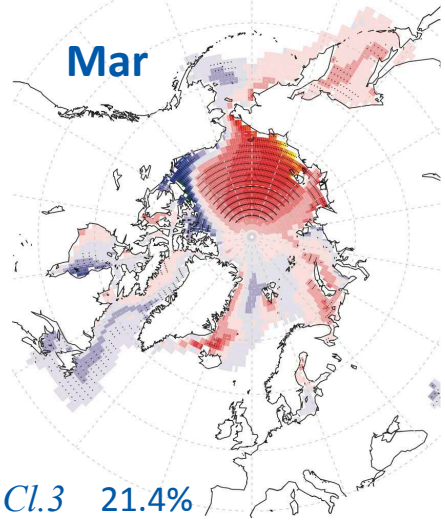
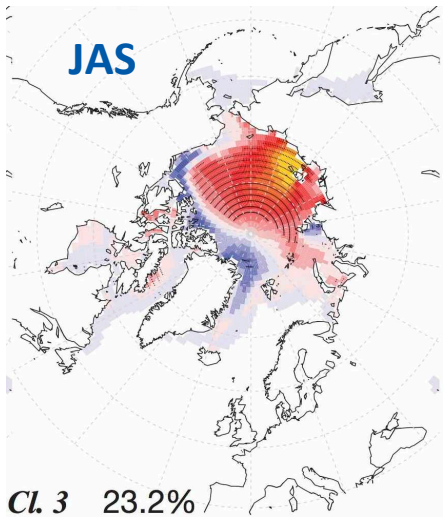
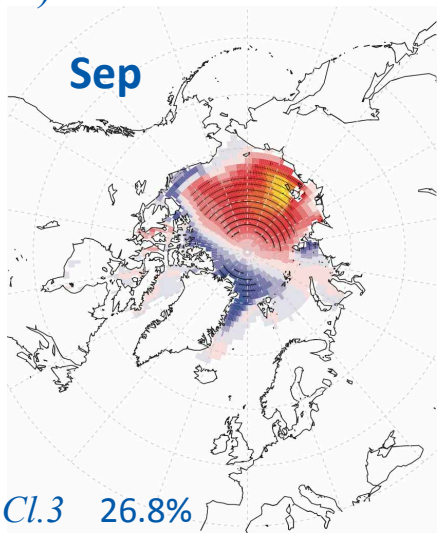
SIT cluster centers & SIC comp.

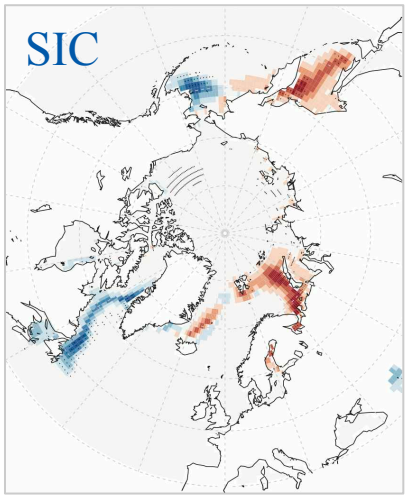
Cluster 3 = Canadian Siberian Dipole (**CSD**) mode **SIT**(SIT$^{(Ar)}$) - r2

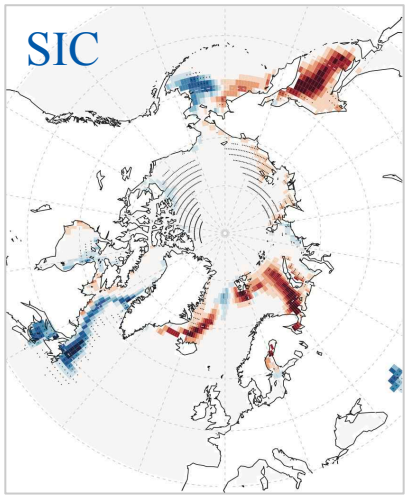


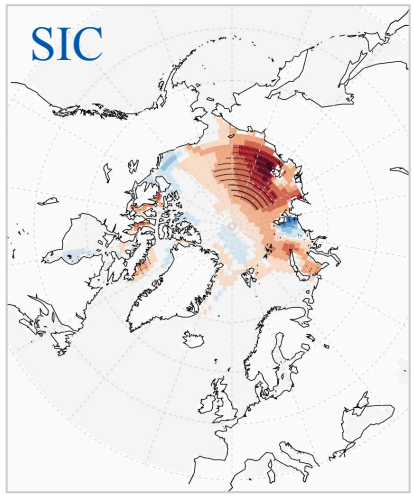


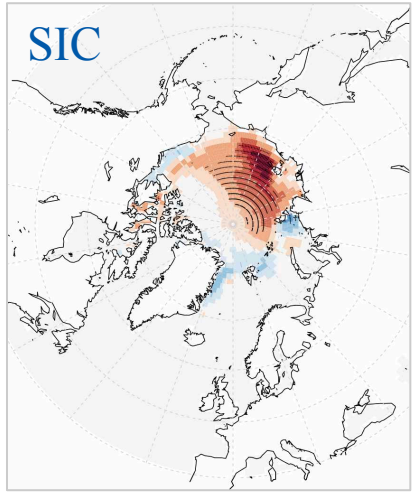












framed by SIT clusters

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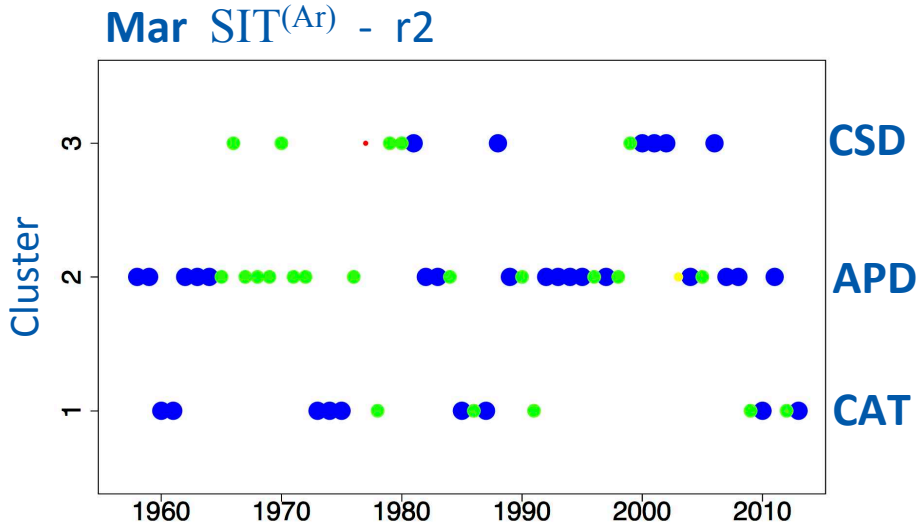
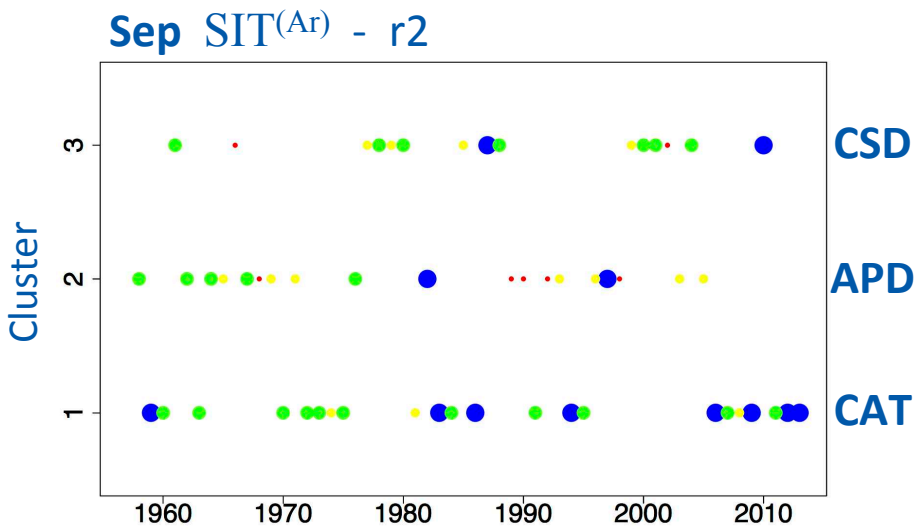
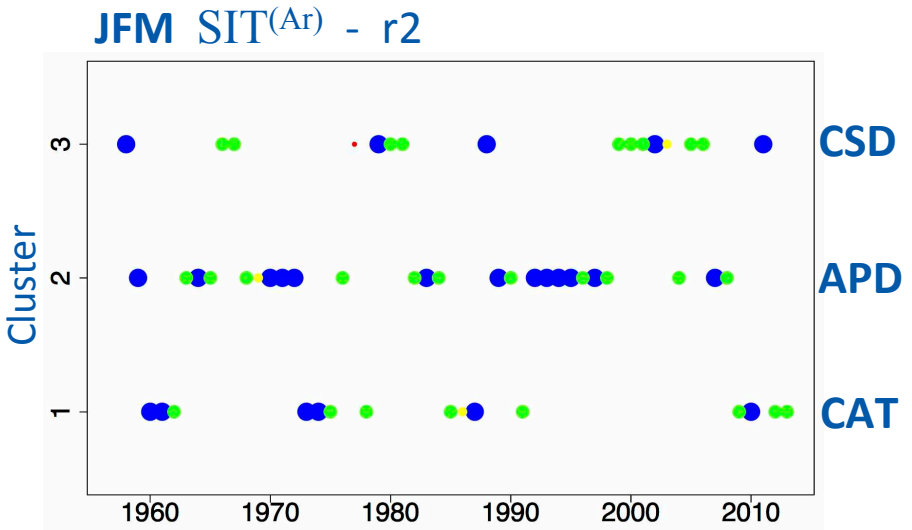
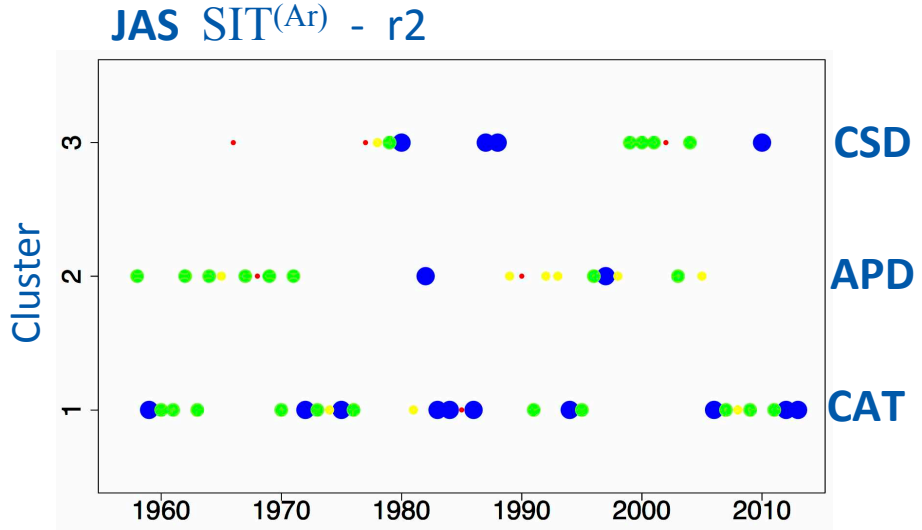
Occurrence of the NH SIT clusters

