ARCTIC FRONTIERS

21-26 January 2018

Arctic sea ice prediction from days to centuries

Are we there yet?

François Massonnet

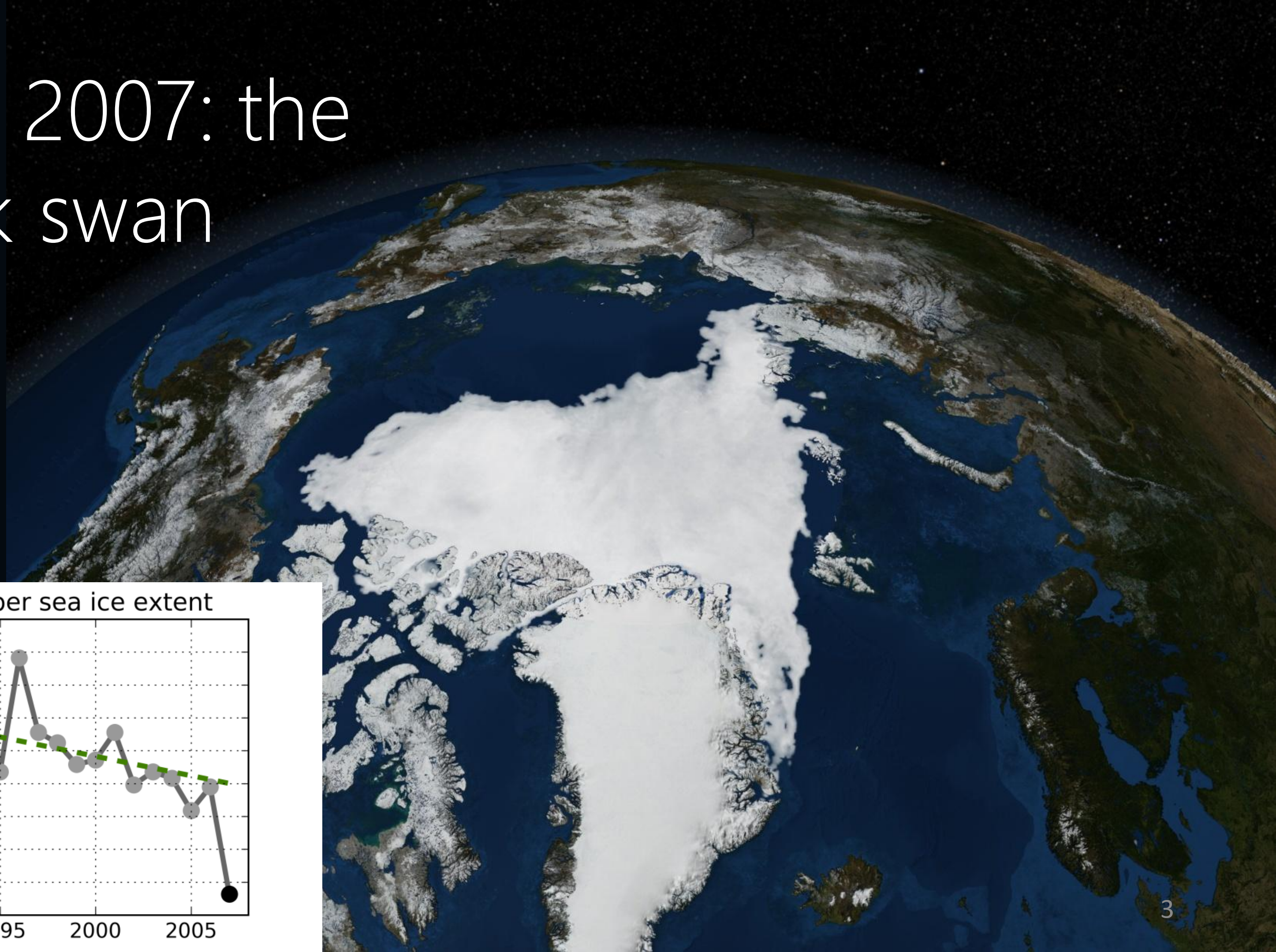
UCL Université catholique de Louvain

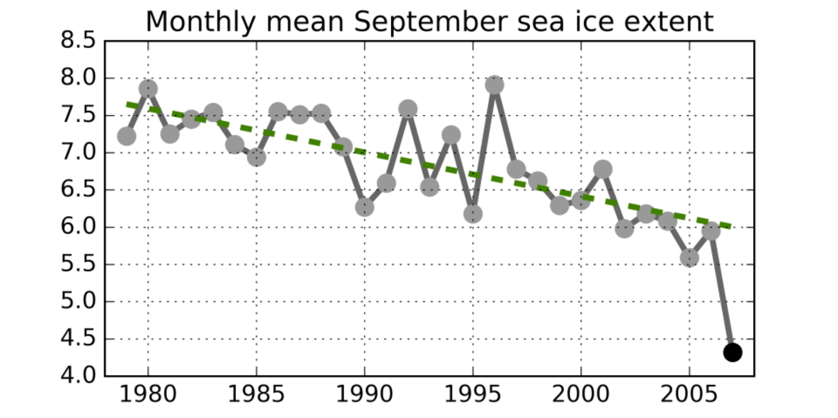
EARTH & LIFE INSTITUTE

BSC Barcelona Supercomputing Center
Centro Nacional de Supercomputación

fnrs FREEDOM TO RESEARCH

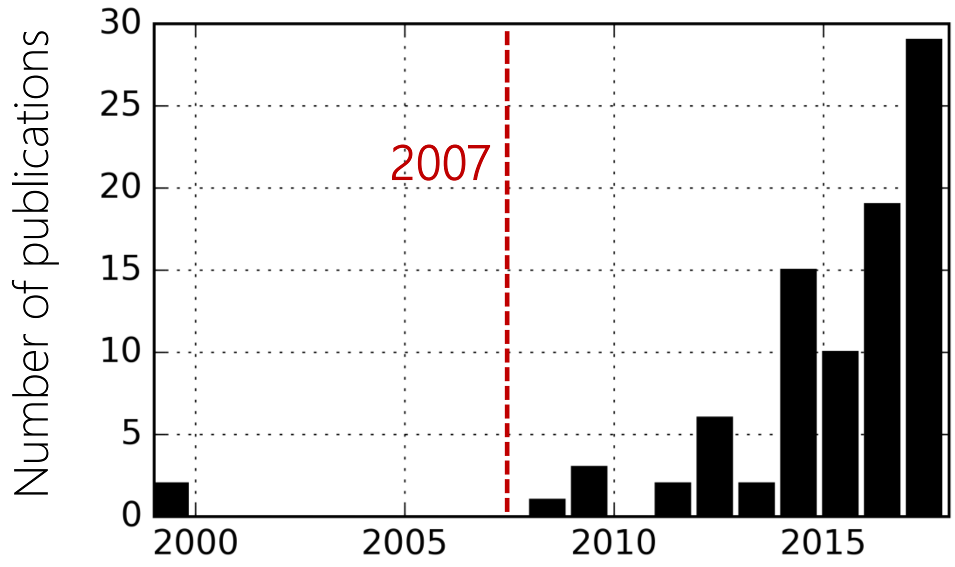
September 2007: the Arctic black swan





Arctic sea ice prediction: an emerging area of research

Number of results from Google Scholar query
« Arctic sea ice prediction » per year of publication



Three excellent articles on Arctic sea ice predictability and prediction

AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER

10.1002/2013GL058755

Key Points:
- Arctic sea ice is potentially predictable for up to 3 years in current GCMs
- Potential prediction errors are amplified at the coasts of the Arctic ocean
- Advective processes are very important for spatial error patterns

Seasonal to interannual Arctic sea ice predictability in current global climate models

S. Tietsche[1], J. J. Day[1], V. Guemas[2,3], W. J. Hurlin[4], S. P. E. Keeley[5], D. Matei[6], R. Msadek[4], M. Collins[7], and E. Hawkins[1]

[1]NCAS-Climate, Department of Meteorology, University of Reading, Reading, UK, [2]Institut Català de Ciències del Clima, Barcelona, Spain, [3]CNRM/GAME, Toulouse, France, [4]Geophysical Fluid Dynamics Laboratory, Princeton, New Jersey, USA, [5]European Centre for Medium-Range Weather Forecasts, Reading, UK, [6]Max Planck Institute for Meteorology, Hamburg, Germany, [7]College of Engineering, Mathematics and Physical Sciences, University of Exeter, Exeter, UK

Aspects of designing and evaluating seasonal-to-interannual Arctic sea-ice prediction systems

Ed Hawkins[a*], Steffen Tietsche[a], Jonathan J. Day[a], Nathanael Melia[a], Keith Haines[b], Sarah Keeley[c]

[a]*NCAS-Climate, Department of Meteorology, University of Reading, UK.*

[b]*Department of Meteorology, University of Reading, UK.*

[c]*European Centre for Medium-range Weather Forecasts, Reading, UK.*

ce to: Department of Meteorology, University of Reading, Reading. RG6 6BB. UK.

