Arctic sea ice predictions and how to evaluate them

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VALENTINE'S DAY 2019: PARAMOUR, THE DANCE AT THE CITY HALL AGAINST AIDS

For Valentine's Day 2019, let's all dance at the City Hall to support the fight against AIDS. Kylie Minogue's star choreographer Hakim Ghorab will host this crazy party to make over 1000 people dance on February 14, 2019.


To celebrate love and fight against HIV, Paris City Hall opens the doors to over 1000 people who can
Arctic sea ice prediction: an emerging area of research

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

Number of publications

<table>
<thead>
<tr>
<th>Year</th>
<th>Publications</th>
</tr>
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<tbody>
<tr>
<td>2000</td>
<td>1</td>
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<td>2005</td>
<td>2</td>
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<td>2010</td>
<td>3</td>
</tr>
<tr>
<td>2015</td>
<td>28</td>
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</tbody>
</table>

2007
September 2007: the Arctic black swan
Four suggested references on Arctic sea ice predictability and prediction.
1. Predictability and prediction of Arctic sea ice from days to centuries

2. Important considerations regarding the evaluation of upcoming PARAMOUR predictions
1. Predictability and prediction of Arctic sea ice from days to centuries

2. Important considerations regarding the evaluation of upcoming PARAMOUR predictions
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)

1/e

Lag [days]

Persistence of anomalies [days]

- Day
- Week
- Month
- Season
- Year

- Sea ice speed (one point)
- Total sea ice kinetic energy
- Sea ice concentration (one point)
- Total sea ice extent
- Total snow on sea ice volume
- Total sea ice area
- Snow on sea ice depth (one point)
- Sea ice thickness (one point)
- Total sea ice volume

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

S2S book - Chapter. 10: sea ice (Chevallier, Massonnet, Guemas, Goessling and Jung)
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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Sources of predictability
-Persistence

June 20th – July 12th 2015, LANCE-MODIS, 2 images per day
https://forum.arcticsea-ice.net/index.php?action=dattach;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
Weekly sea ice extent predictability stems from persistence

![Graph depicting Arctic sea ice extent](image)
Weekly sea ice extent predictability stems from persistence but can be affected by synoptic events.

Departure of summer 2012 Arctic sea ice extent from 1980-2011 average

Sea Level Pressure 6th Aug 2012 1800 UTC (NCEP-CFSR)

Example of reemergence: melt to freeze up

Auto-correlation from May sea ice extent anomalies

- Persistence
- Reemergence through ice area-SST coupling

Correlation date of ice retreat vs date of ice advance (1979-2010)

Data: NSIDC

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

MATTHIEU CHEVALLIER, DAVID SALAS Y MÉLIA, AUREOURE VOLDIOIRE, 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

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

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
Sea ice data assimilation yields encouraging results for seasonal predictions.

Forecasting September 2007 (ocean-sea ice model)

- March 2007 sea ice thickness
- September 2007 sea ice concentration

CONTROL

INITIALIZED

Sea ice thickness initialized from observations (CryoSat-2)

Forecasting September 2012 (coupled model)

Sea ice thickness not initialized

Massonnet et al., Ocean Model., 2015

Blockley and Peterson., Cryosphere, 2018
Interannual time scales: «grey zone» of sea ice predictability

Ensemble spread of total sea ice volume from 4 GCMs

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

(a) Present-day case study

Truth (model)

Climatology

Data assimilation

Damped persistence

«Perfect» prediction

ens. 1σ

Tietsche et al., Clim. Dyn., 2013
Interannual time scales: « grey zone » of sea ice predictability

(a) Present-day case study

(b) Mid-century case study

Tietsche et al., Clim. Dyn., 2013
Interannual time scales: « grey zone » of sea ice predictability

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

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

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

Arctic sea ice area is slaved to the forcing...
Arctic sea ice area is slaved to the forcing...

but thinning rate depends on initial thickness
Has Arctic sea ice passed a tipping point?

Anomalies of Arctic sea ice extent relative to the 1979-2018 seasonal cycle

- High mean, low variance
- Low mean, high variance

Data: NSIDC sea ice index
Simple, conceptual models *can* exhibit multiple equilibria, but this is a parameter-dependent feature.

No evidence for Arctic sea ice irreversibility from comprehensive models

Li et al., *J. Climate*, 2013
Arctic sea ice predictions: conclusions

- 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
- There is a « grey zone » of Arctic sea ice predictability at interannual-to-decadal time scales
2. Important considerations regarding the evaluation of upcoming PARAMOUR predictions
Why don’t models and observations match each other?
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It’s the modelers fault
- Physical equations are wrong
- Equations are discretized
- Forcing is not correct
- Initial conditions are not correct
- Processes are parameterized
- There are computational errors

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- Algorithm errors
- Assumptions (e.g. hydrostatic)
- Sampling errors

[ Ivanova et al., Cryosphere, 2014; Zygmuntowska et al., Cryosphere, 2014; Worby et al., J. Geophys. Res., 2008 ]
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No scale-awareness
No definition-awareness

[Kay et al., J. Geophys. Res., 2016]
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It’s no one’s fault
Internal variability

[Notz, Phil. Trans. Roy. Soc., 2015]
Seasonal sea ice prediction skill is significantly affected by the choice of the verification product.
Why do models score better for the two most advanced and recent products?

Models simulate directly sea ice concentration and output it as a physical variable; observations don’t. Models can be really good references in that case!

Observations have deficiencies that models don’t have e.g. concentration of thin ice

Satellite estimation of sea ice concentration where it’s known to be 100%

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<tr>
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Challenges related to ensemble size, statistical power and statistical testing
Imagine 1000 forecast systems trying to predict the Arctic sea ice. Assume that 20% (200) are good enough to be skillful (actual correlation with obs is positive)
Due to limited statistical power (say, 50%), not all of the skillful systems will be recognized as skillful (100). All positive results will be published (100), while only few of the negative results (10%) will be published (10).
In addition, 5% of the nonskillful forecast systems (40) will produce skillful results just by chance, and all will be published. Again, only a limited number (10%) of negative results will be published (80).
Conclusion: From 230 published studies, 140 (61%) will report skillful results even though only 20% are actually skillful.

Due to low statistical power and unreported negative results, climate predictions are probably less often skillful than suggested by the literature.
Final remarks: data

- At UCLouvain we are hosting much sea ice and related data:
  - Observational references
  - Reanalyses
  - Model output (CMIP5, now CMIP6)
- We are keen to provide support or expertise when PARAMOUR people outside UCLouvain would like to use them