SIT cluster occurrences

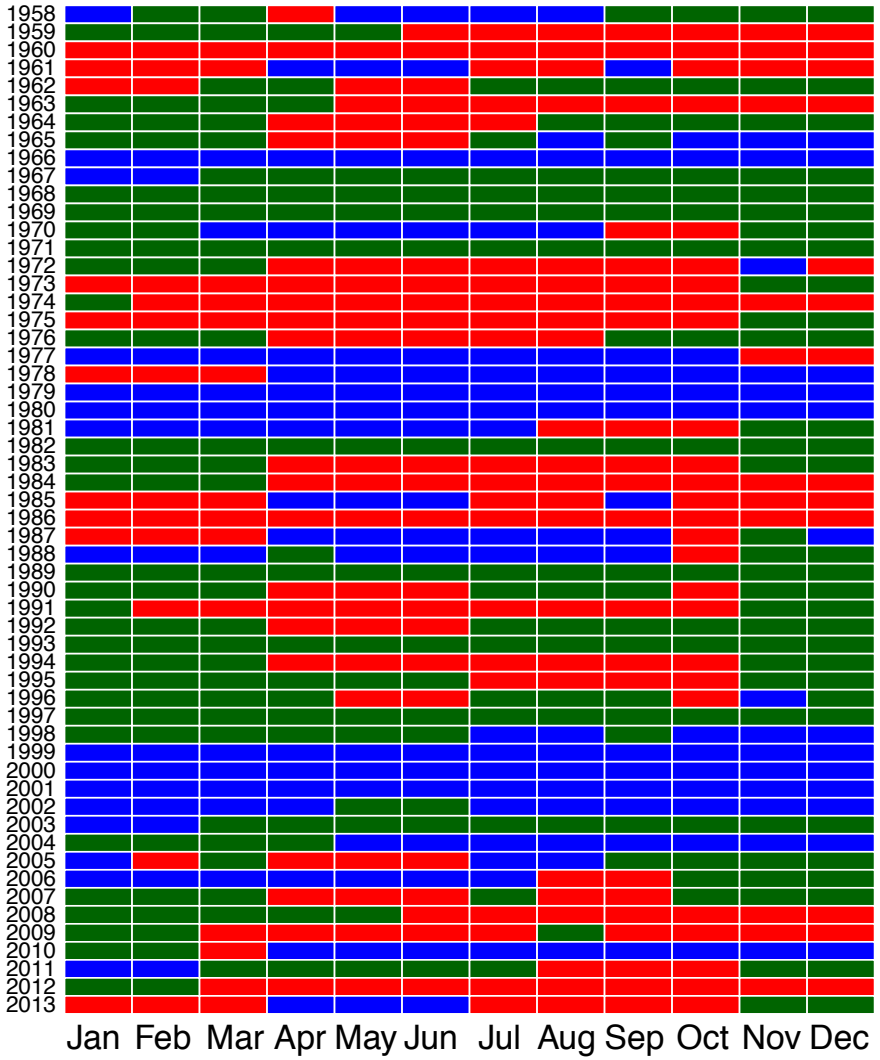








Persistence of SIT clusters



→ 3 identified SIT clusters (CAT, APD and CSD) often show persistence reaching into interannual time scales

← monthly SIT cluster occurrences

X(t+1)	CAT	APD	CSD
P{ X(t+1) | CAT(t) }	81.36%	13.18%	5.45%
P{ X(t+1) | APD(t) }	10.69%	85.12%	4.20%
P{ X(t+1) | CSD(t) }	6.87%	5.82%	87.30%

Conditional probability of the transition between Arctic SIT clusters (1958-2013)

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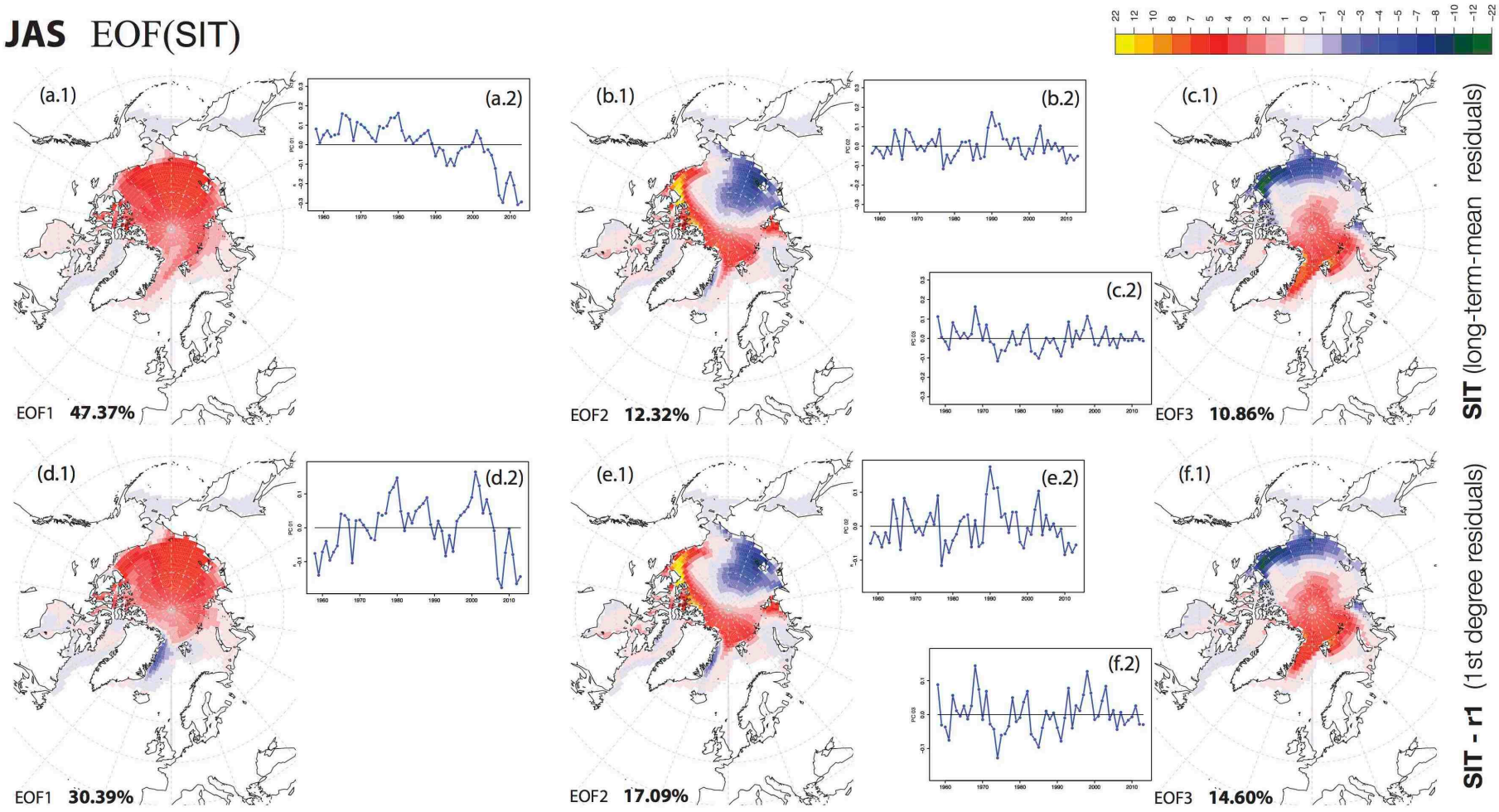
What about EOF analysis?