E-mail: e.hawkins@reading.ac.uk

Quarterly Journal of the Royal Meteorological Society — *Q. J. R. Meteorol. Soc.* (2014) DOI:10.1002/qj.2401

RMetS Royal Meteorological Society

A review on Arctic sea-ice predictability and prediction on seasonal to decadal time-scales

Virginie Guemas,[a,b*] Edward Blanchard-Wrigglesworth,[c] Matthieu Chevallier,[b,d] Jonathan J. Day,[e] Michel Déqué,[b] Francisco J. Doblas-Reyes,[a,f] Neven S. Fučkar,[a] Agathe Germe,[b,g] Ed Hawkins,[e] Sarah Keeley,[h] Torben Koenigk,[i] David Salas y Mélia[b] and Steffen Tietsche[e]

Arctic sea ice prediction

1. From days to centuries

2. What are the ways forward?

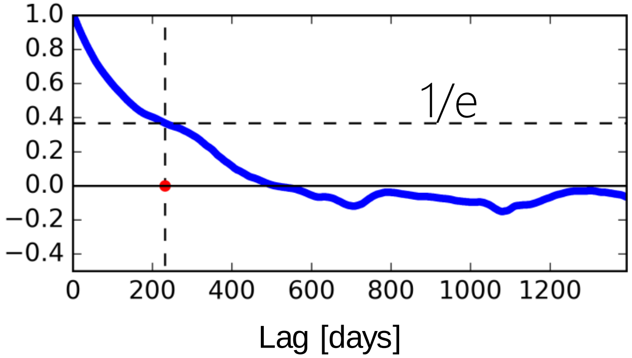
Arctic sea ice prediction

1. From days to centuries

2. What are the ways forward?

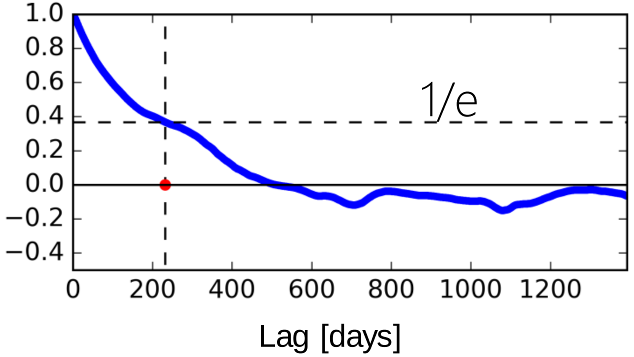
Persistence

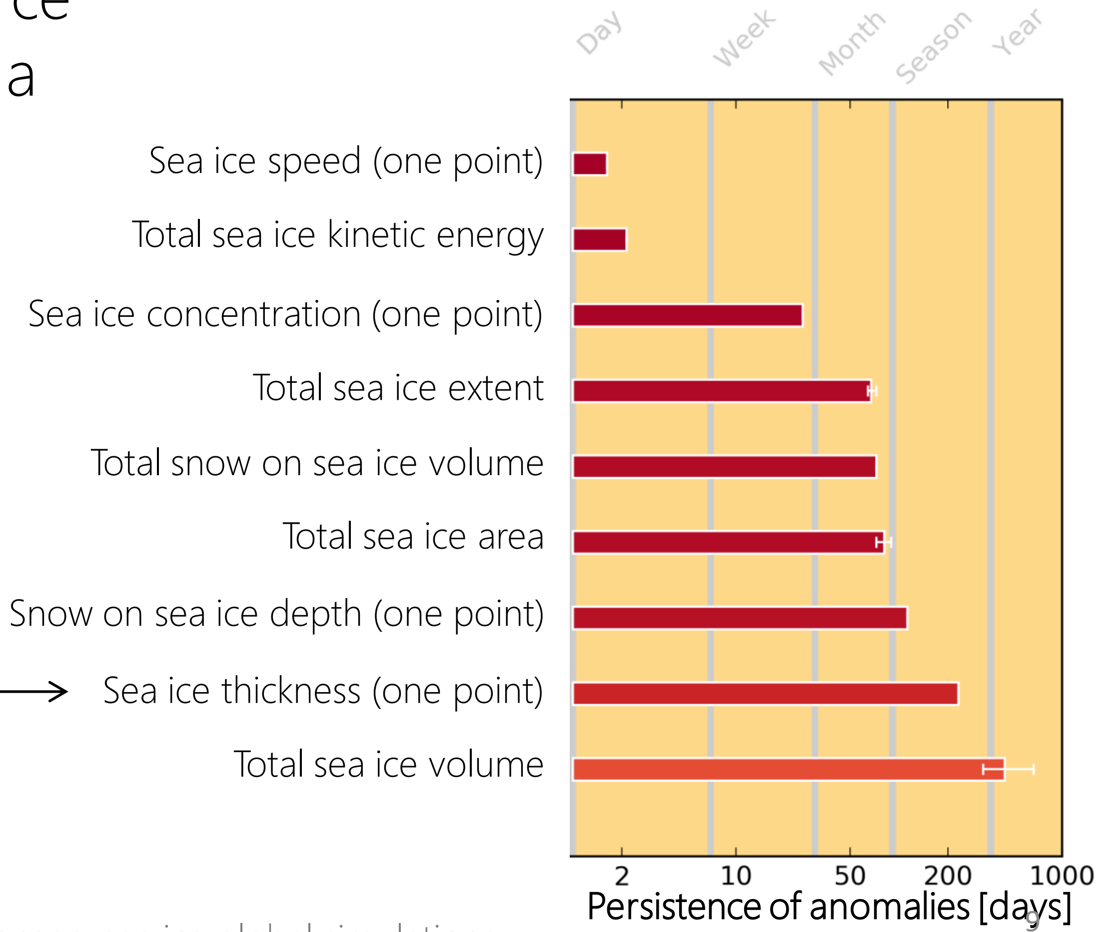
Autocorrelation of 1979-2015 sea ice thickness (model output, one grid point)



Persistence: a primary source of sea ice predictability on a spectrum of time scales

Autocorrelation of 1979-2015 sea ice thickness (model output, one grid point)





Data: satellite (NSIDC) + reanalysis (PIOMAS) + ocean-sea ice global simulations


days
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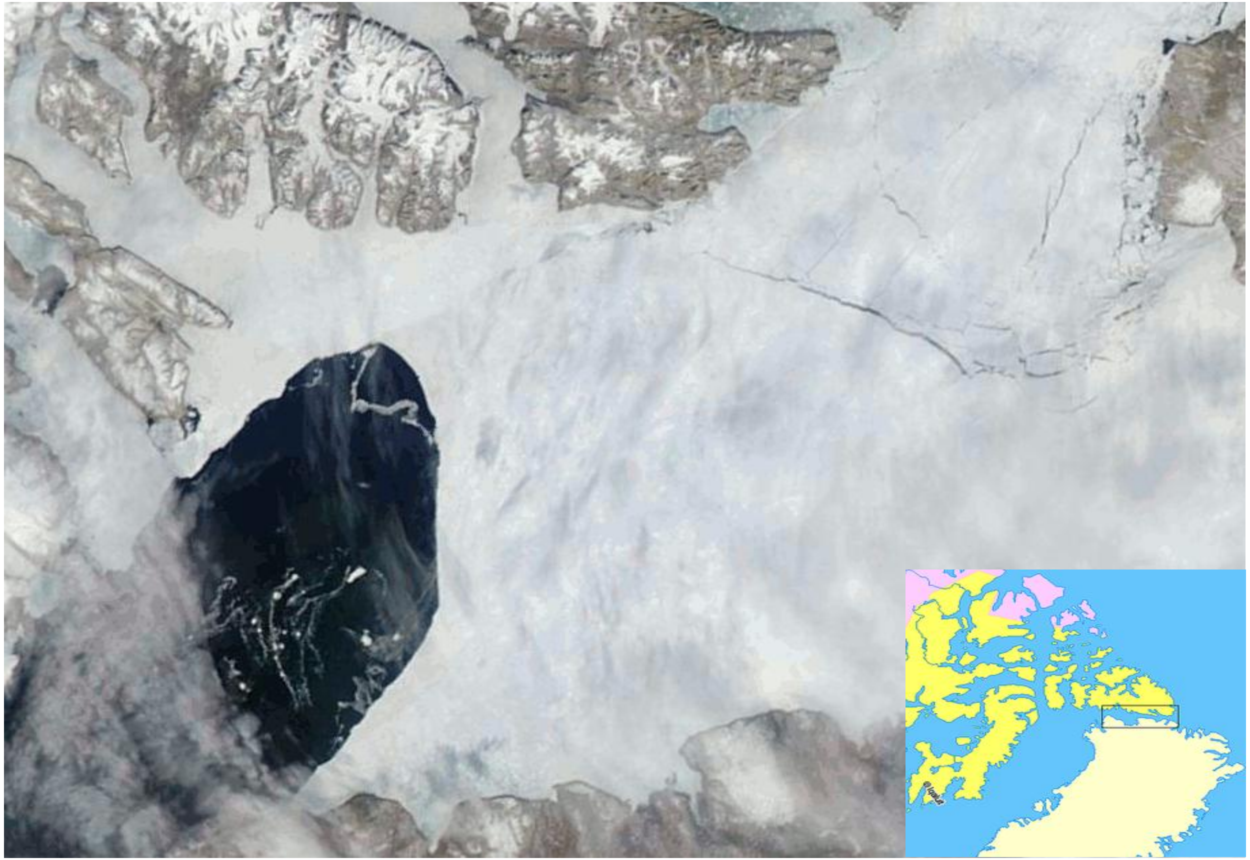

June 20th – July 12th 2015, LANCE-MODIS, 2 images per day
https://forum.arctic-sea-ice.net/index.php?action=dlattach;topic=176.0;attach=18238;image