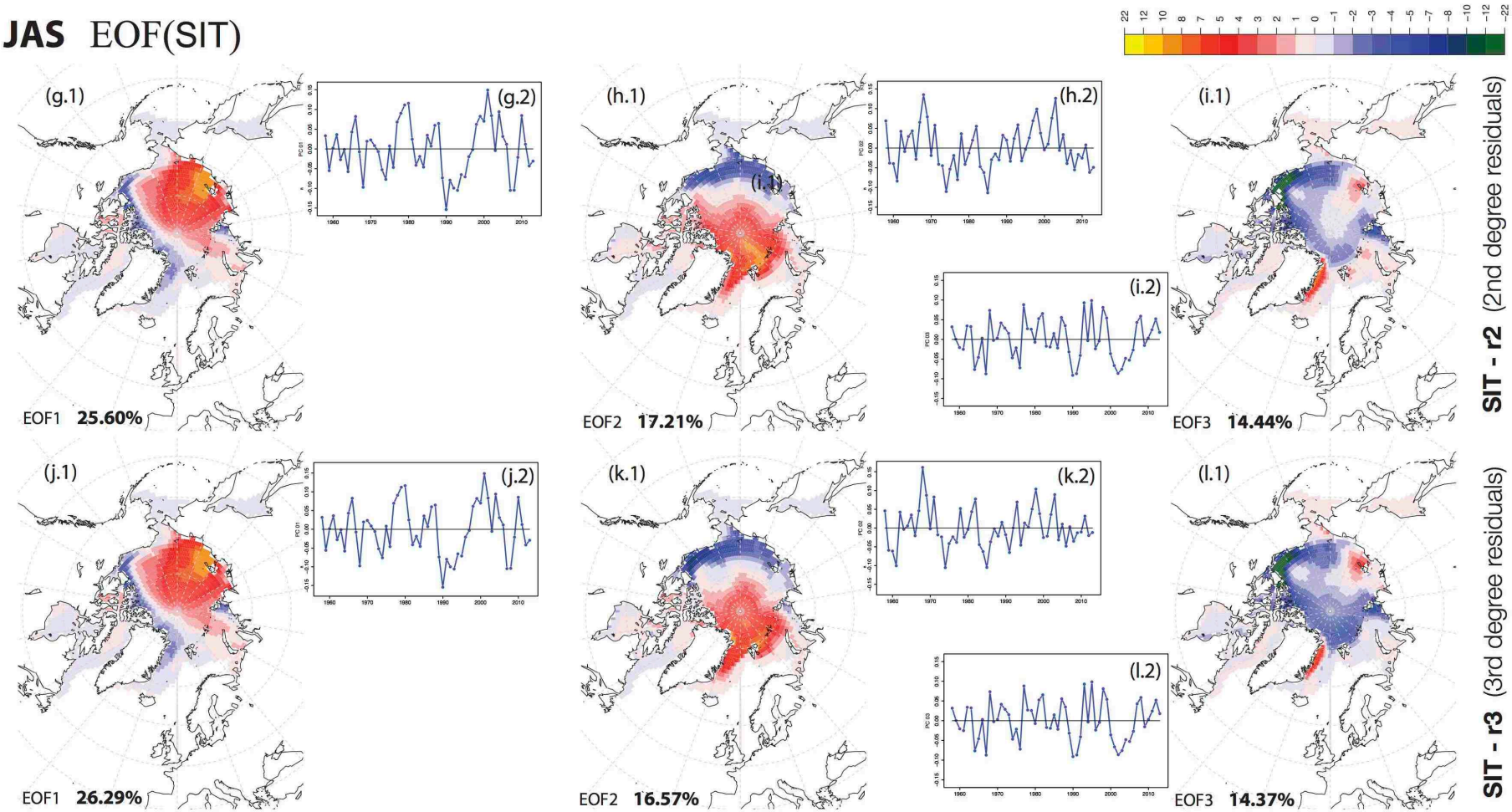
Connection to PCA

Is PCA also sensitive to how we represent long-term change?

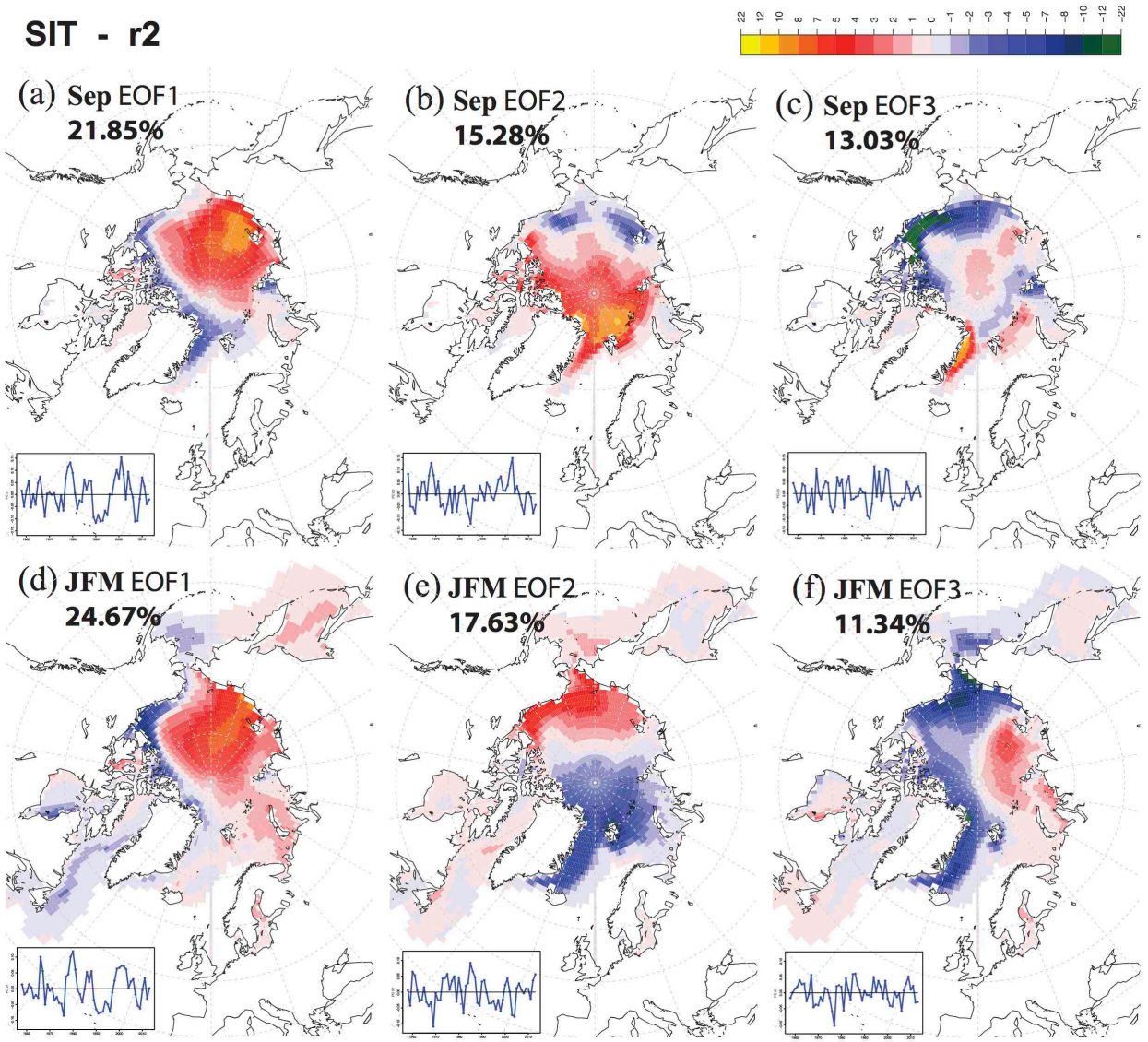


Connection to PCA

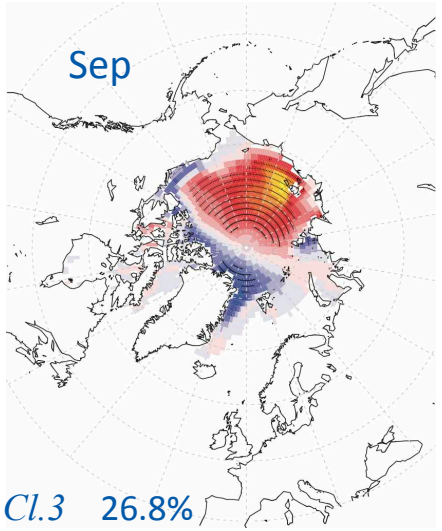
⇒ **1st EOF mode matches cluster 3 (CAT)** and also we have to remove 2nd order polynomial approximation of the long-term climate change to find robust EOFs

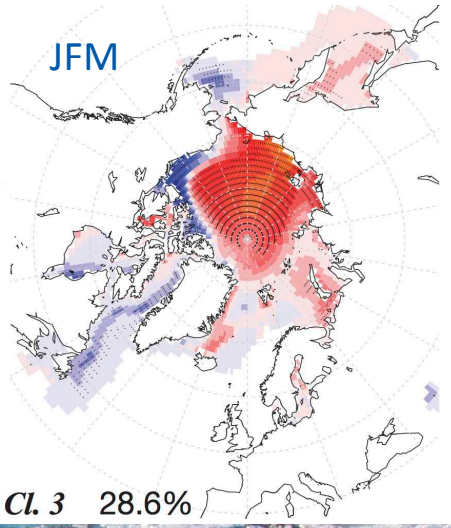


Connection to PCA



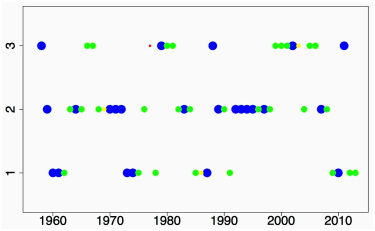
CSD mode

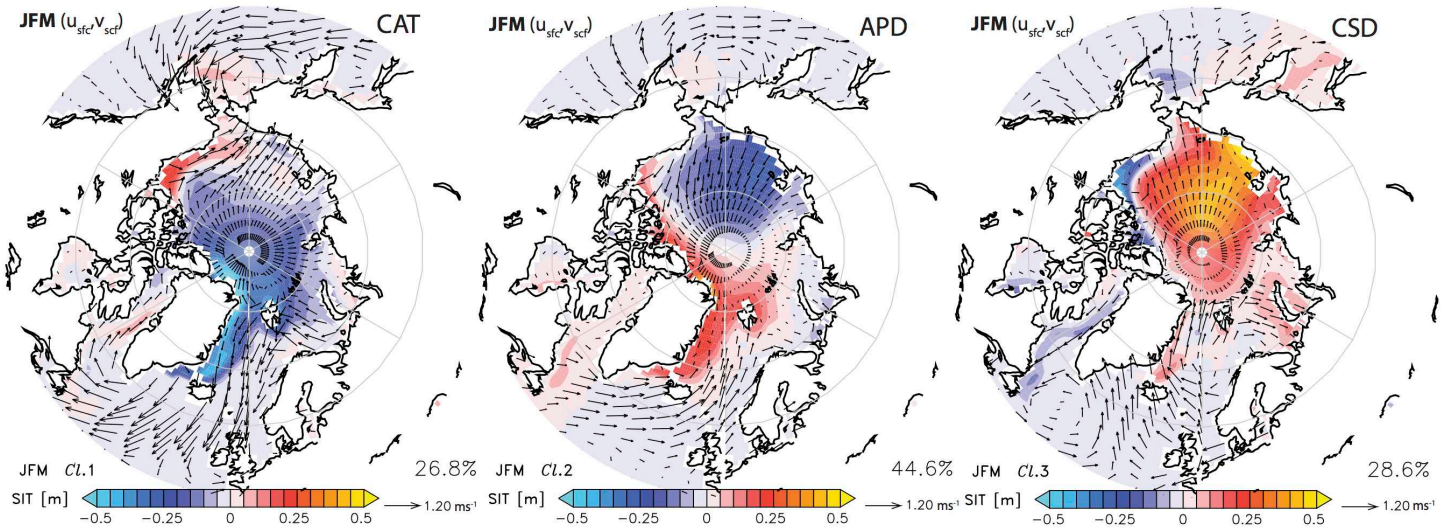


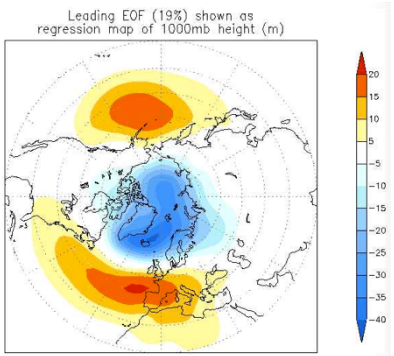


Mechanisms underlying the NH SIT clusters

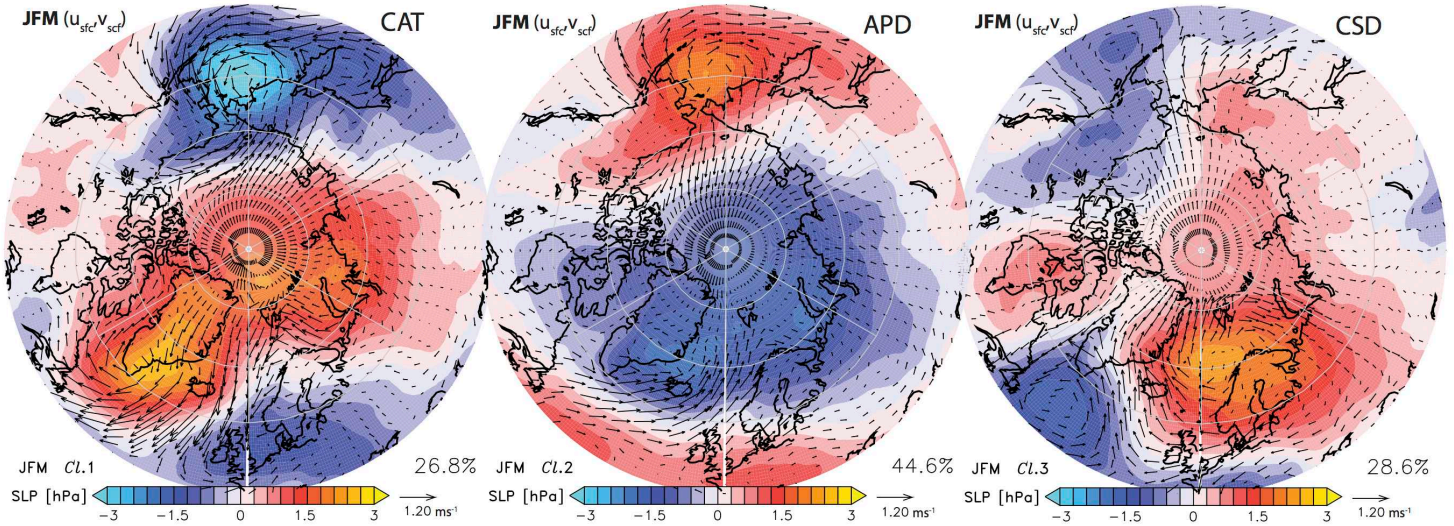
Key influence of surface winds







NAM/AO



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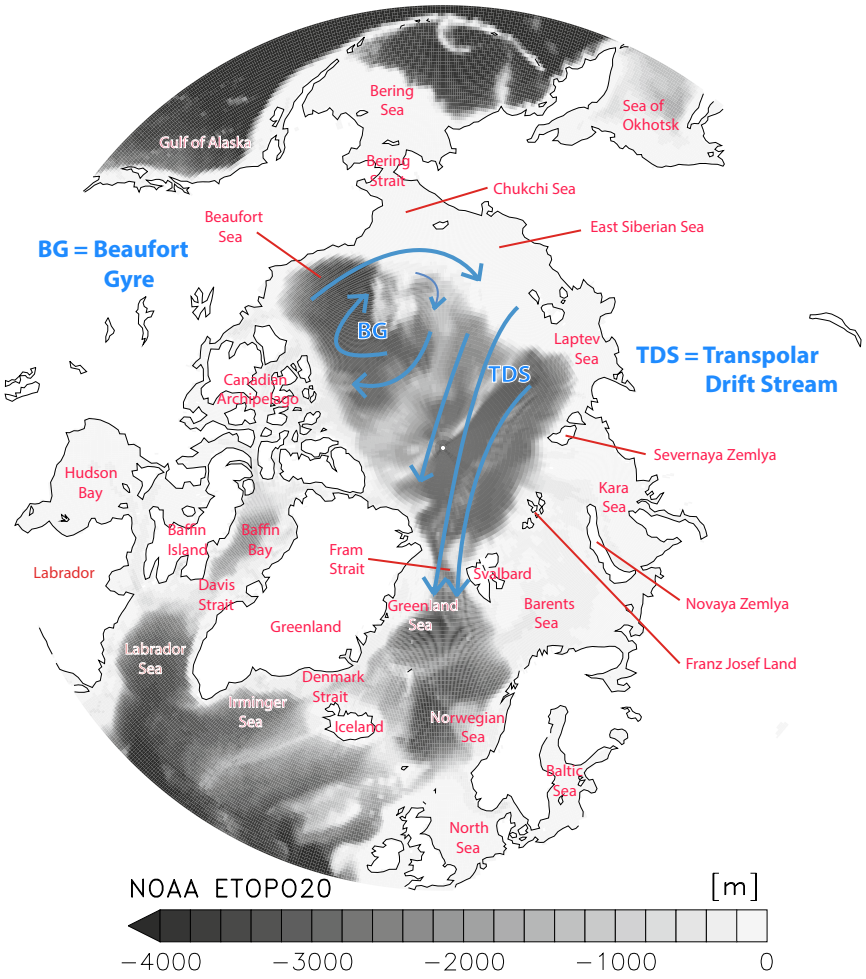
Key influence of surface winds



- SIT across the Arctic primarily varies due to sea ice motion driven by surface winds and ocean currents

→ Compositing analysis indicates that surface winds in winter could be the key factor determining the structure of the SIT variability cluster patterns and driving their occurrences

→ SIT is a better integrator of the atmospheric conditions than SIC on time scales longer than seasonal

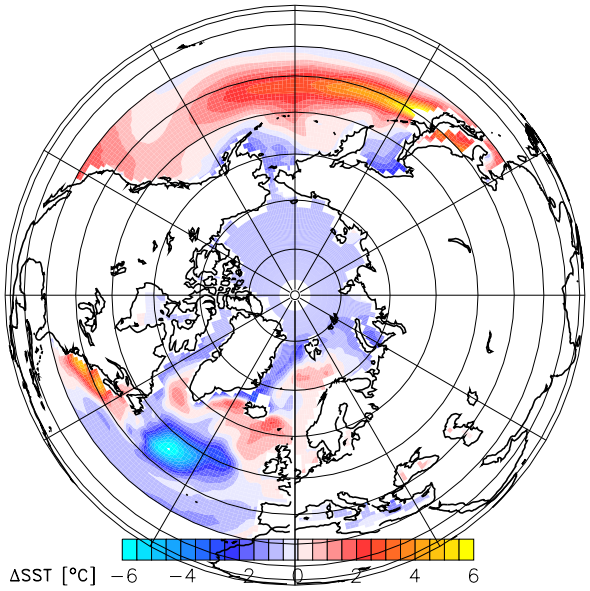
Dynamical prediction of the NH SIT clusters

EC-Earth2.3 seasonal prediction

Seamless Earth-System Model

→ aims to forge weather and climate forecasting, and climate change studies in a single framework