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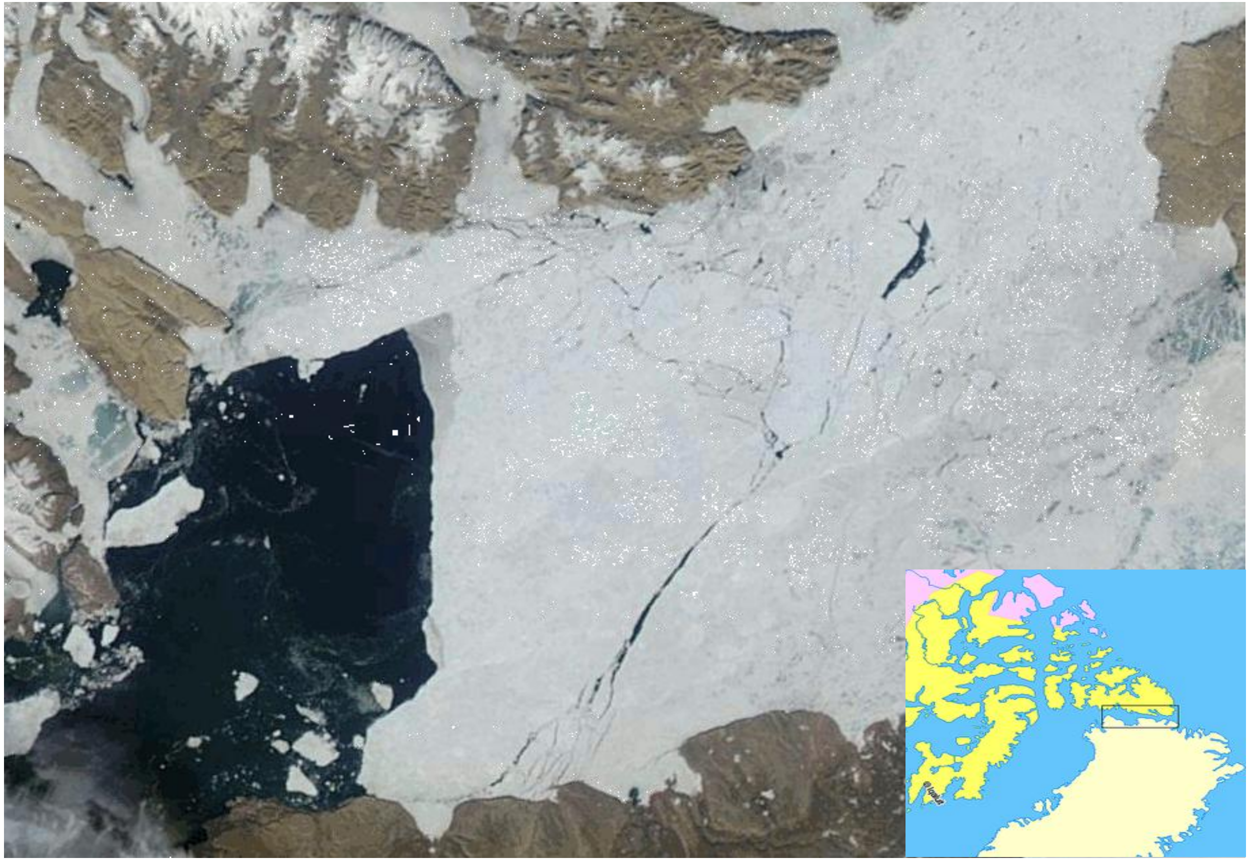

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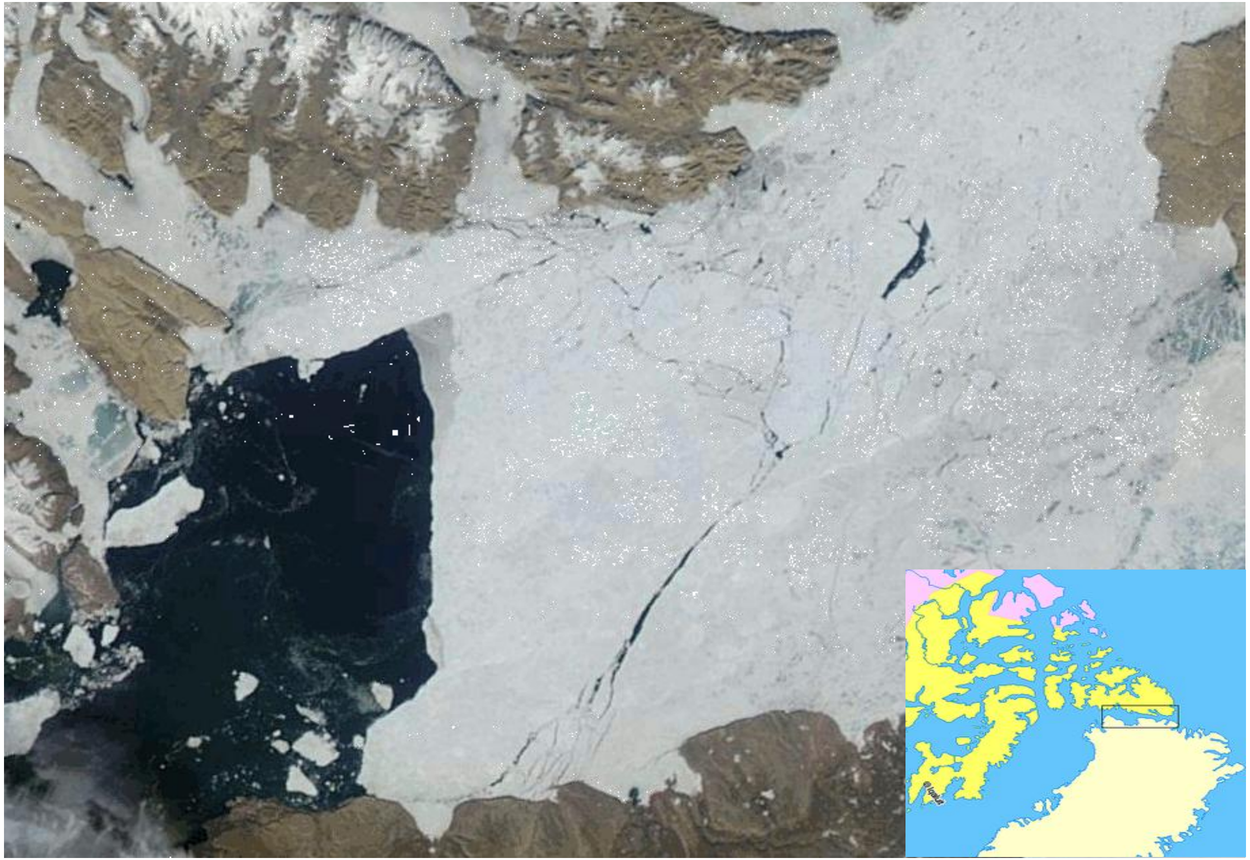
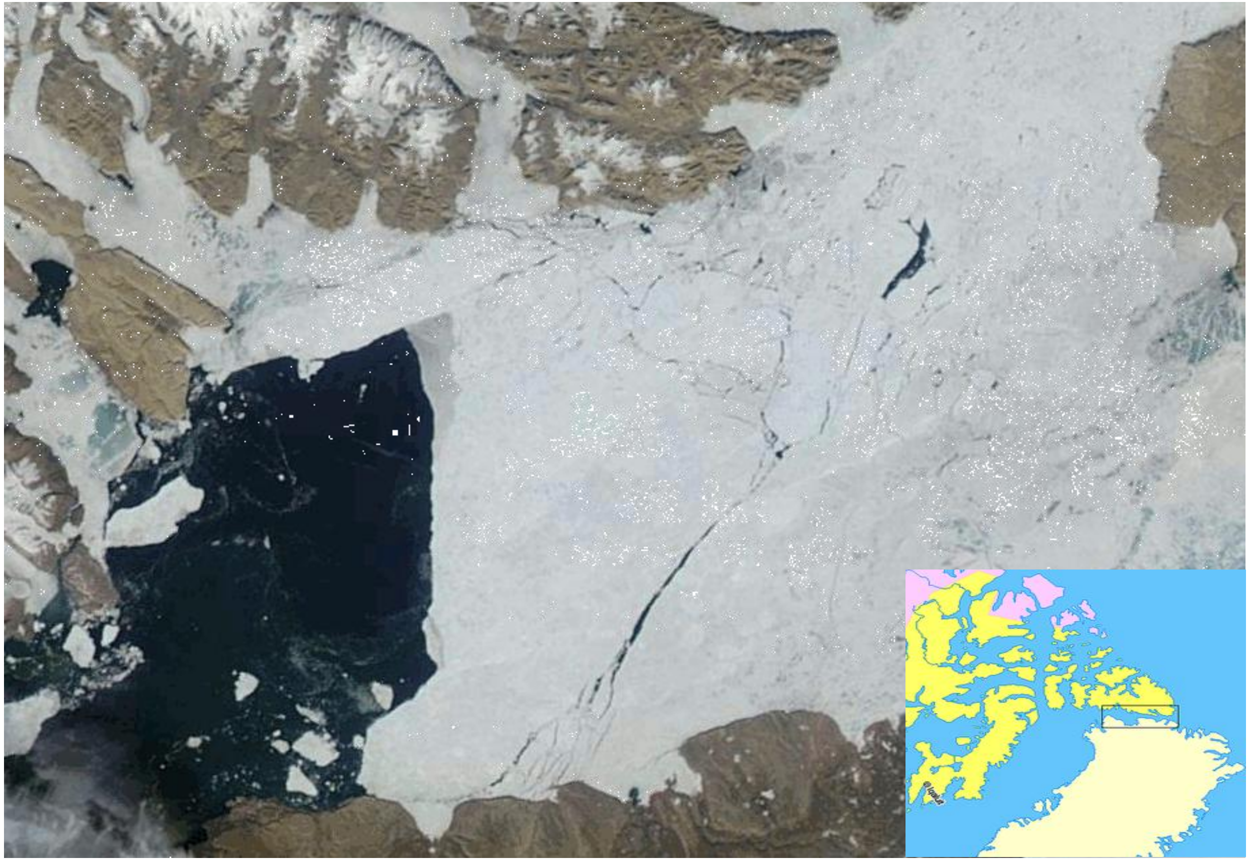


Sources of predictability -Persistence

June 20th – July 12th 2015, LANCE-MODIS, 2 images per day
https://forum.arctic-sea-ice.net/index.php?action=dlattach;topic=176.0;attach=18238;image