Atmosphere: ECMWF's Integrated Forecasting System (IFS) T159 and L62 (up to 5 hPa)
Land: H-TESSEL (part of IFS)
Ocean: Nucleus for European Modeling of the Ocean (NEMO) v3.2 in ORCA1L42
Sea ice: Louvain-la-Neuve sea Ice Model (LIM) V2 (part of NEMO)



EC-Earth2.3 <1979-2012>
- ERSSTv3b <1979-2012>

→ focus on seasonal (12-month) prediction using full-field initialization (using ERA-Interim for atmospheric IC, ORAS4 for oceanic IC and sea ice IC from reconstruction used to identify SIT clusters) with May 1st and November 1st start dates from 1979 to 2010

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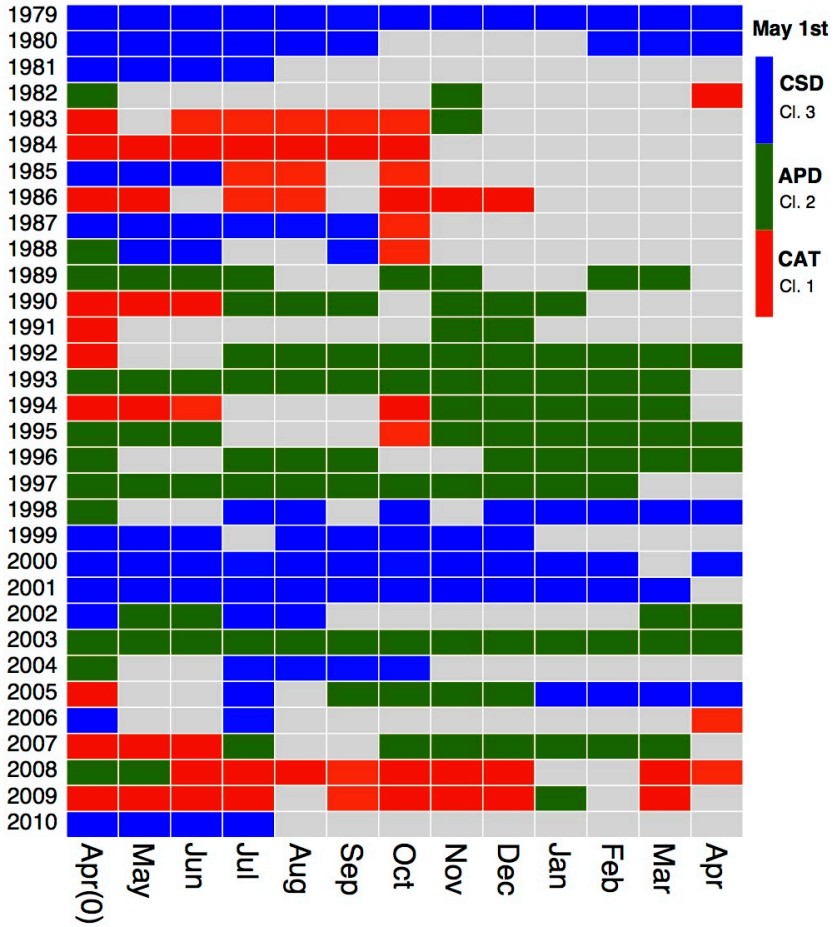
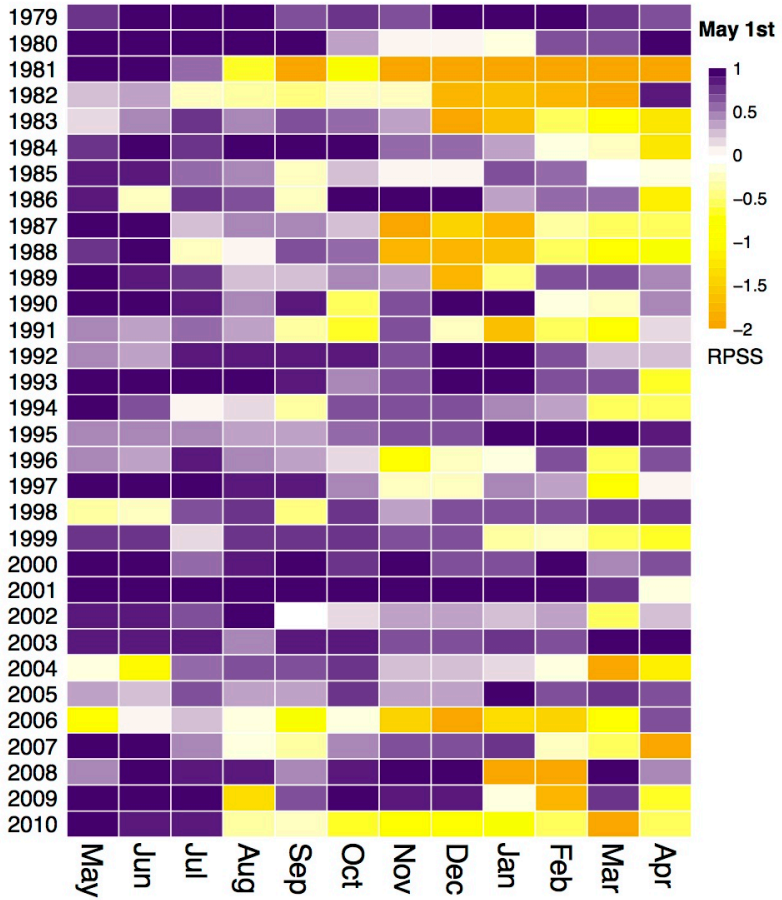
Skill of May 1st start dates

Success of multi-member dynamical SIT cluster forecast

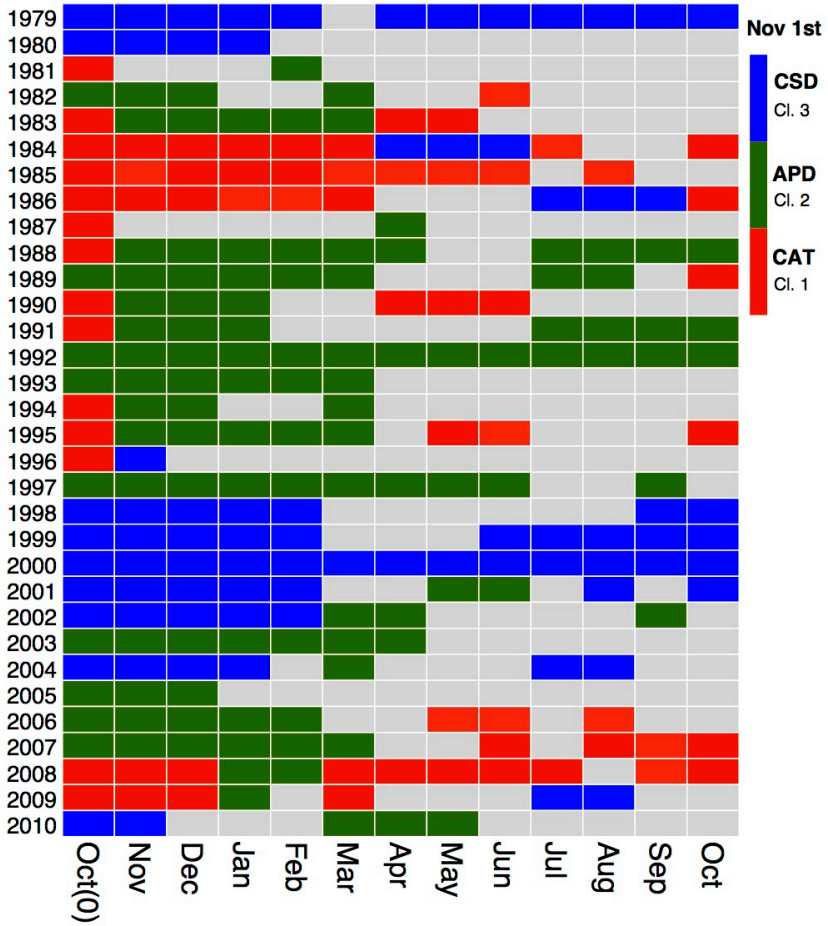


Rank Probability Skill Score (ref. – 1st order Markov chain)

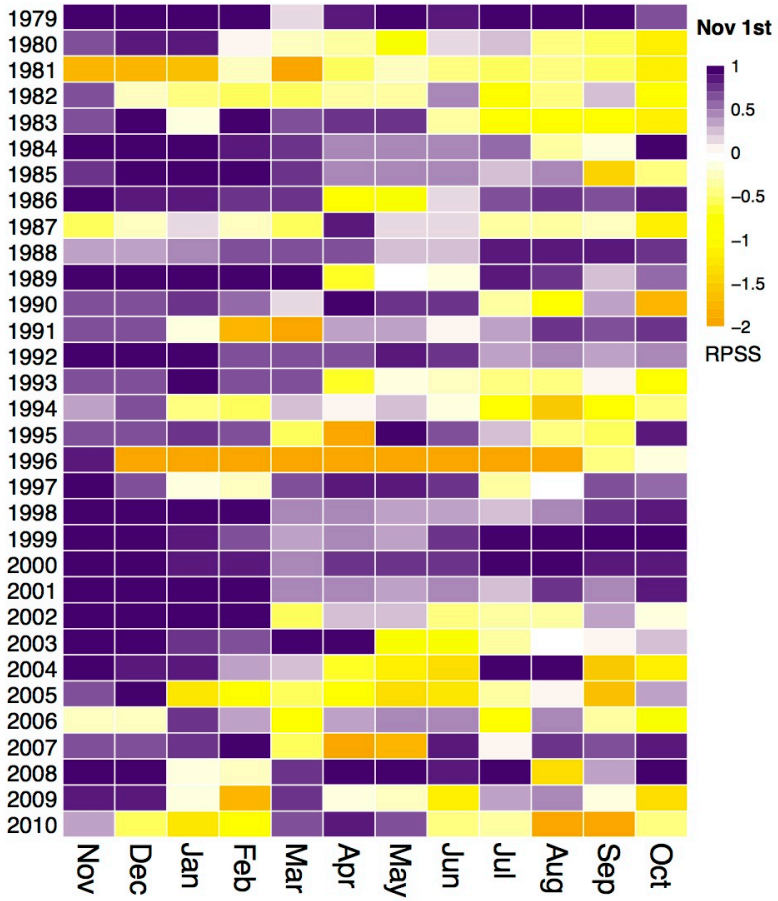


Skill of November 1st start dates

Success of multi-member dynamical SIT cluster forecast



Rank Probability Skill Score (ref. – 1st order Markov chain)