Sources of predictability

-Persistence

-Mechanical forcing by wind

-Current ice state (deformation, age, thickness , compactness)

June 20th – July 12th 2010, LANCE-MODIS, 2 images per day

https://forum.arctic-sea-ice.net/index.php?action=dlattach;topic=176.0;attach=18238;image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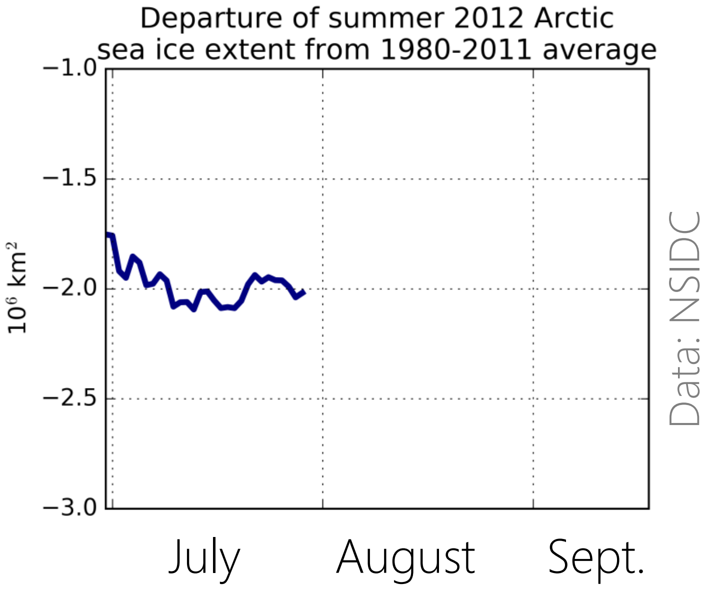
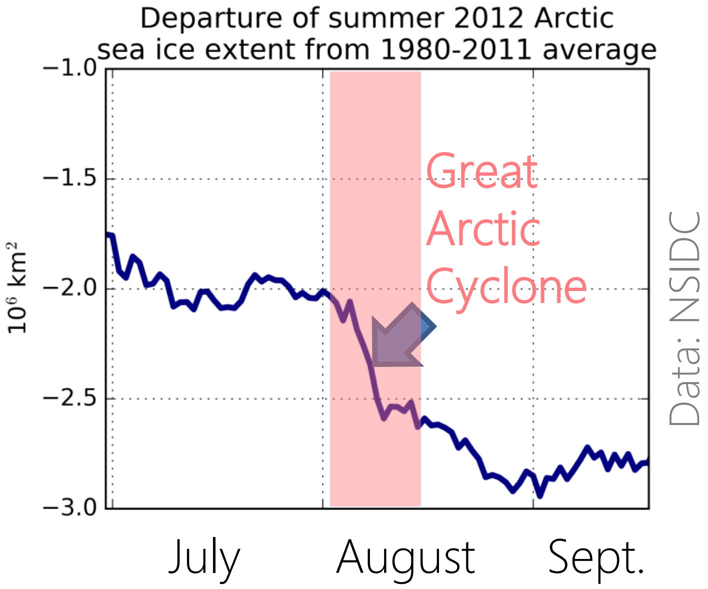
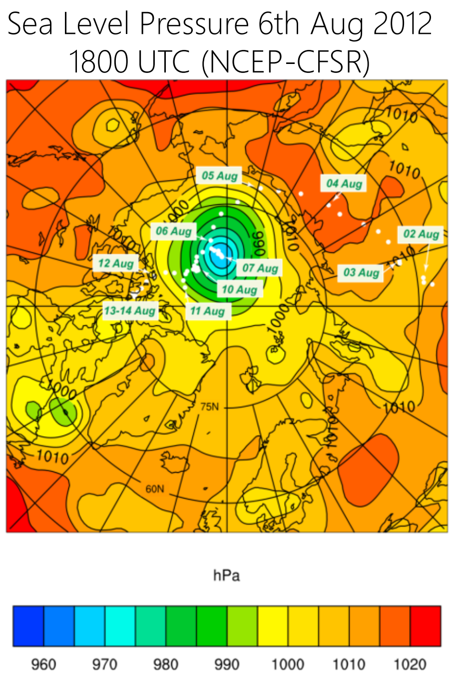
Weekly sea ice extent predictability stems from persistence



days weeks months seasons years decades centuries

Weekly sea ice extent predictability stems from persistence but can be affected by synoptic events





[Simmonds and Rudeva, *Geophys. Res. Lett*, 2012, Zhang et al., *Geophys. Res. Lett.*, 2013; Parkinson and Comiso, *Geophys. Res. Lett.*, 2013]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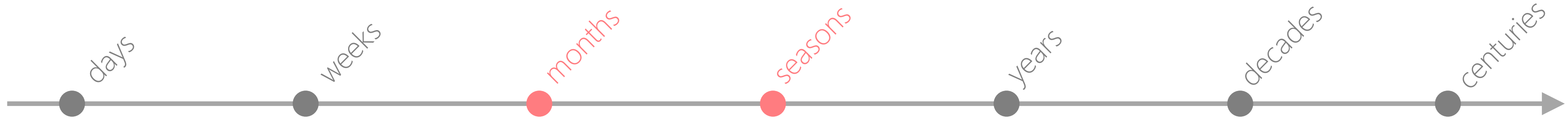
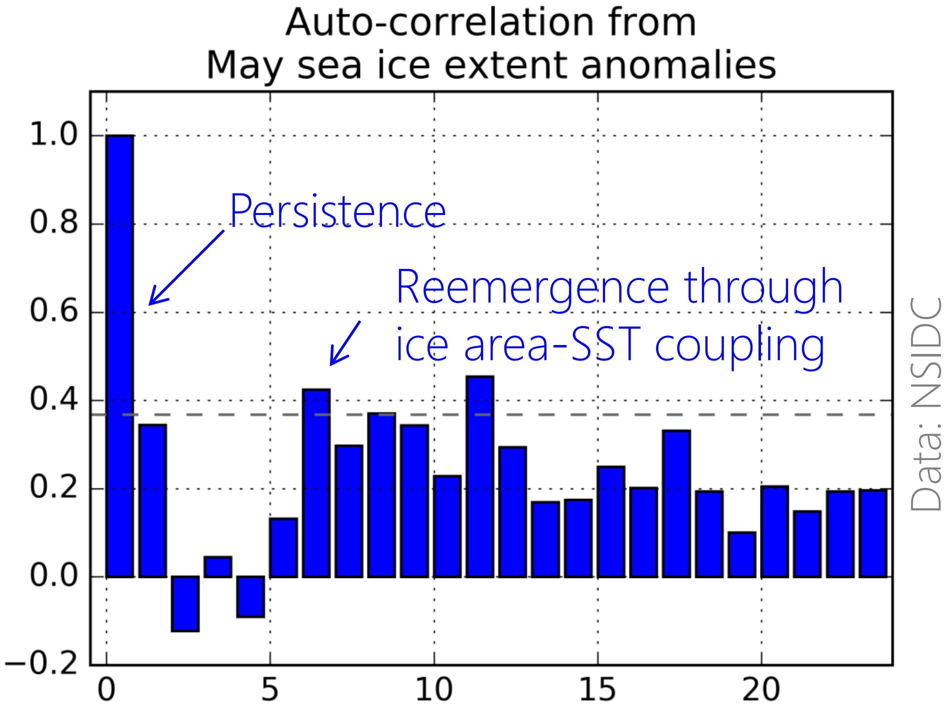
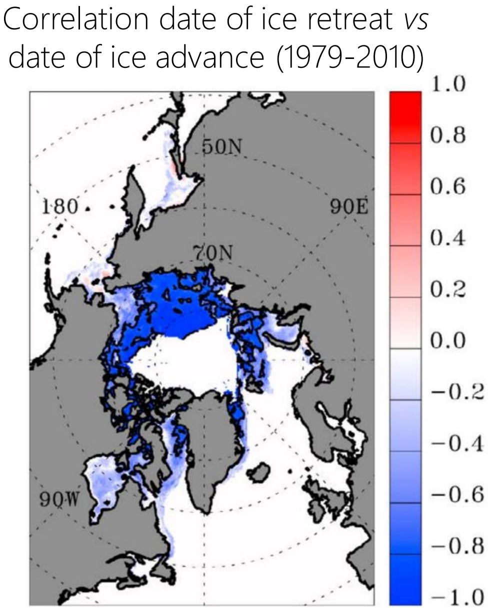


Example of reemergence: melt to freeze up





Blanchard-Wrigglesworth et al., *J. Clim.*, 2011; Chevallier et al., *J. Clim.*, 2012; Day et al., *J. Clim.*, 2014, Stammerjohn et al., *Geophys. Res. Lett.*, 2012

AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER
10.1002/2017GL073155

Skillful regional prediction of Arctic sea ice on seasonal timescales

Mitchell Bushuk[1], Rym Msadek[2], Michael W
Anthony Rosati[3], and Xiaosong Yang[3]

[1]Atmospheric and Oceanic Sciences Program, Princeton U
UMR 5318, Toulouse, France, [3]National Oceanic and Atmo
Princeton University, Princeton, New Jersey, USA, [4]Depart
Jersey, USA

Key Points:
- Coupled dynamical prediction system skillfully predicts regional sea ice extent on seasonal timescales
- Ocean subsurface temperature initialization yields North Atlantic regional winter skill at lead times of 5-11 months
- Sea ice thickness initialization

AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER
10.1002/2016GL069314

Special Section:

Using timing of ice retreat to predict timing of fall freeze-up in the Arctic

Julienne C. Stroeve[1,2], Alex D. Crawford[1], and Sharon Stammerjohn[3]