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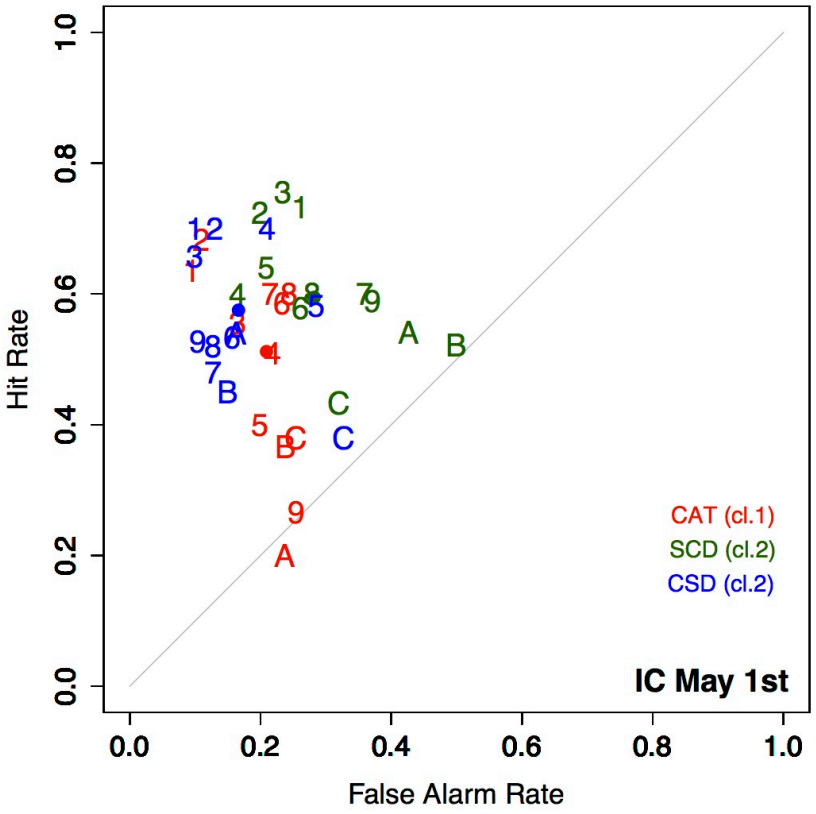
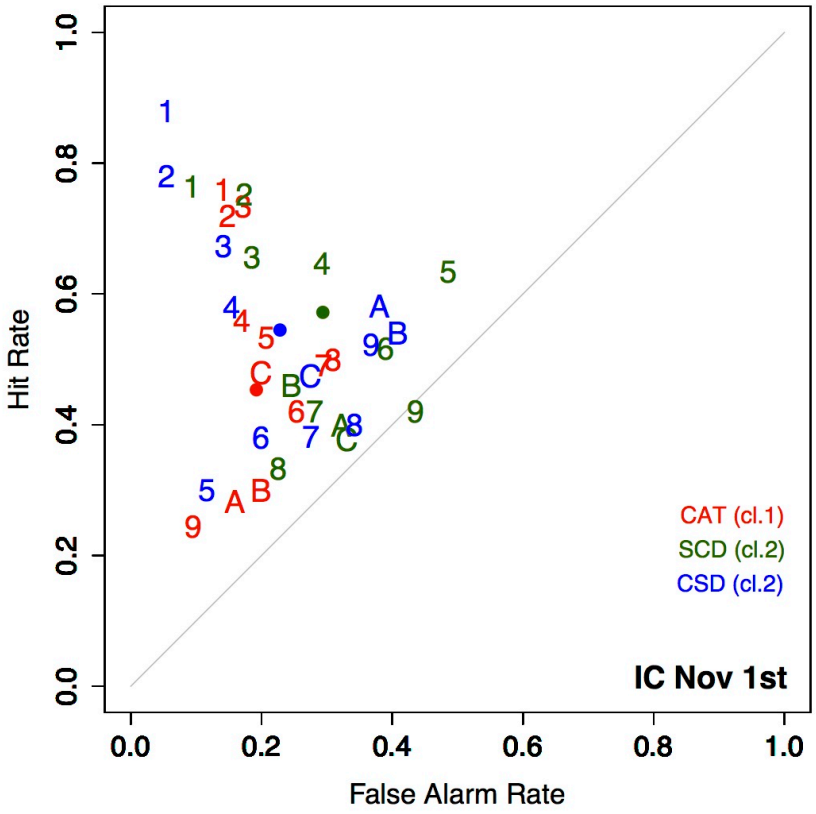
ROC diagrams of SIT clusters





→ Dynamical SIT cluster predictions initialized in summer (May 1st) show initially lower skill that predictions initialized in winter (Nov 1st), but prediction skill in summer is deteriorated at slower rate than in winter

Take-home points

Summary and conclusions

➠ Removing quadratic approximation of long-term climate change in the Arctic yields robust K-means SIT cluster patterns (as well as EOF patterns)

➠ Optimal number of the NH SIT K-means clusters is **K=3**:
Cl. 1 = **CAT mode**, Cl. 2 = **APD mode**, and Cl. 3 = **CSD mode**, and they have rather consistent patterns in different months and seasons
(SIT CSD pattern matches 1ts EOF pattern)

➠ Time series of SIT cluster occurrences show persistence from seasonal to interannual time scales

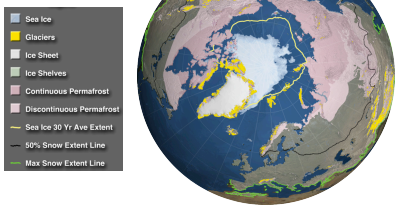
➠ Wind in winter appears as the most crucial for the formation, structure and occurrence of SIT clusters

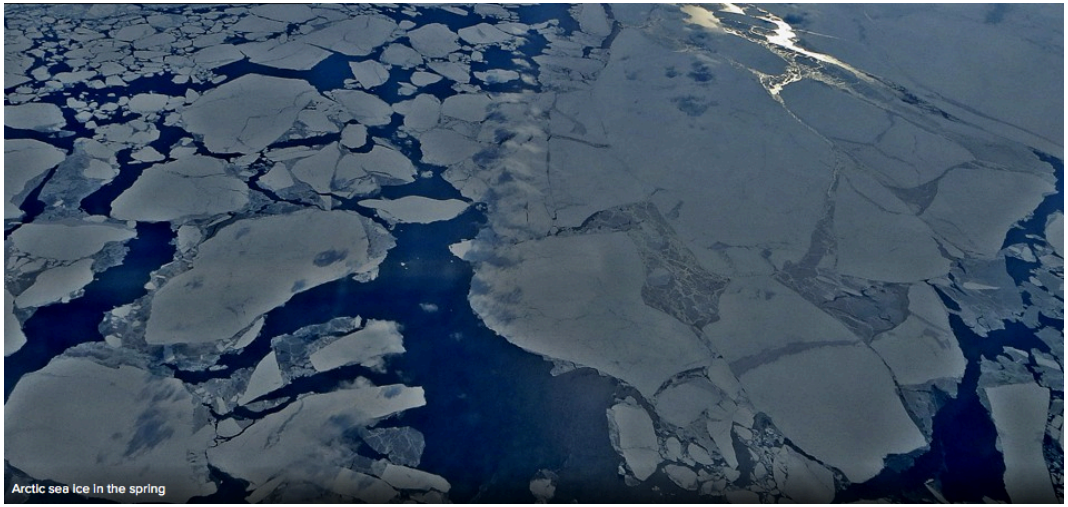
➠ EC-Earth2.3 shows substantial prediction skill of SIT clusters also indicating that obs. IC in summer are more important that in winter

Thank you for your attention

Merci pour votre attention

Avez-vous des questions?





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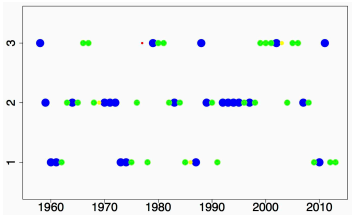
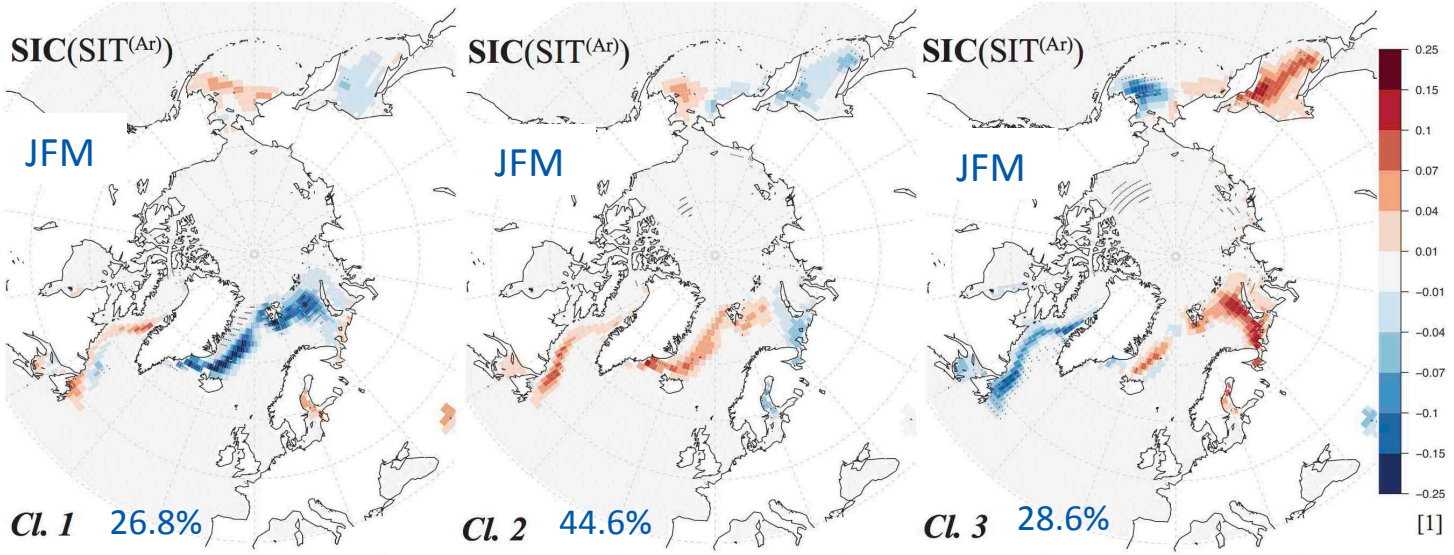
Reconstruction vs HadISST SIC

JFM $SIT^{(Ar)}$ - r2

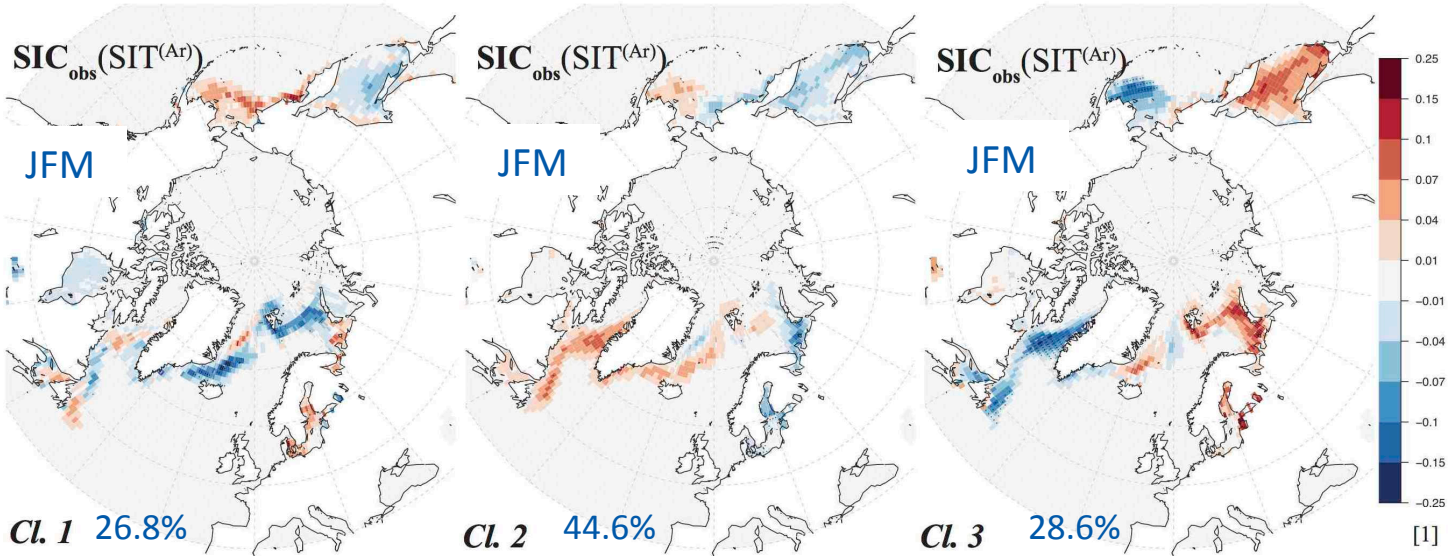


reconstruction



A posteriori validation through SIC composites ✓

HadISST



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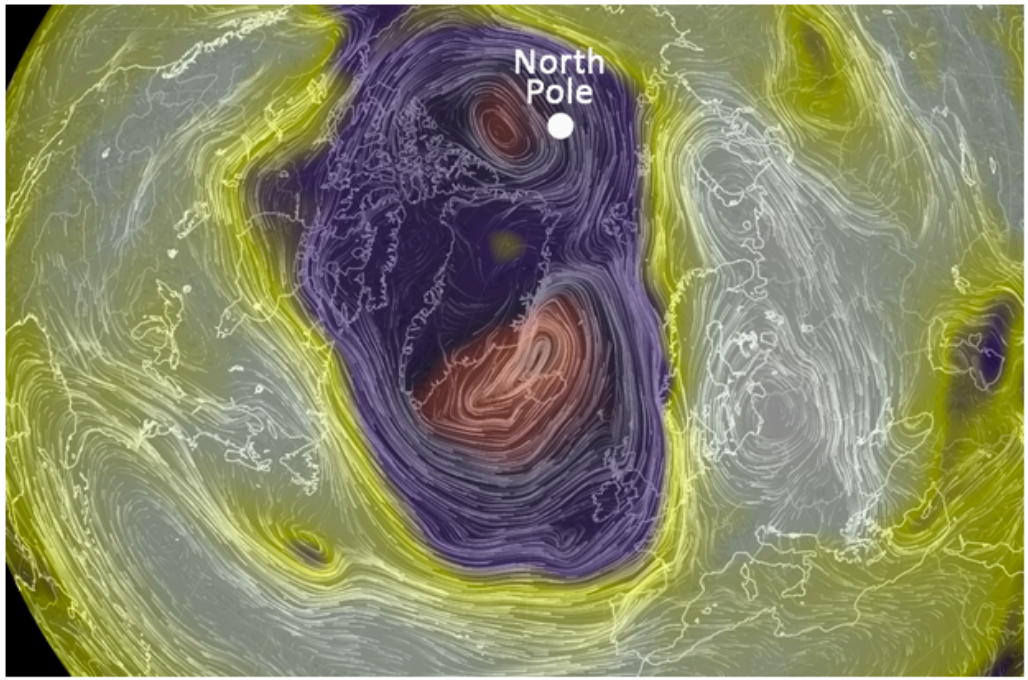
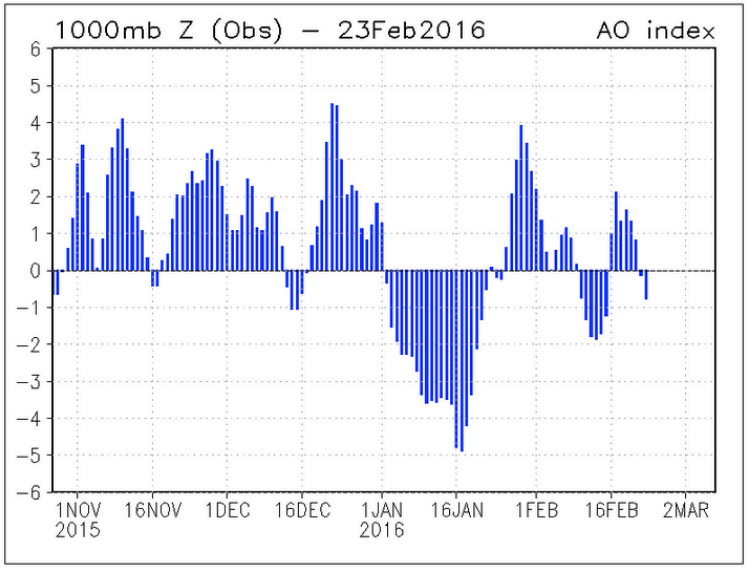
Storm “Frank” and AO index



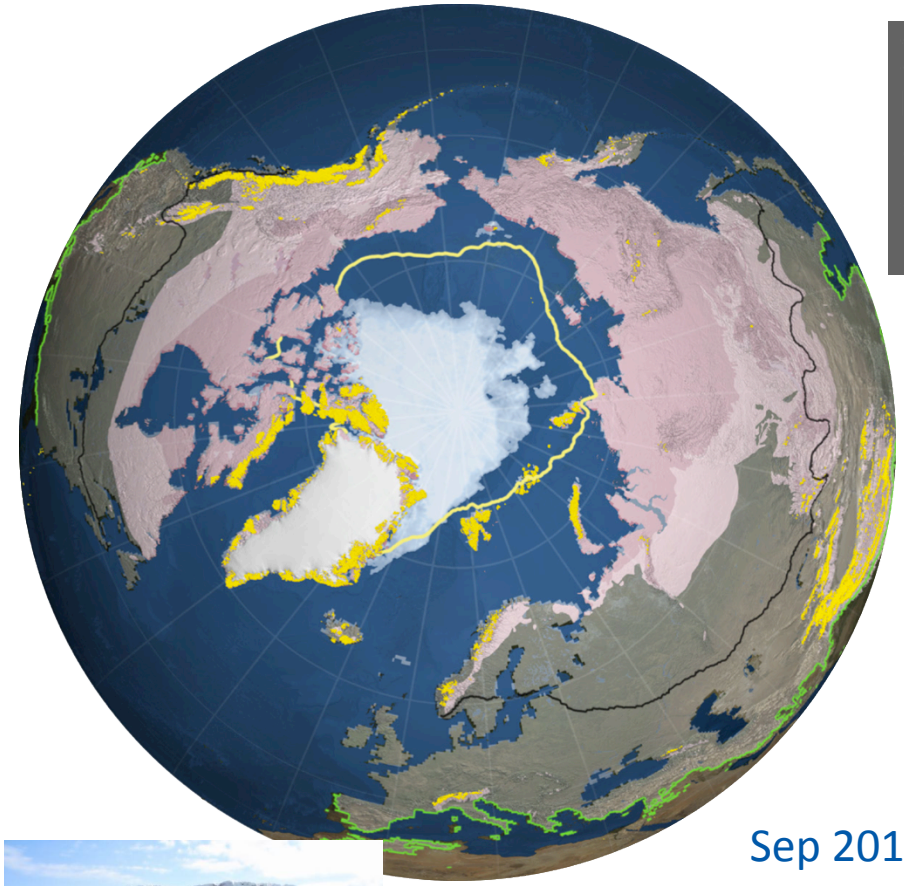
This storm in the far North Atlantic is the same storm that caused two tornado outbreaks and widespread flooding in the United States. Now, it's pushing temperatures at the North Pole well above average. (earth.nullschool.net)