Seasonal Forecasts of the Pan-Arctic Sea Ice Extent Using a GCM-Based Seasonal Prediction System

MATTHIEU CHEVALLIER, DAVID SALAS Y MÉLIA, AURORE VOLDOIRE, AND MICHEL DÉQUÉ

Centre National de Recherches Météorologiques/Groupe d'Etude de l'Atmosphère Météorologique, Météo-France, CNRS, Toulouse, France

GILLES GARRIC

Mercator-Océan, Ramonville Saint-Agne, France

Clim Dyn (2015) 44:147–162
DOI 10.1007/s00382-014-2190-9

Assessing the forecast skill of Arctic sea ice extent in the GloSea4 seasonal prediction system

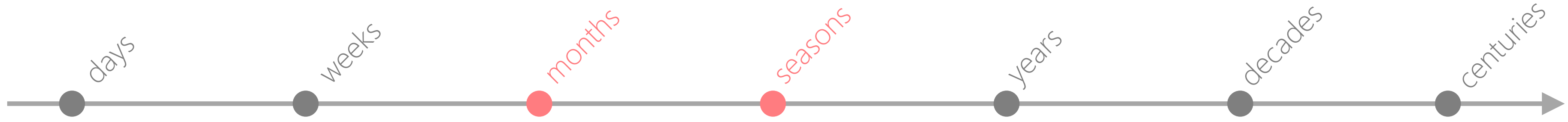
K. Andrew Peterson · A. Arribas · H. T. Hewitt · A. B. Keen · D. J. Lea · A. J. McLaren

ill of Arctic sea ice area in a dynamical forecast system

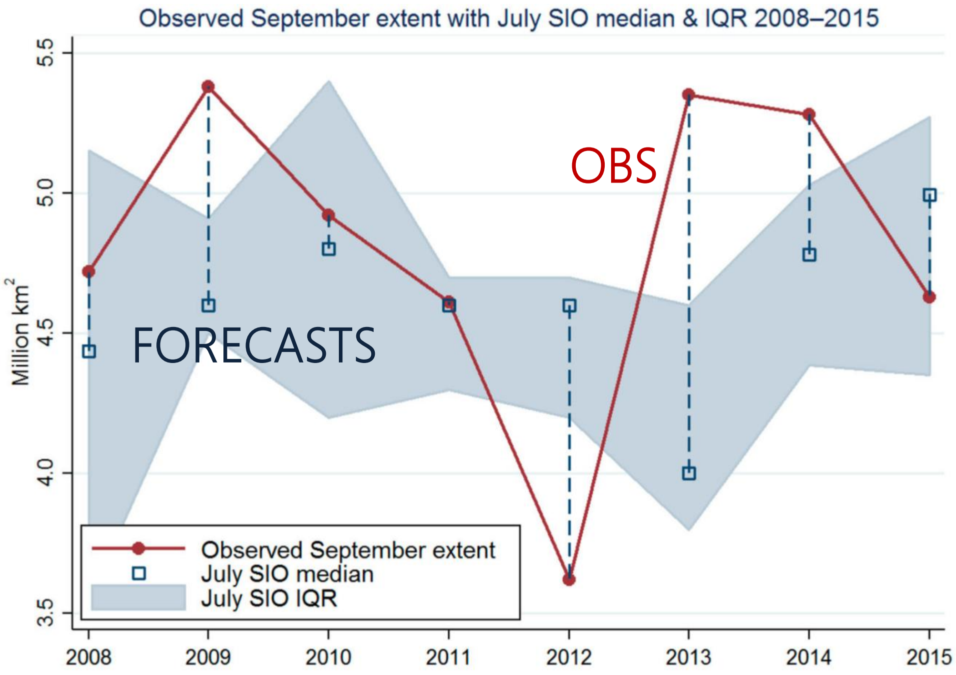
G. M. Flato,[2] V. V. Kharin,[2] and W. J. Merryfield[2]

7 December 2012; accepted 27 December 2012; published 7 February 2013.

Chevallier et al., *J. Clim.*, 2013; Msadek et al., *Geophys. Res. Lett.*, 2014; Sigmond et al., *Geophys. Res. Lett.*, 2013; Peterson et al., *Clim. Dyn.*, 2015; Massonnet et al., *Ocean Model.*, 2015; Merryfield et al., *Geophys. Res. Lett.*, 2013; Bushuk et al., *Geophys. Res. Lett.* 2017



SIPN Sea Ice Prediction Network



Hamilton and Stroeve, *Polar Geography*, 2016

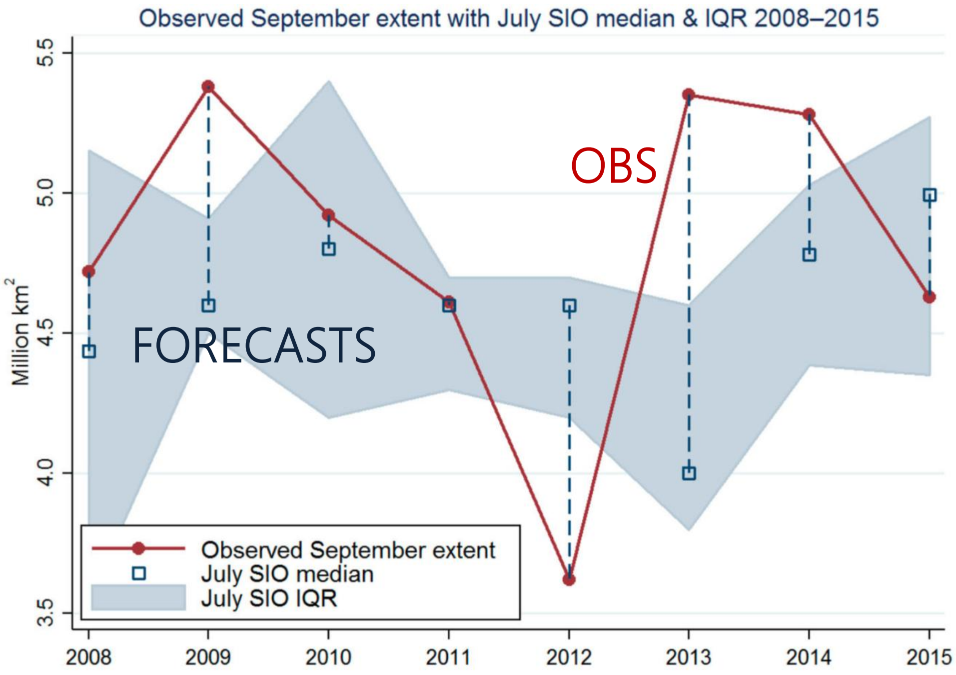
SIPN Sea Ice Prediction Network

Predictions are unfortunately not skillful in « operational » mode.

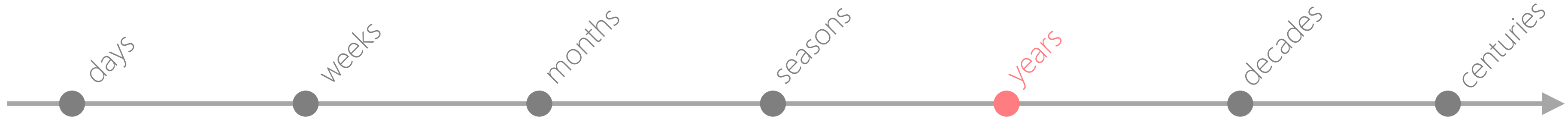
Possible reasons:

• Technical issues (e.g., fields not available at time of forecast) imply that groups cannot perform as well as on retrospective predictions

• Predicting sea ice is tougher today than it used to be



Hamilton and Stroeve, *Polar Geography*, 2016


days
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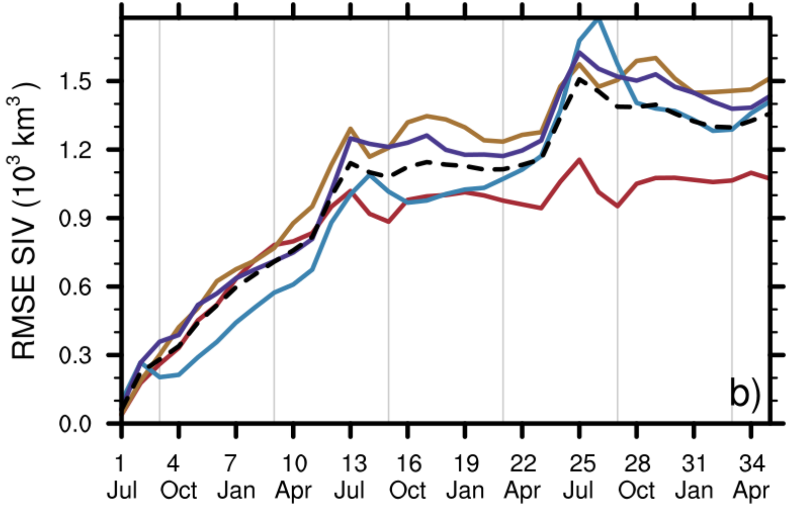
Interannual time scales: « grey zone » of sea ice predictability