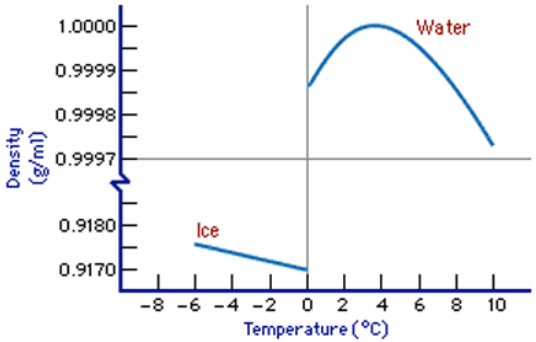
NOAA/NCEP

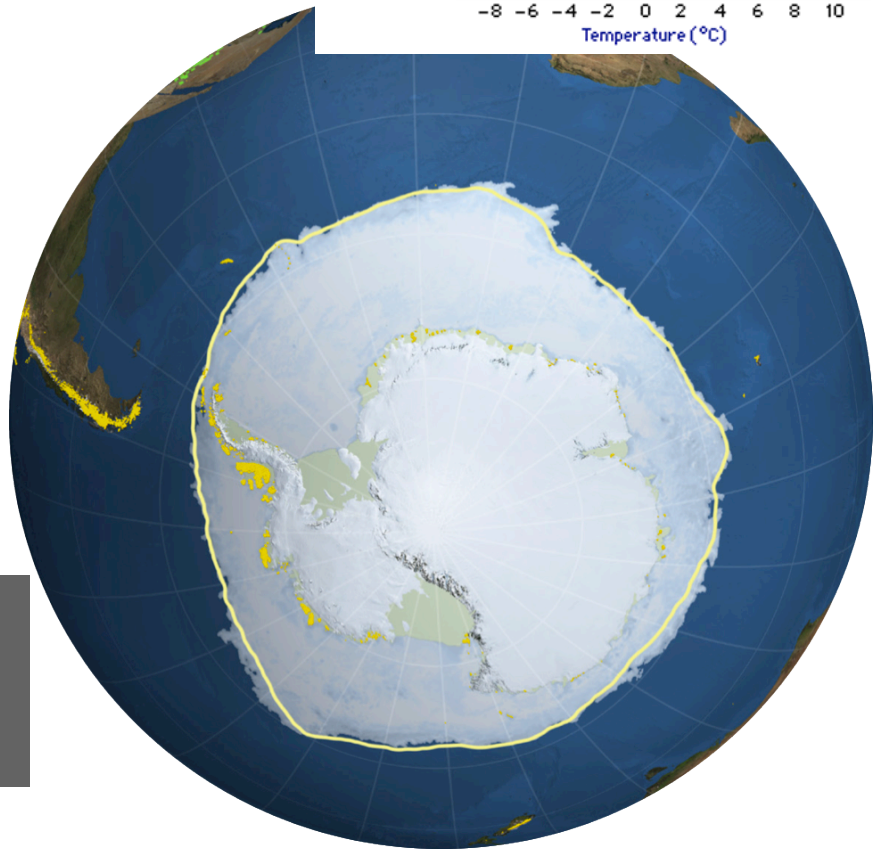
≈ December 30th, 2015 (storm Frank)

Cryosphere (sea ice, snow, glaciers, permafrost, ..)

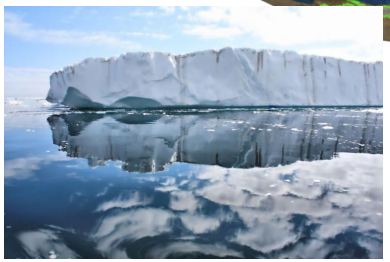


Continuous Permafrost
Discontinuous Permafrost
Sea Ice 30 Yr Ave Extent
50% Snow Extent Line
Max Snow Extent Line





Sep 2012

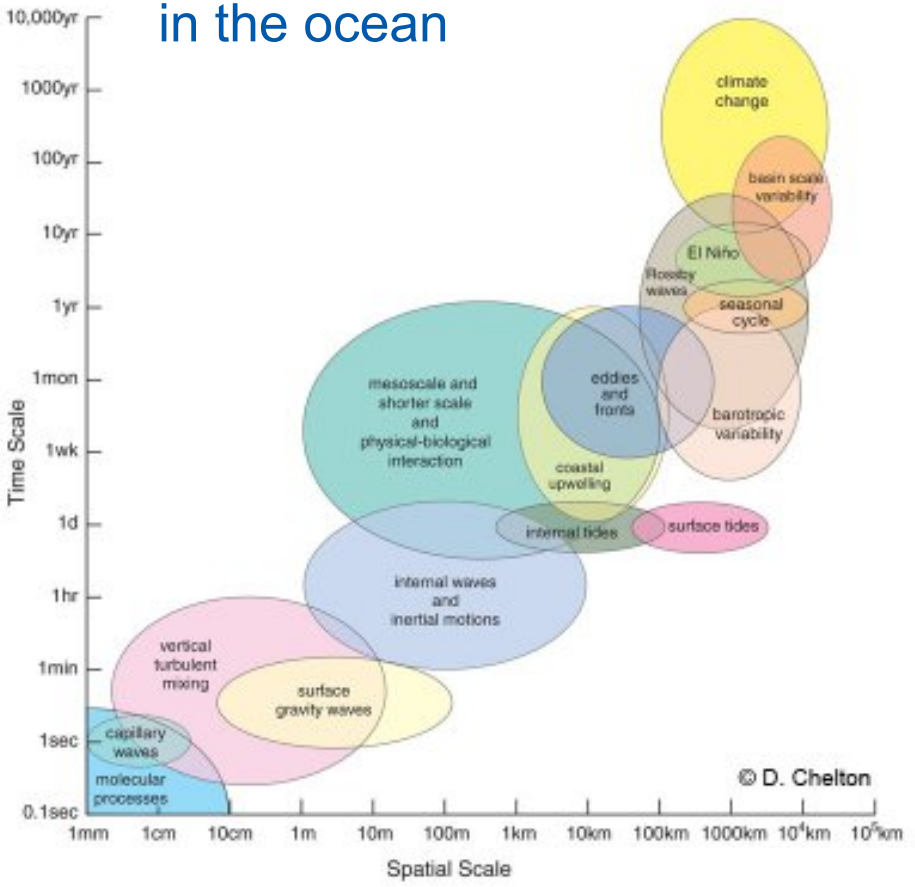


Sea Ice
Glaciers
Ice Sheet
Ice Shelves

Some characteristic time and spatial scales

Component of the Climate System	Process	Characteristic time scale	Characteristic spatial scale
Atmosphere	Collision of droplets during cloud formation	10^{-6}–10^{-3} s	10^{-6} m
	Formation of convection cells	10^{4}–10^{5} s	10^{2}–10^{4} m
	Development of large-scale weather systems	10^{4}–10^{5} s	10^{6}–10^{7} m
	Persistence of pressure distributions	10^{6} s	10^{6}–10^{7} m
	Southern Oscillation	10^{7} s	10^{7} m
	Troposhere–stratosphere exchange	10^{7}–10^{8} s	global
Hydrosphere	Gas exchange atmosphere–ocean	10^{-3}–10^{6} s	10^{-6}–10^{3} m
	Deep water formation	10^{4}–10^{6} s	10^{4}–10^{5} m
	Meso-scale oceanic gyres	10^{6}–10^{7} s	10^{4}–10^{5} m
	Propagation of Rossby waves	10^{7} s	10^{7} m
	El Niño	10^{7}–10^{8} s	10^{7} m
	Turnover of deep water	10^{9}–10^{10} s	global
Cryosphere	Formation of permafrost	10^{7}–10^{9} s	1–10^{6} m
	Formation of sea ice	10^{7}–10^{8} s	1–10^{6} m
	Formation of land ice masses	10^{8}–10^{11} s	10^{2}–10^{7} m
Land surface	Changes in reflectivity	10^{7}–10^{8} s	10^{2} m – global
	Isostatic equilibration of the crust by covering ice masses	10^{8}–10^{11} s	10^{6} m – global
Biosphere	Exchange of carbon with the atmosphere	10^{4}–10^{8} s	10^{-3} m – global
	Transformation of vegetation zones	10^{9}–10^{10} s	10^{2}–10^{7} m

Spatial and temporal scales in the ocean



Filtering of fast processes is key for stable integration of climate models