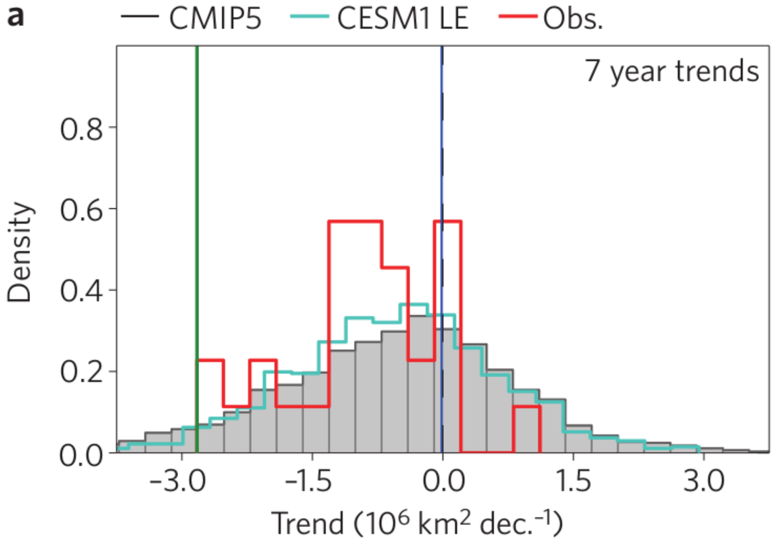
Ensemble spread of total sea ice volume from 4 GCMs



Tietsche et al., *Geophys. Res. Lett.*, 2014

Interannual time scales: « grey zone » of sea ice predictability

Distribution of all possible 7-yr trends (1979-2013) in September sea ice extent



Swart et al., *Nature Clim. Change*, 2014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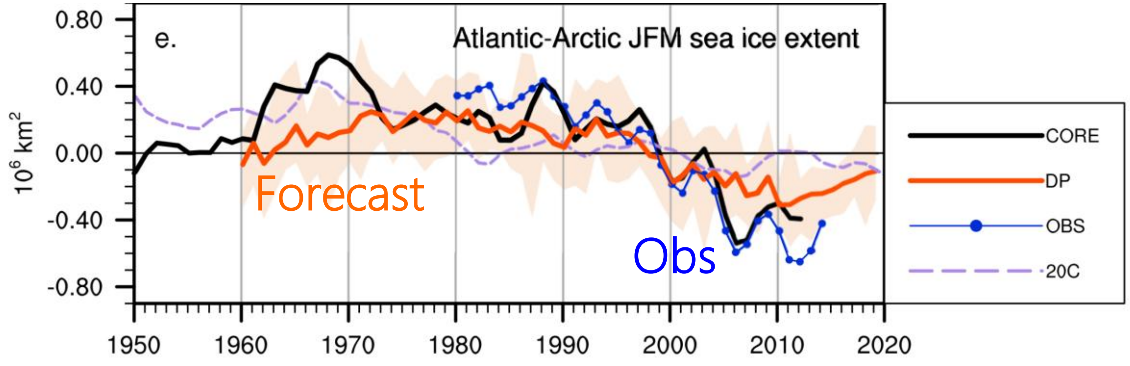
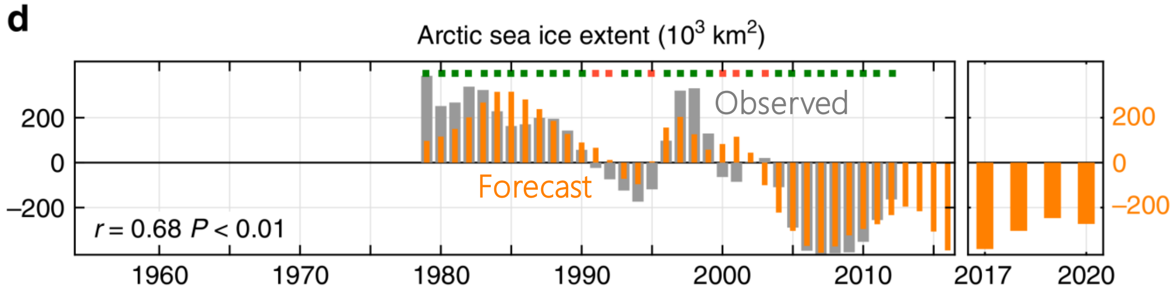
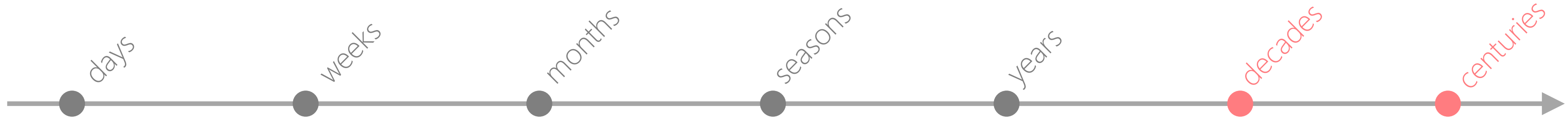




Decadal predictions are mostly skillful
-In winter
-In the Atlantic Sector

Skill stems from poleward oceanic heat transport and from radiative forcing (trend)

Yeager et al., *Geophys. Res. Lett.*, 2015; Årthun et al., *Nat. Comm.*, 2017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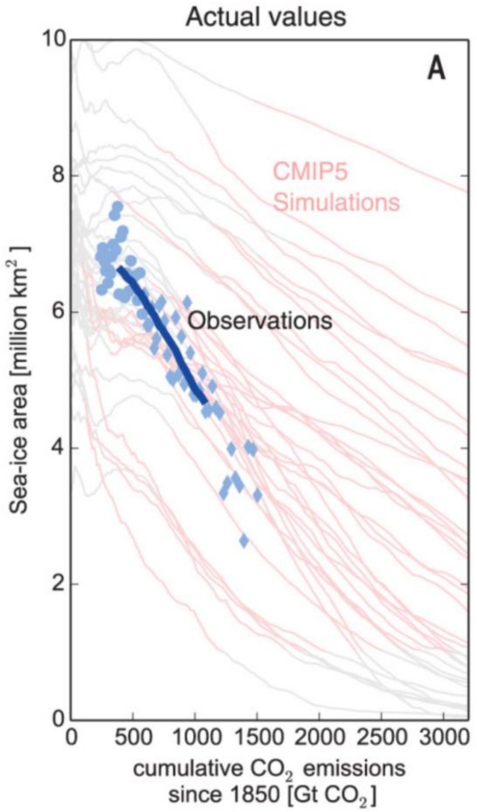
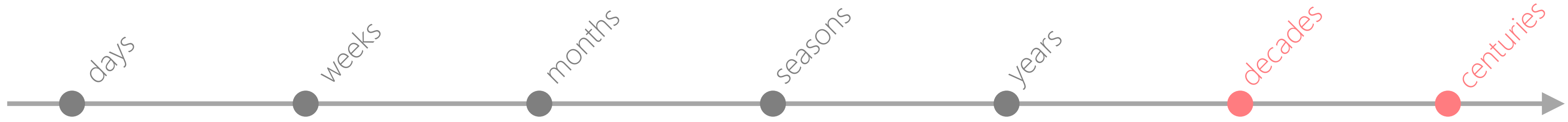
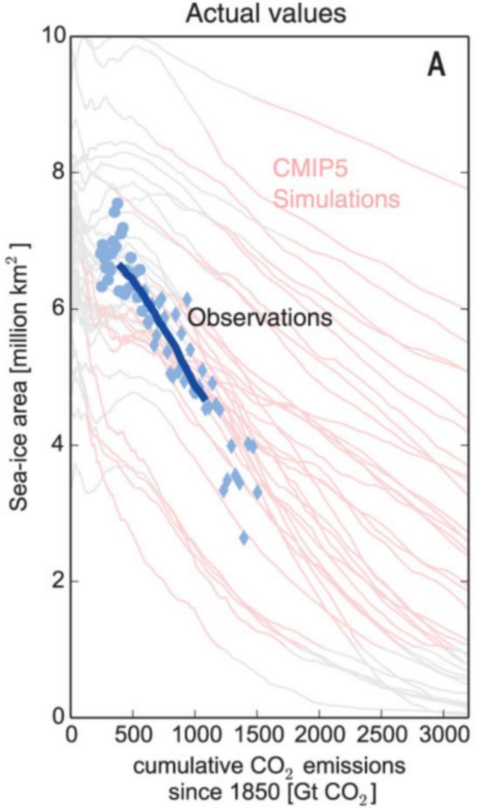


Arctic sea ice area is slaved to the forcing

...

Notz and Stroeve, *Science*, 2016



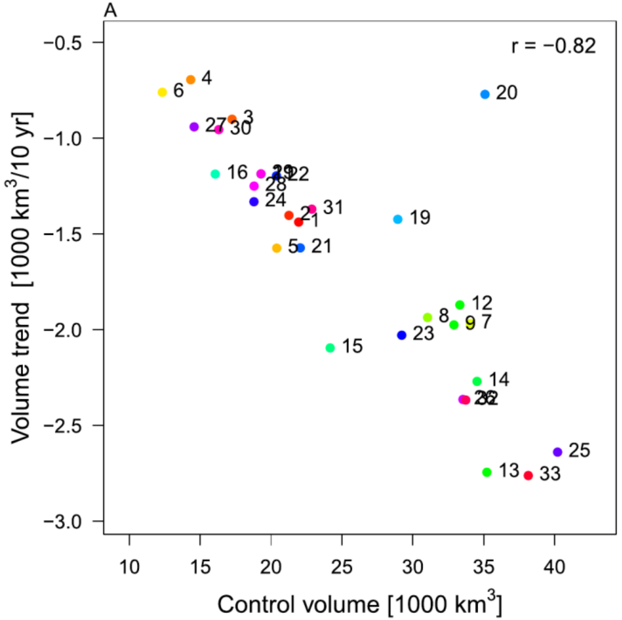


Arctic sea ice area is slaved
to the forcing

...

but thinning rate depends
on initial thickness

CMIP5 models



Notz and Stroeve, *Science*, 2016; Bitz and Roe, *J. Clim.*, 2004; van der Linden et al., *J. Clim.*, 2015

Arctic sea ice prediction

1. From days to centuries

- There is in general predictability beyond persistence, but predictive capacity depends on
  - Time scale considered
  - Season considered
  - Region considered
  - Parameter considered
- Knowledge of baseline sea ice+ocean state is key to perform skillful predictions

2. What are the ways forward?

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2. What are the ways forward?

What Is a Good Forecast?
An Essay on the Nature of Goodness in Weather Forecasting

ALLAN H. MURPHY

College of Oceanic and Atmospheric Sciences, Oregon State University, Corvallis, Oregon

(Manuscript received 11 August 1992, in final form 20 January 1993)

ABSTRACT

Differences of opinion exist among forecasters—and between forecasters and users—regarding the meaning of the phrase "good (bad) weather forecasts." These differences of opinion are fueled by a lack of clarity and/or understanding concerning the nature of goodness in weather forecasting. This lack of clarity and understanding complicates the processes of formulating and evaluating weather forecasts and undermines their ultimate usefulness.

Three distinct types of goodness are identified in this paper: 1) the correspondence between forecasters' judgments and their forecasts (type 1 goodness, or *consistency*), 2) the correspondence between the forecasts and the matching observations (type 2 goodness, or *quality*), and 3) the incremental economic and/or other benefits realized by decision makers through the use of the forecasts (type 3 goodness, or *value*). Each type of goodness is defined and described in some detail. In addition, issues related to the measurement of consistency, quality, and value are discussed.

Relationships among the three types of goodness are also considered. It is shown by example that the level of consistency directly impacts the levels of both quality and value. Moreover, recent studies of quality/value relationships have revealed that these relationships are inherently nonlinear and may not be monotonic unless the multifaceted nature of quality is respected. Some implications of these considerations for various practices related to operational forecasting are discussed. Changes in these practices that could enhance the goodness of weather forecasts in one or more respects are identified.

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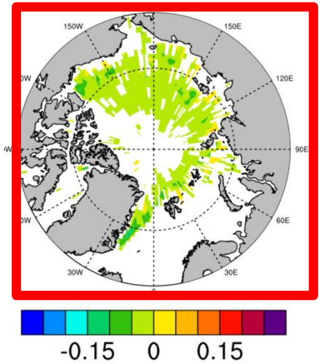
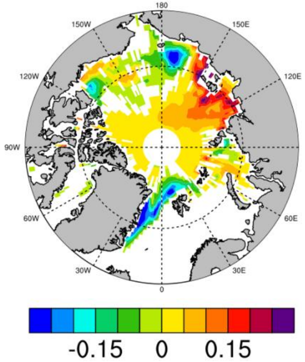
Reanalyzed thickness: all over the place

September 1993-2007
mean sea ice
concentration bias

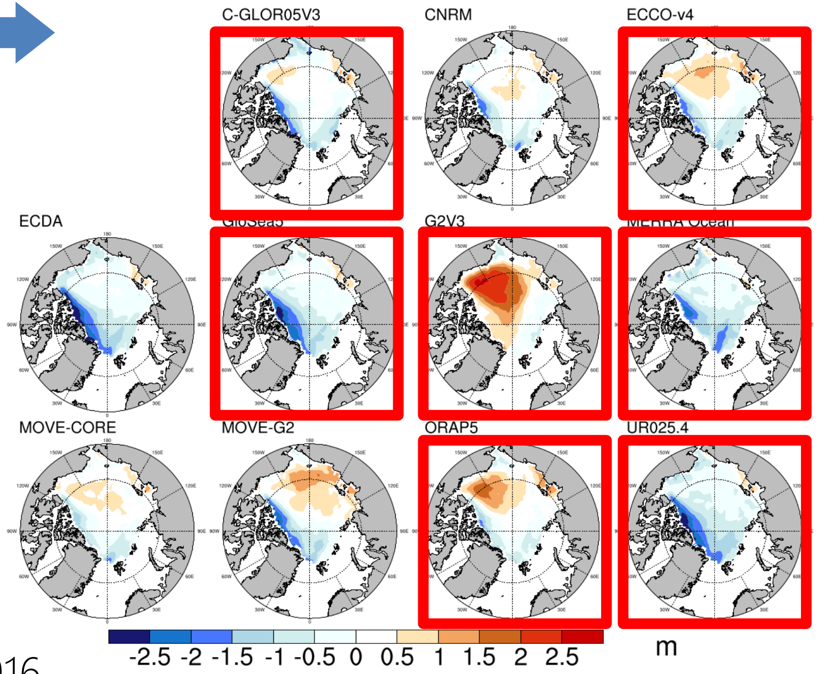


With DA



Without DA

March 1993-2007 mean sea ice
thickness bias (wrt IceSat)



Chevallier et al., *J. Clim.* 2016

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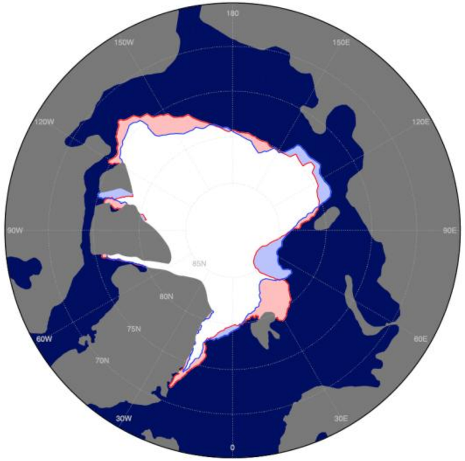
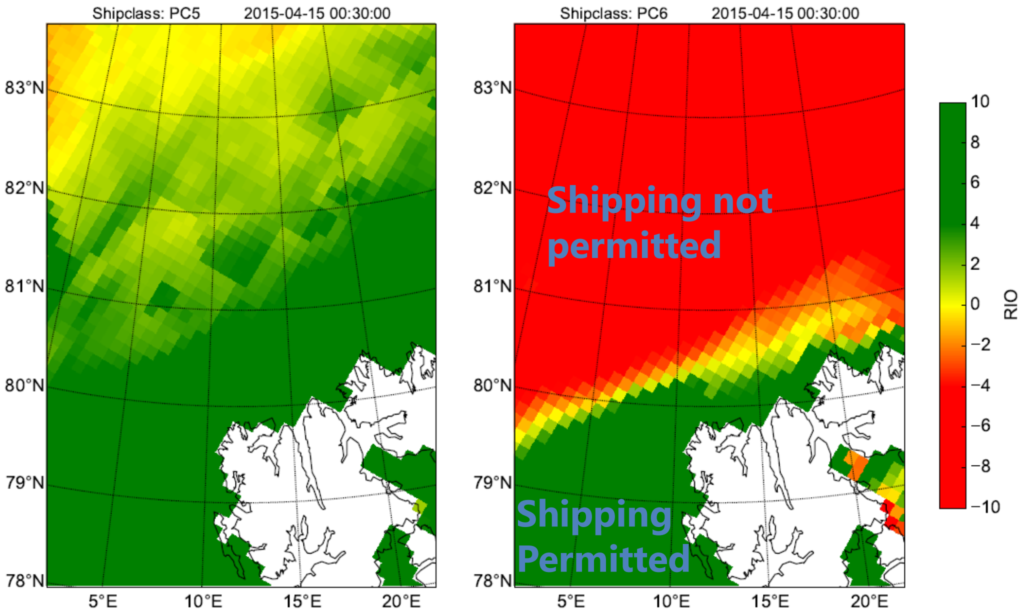
Need for new metrics and diagnostics



Error = OVERESTIMATION + UNDERESTIMATION

Goessling et al., *Geophys. Res. Lett.*, 2016



Courtesy Andrea Gierisch

Arctic sea ice prediction

1. From days to centuries

2. What are the ways forward?

Concluding thoughts

Concluding thoughts

- Arctic sea ice prediction is « in the making »

Concluding thoughts

- Arctic sea ice prediction is « in the making »
- A seamless polar prediction community is building

Concluding thoughts

- Arctic sea ice prediction is « in the making »
- A seamless polar prediction community is building
- We are chasing a moving target

Thank you!

@FMassonnet

@ francois.massonnet@uclouvain.be

www www.climate.be/u/fmasson

Arctic sea ice prediction from days to centuries

Are we there yet?

January 25th, 2018

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This text is an approximate transcript of the keynote presentation I gave during the Arctic Frontiers conference (22-26 January, 2018, Tromso). The numbers [1], [2], … are meant to refer to the slide page.

[1] Everyone in this room has in mind his or her favourite book. One of my favourite books is undoubtly the Black Swan by Nicholas Taleb.

[2] A black swan is an event that is at the same time (1) extreme in a statistical sense, (2) impactful in terms of consequences and (3) unpredictable. There are many examples of black swans in many disciplines. When Christopher Columbus left Europe to discover India, no one would have bet one penny on the fact that he would then discover a whole new continent. Nobody understood that disruptive events like the 9 11 attacks in New York and Washington could possibly occur, before they actually happened. And nobody had seen the 2008 financial crisis coming with all the dramatic and far-reaching consequences that this crisis incurred.

The black swan of Polar Scientists undoubtly showed up on September 16th, 2007.

[3] Arctic sea ice had been on decline already since decades, but <u>that event</u> literally shook the scientific community. Nobody until then had imagined that the Arctic could resemble anything like that before 2020 or 2030, at least. This event suddenly put the lights on the Arctic and since then, …

[4] … the scientific literature on Arctic sea ice prediction has literally exploded. The figure behind me shows a rough estimation of the number of papers published with the title « Arctic sea ice prediction » in them. Clearly, 2007 has been a pivotal event for the community.

I started doing research two years later, in 2009, and one of the questions that has guided my research since then is whether this type of events, and the Arctic sea ice in general, is predictable at all, from a few days up to centuries. In the next twenty minutes or so I would like to review what we know about Arctic sea ice prediction. I would like to warmly thank the organizers for having invited me to Tromso to share my views on this very exciting area of research.

Now I will not make a comprehensive review of anything that has been published on the topic for two reasons: (1) 20 minutes is just not enough to make a good review in a professional way and (2) There are excellent ….

[5] And I stress the word, especially because I'm not co-author of these studies, they're excellent, they're comprehensive and they're extremely well written . So I strongly urge you to take one day in your busy agendas to shut down your computers, ignore you e-mails, and take the time to read these three papers. So instead of reviewing something that has been done very well by others, [6] … I decided to attempt a journey over timescales, from day to centuries, and to identify for each time scale (1) the factors that are thought to give predictability on these time scales, and (2) to review the current practical limitations that should be addressed with highest priority in order to significantly advance our prediction capabilities.

[7] OK let's get started. There is one thing to keep in mind at all times: Nature is very generous and it always offers some baseline, trivial predictability. This trivial predictability: persistence.

[8] The idea of persistence is very simple: take the parameter you want to study, remove seasonal cycle, estimate the auto-correlation of anomalies, so the correlation with itself at different lags and determine when this correlation drops below a given threshold, usually 1/e. This gives you a window, called persistence, over which the parameter remembers itself and therefore carries predictive information.

I repeated this exercise of computing persistence for many other sea ice parameters

[9] And what comes very clearly out of this analysis is that sea ice exhibits persistence on a fairly wide and fairly long range of time scales. Dynamic parameters like the sea ice speed at one point have of course little persistence – only one day or so – but others like the sea ice thickness at one point or the total Arctic sea ice volume display persistence from seasons to years.

Of course there might be predictability beyond those horizons, but then it must come from more subtle mechanisms, from external drivers or from other slower components

[10] Now let's start our journey by first looking at what's going on at really fast, daily time scales

[11] What you can see behind me is a composite of 12 snapshots taken every second day in Nares Strait by the LANCE-MODIS satellite during summer 2015.

If I now…

[12] … stop this animation and ask what it will look like two days later, in other words if I'm asking the question of sea ice prediction with a 2-day lead time, without big surprise it will be fairly similar.

[13] Similar, but not exactly identical and you see that in the mean time a huge lead, a huge crack has developed. Being able to predict when and where such lead would open is extremely important for navigation purposes for instance.

[14] So while the best guess for predicting sea ice at these time scales is to simply persist the existing field, knowledge…

[15] … on the wind field and on the current sea ice state (including where it is more prone to break up) is crucial to predict the fine details of its evolution

[16] Let's move a bit in time

[17] Let’s look this time at the total Arctic sea ice extent in summer 2012. I’m showing here the anomalies of total sea ice extent for the month of July. If you remember my figure on persistence I showed that sea ice extent is persistent for something like one to two months. And the reason why anomalies do not persist for ever is that the Arctic is constantly crossed by synoptic systems, like

[18] Storms and other powerful cyclones that bring huge amounts of heat and moisture above the ice but also induce a significant dynamical break up of the ice.

In 2012, a massive cyclone entered the Arctic on August 2nd. The onset of such events is by definition very difficult to forecast but if they are detected early enough, then their impact on sea ice can be anticipated and give predictability at weekly time scale.

Let’s continue forward

[19] I will treat monthly and seasonal prediction timescales together because similar mechanisms are at play. Also, I will spend a little bit more time on these time scales because

1) This is the timescale for which there is currently the most literature
2) There are specific physical mechanisms that push predictability well beyond persistence
3) There is a strong interest from a wide range of users in monthly to seasonal predictions.

The physical basis for the feasibility of monthly to seasonal sea ice predictions relies on a work that was done

[20] In 2011 Ed Blanchard and colleagues discovered a quite interesting mechanism of reemergence of sea ice area anomalies. By reemergence, we mean that the autocorrelation of sea ice extent anomalies from one given month, for instance May, drop rapidly before reemerging a few months later. The mechanism is actually quite simple. Suppose that the ice is retreating a bit earlier in spring than normal. Then extra energy will be absorbed in the first meters of the ocean, so that when comes the fall, freeze up will be delayed by a few days due to higher than normal sea surface temperatures.

This mechanism is very robust, has been identified in different models, in observations and is supported by good physical understanding.

There are other mechanisms like this that operate between summer and winter, I won’t detail them, but the bottom line is that such mechanisms can push predictability of sea ice beyond classical persistence scales.

These results have prompted a number of research groups to start undertaking actual predictions using a variety of methods (dynamical forecasting, statistical forecasting)

[21] … and it is now quite common to see in the sea ice literature big headlines like « skillful sea ice predictions »

However (because there is a however), these predictions are all retrospective, not prospective. That means that they’re done on past cases, not in an operational way.

[22] There is one thing that still puzzles everyone, it' s that the skill of actual predictions doesn't seem to be that high.

What you see on the right in blue is a set of forecasts that were collected by the Sea Ice Prediction Network each year in July for a September sea ice extent forecast. There are two problems here:

1) The ensemble seems to be overconfident

2) The ensemble median does not seem to forecast the year-to-year variations in observed extent

You will frequently hear sentences about this graph like « the forecasts are good for normal years and they're not doing good for anomalous years » this is to me equivalent to saying that the forecasts can predict the overall decline of Arctic sea ice but not its interannual variability.

So there is a paradox here. On the one hand we have this literature that says « hey, we're doing good retrospective forecasts », and these results that say « wo, we're not skillful on prospective forecasts »

[23] I see at least two possible reasons

(1) Running prospective forecasts is technically not easy, you often need real-time data sets that are not always available

(2) I'm afraid that we are chasing a moving target. Arctic sea ice has changed dramatically in the past years and many studies have shown that the predictability itself might become shorter as the ice gets thinner.

[24] Let's now continue to yearly time scales.

[25] We're entering what I would call a grey zone. I'm calling that a grey zone because at these time scales the predictability of even the most predictable parameters like sea ice volume starts to dissipate. In otherwords initial-value predictability is almost gone

And at the same time the boundary-value predictability is not taking over yet

[26] To make this point clearer, have a look on the right. You can see a distribution of all possible 7-yr trends in summer sea ice extent over 1979-2013

What you want to take out of this histogram is that at these time scales, internally generate climate variability is prominent and can significantly mask the forced, predictable decline of Arctic sea ice.

That's also a time scale for which there is a lack of knowledge as to how remote regions of the planet like the tropics affect sea ice variations

[27] Let's move ahead

[28] At interannual to decadal time scales things become interesting again. I would like to single out two studies. Both studies have shown consistently that sea ice in the Atlantic sector or the Barents Sea is predictable from a few years to a decade, because of the strong role exerted by the ocean heat convergence on the position of the sea ice edge.

What is interesting is that one study utilizes a global climate model while the other uses a statistical approach, showing that both approaches are valid and perhaps complementary.

[29] Let's finish by looking at very long time scales, decades to centuries. Here, internal variability is fading out

[30] And research has shown that the sea ice area is strongly controlled by the external forcing

This figure shows a relationship between the sea ice area and the cumulative emissions of CO2 in our atmosphere, but you would see similar behaviour if you would plot sea ice area versus global mean temperature

[31] But interestingly, sea ice volume trends still remember their initial conditions, in other words the response of sea ice thickness is not entirely slaved to the forcing.

[32] So, in a nutshell, this is what we know or – this is what I know that we know about sea ice prediction. I'd like you to take two points

1) One cannot talk about sea ice predictability as such
2) The knowledge of initial conditions is important

So for a science that is 10 year old, I think very good progress had been made though there are still areas of shadow. Now, how can we make sure to get progress?

[33] Until now I've talked a lot about mechanisms and skill, but not about value.

[34] This paper was recommended to me by Laurent Bertino, and that paper written in 1993 tries to define what a good forecast is.

[35] It says first that there should be consistency in the forecasts, mechanical understanding of these forecasts. If you make a forecast, can you at least understand, as an expert, the underlying physical reasons behind the forecast?

[36] Second, the forecast must match some observational reference (and this is what we usually call skill).

In terms of skill my feeling is that much skill can still be gained by improving the way we estimate initial conditions in the forecasts

[37] Today most seasonal prediction systems start from reanalyzed sea ice thickness.

What this figure from Matthieu Chevallier and Colleagues show, is that assimilation is very efficient at constraining the variable that is assimilated (here, sea ice concentration), but that it is not able to reduce the bias in other variables, for example sea ice thickness. That means that most of the time, predictions start from incorrect initial sea ice thickness fields, an therefore the skill is not as high as it could be expected.

[38] And third, the forecast should have value for decision makers, for those who need the forecast most. What does that mean? Well, suppose that I'm developing a brand-new prediction system and I'm going to the shipping industry saying that my system skilfully predicts 97% of the observed

variance in monthly mean sea ice extent, the first thing they will tell me is two words: so what? Monthly mean sea ice extent is like annual mean global temperature: an interesting statistical index with absolutely no practical value.

[39] This is why a number of researchers have started to define new metrics and diagnostics that at least recognize the importance of spatial variations, and recognize the importance to communicate information in a language that can be interpretable. On the left is a new metric proposed by Helge Goessling and colleagues to diagnose model-observation mismatch that accounts for spatial misplacement of the ice. And on the right is a proposed diagnostic to inform a ship captain on the risks associated with the navigation in an area around Svalbard, green meaning OK while red means no go, depending on the ship class.

[40]

[41] It's time to wrap up.

[42] This presentation like many others in this session and in this conference, would not have been possible 10 years ago. And likewise I'm sure that the person that will be standing here in 10 years will have a lot of things to say that haven't been said today.

[43] Along with these exciting research questions a seamless polar prediction community is building: seamless across time scales, seamless acro discplines, seamless across continents

[44] We're not just trying to predict something that will be there forever. As I said multiple times the Arctic is on decline, and with that comes strong shifts in predictability regimes.

This brings me back to my black swan book. We are very good at predicting things retrospectively, but the real challenge is, to me, to predict things prospectively.

[45] Thank you.