Environment and Climate Change Canada
Environnement et Changement climatique Canada
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Seasonal forecasts of sea ice

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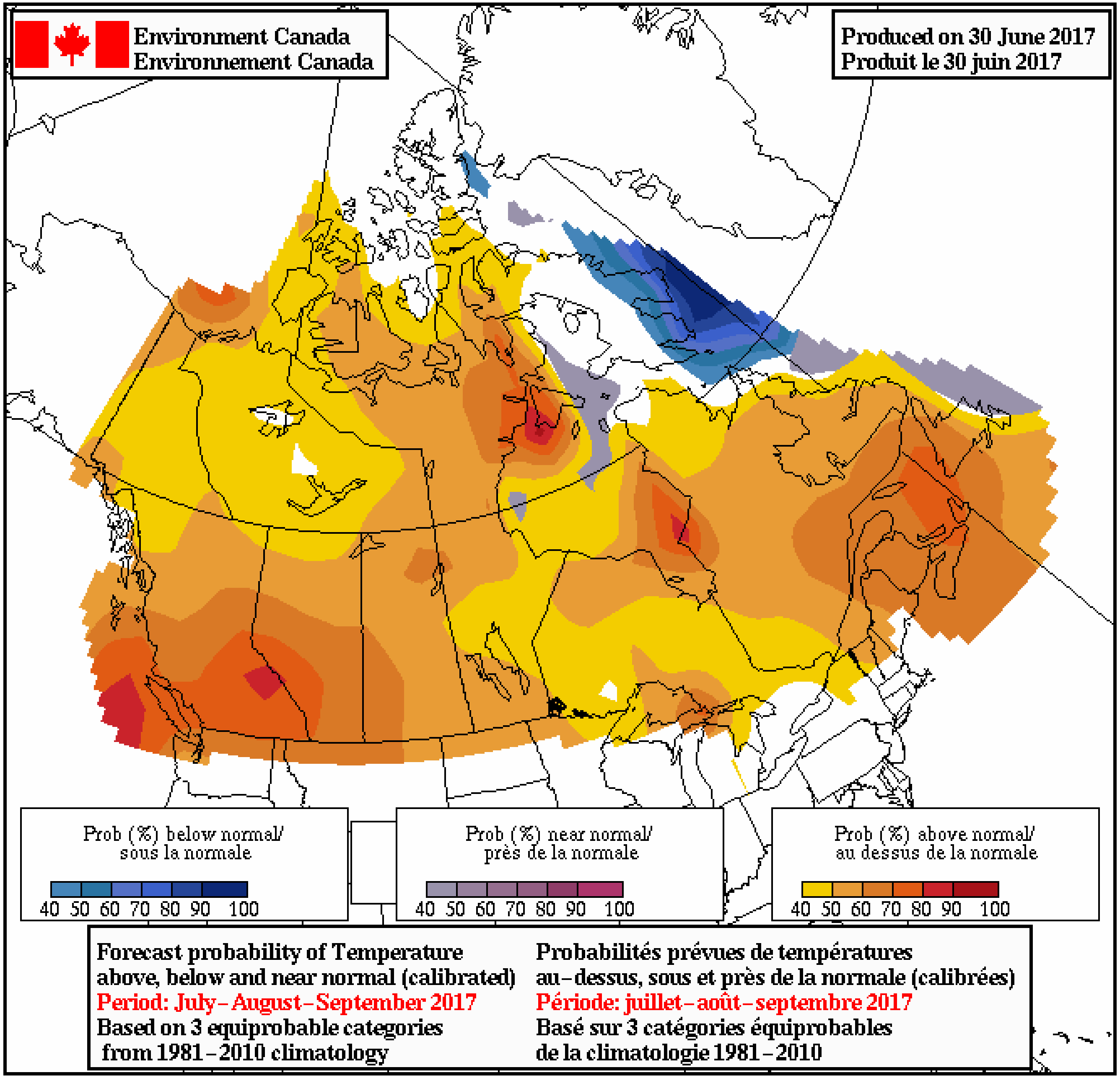


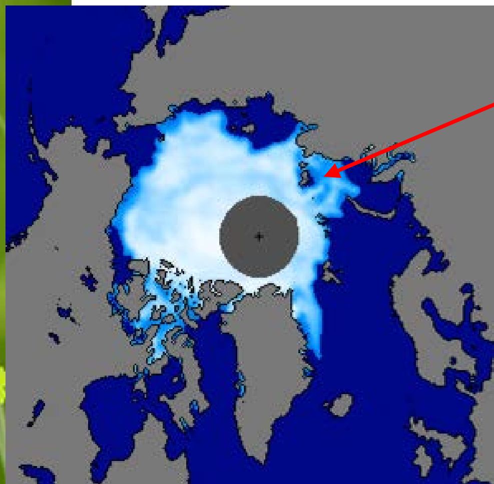
https://weather.gc.ca/saisons/image_e.html?img=s123pfe1t_cal_comb

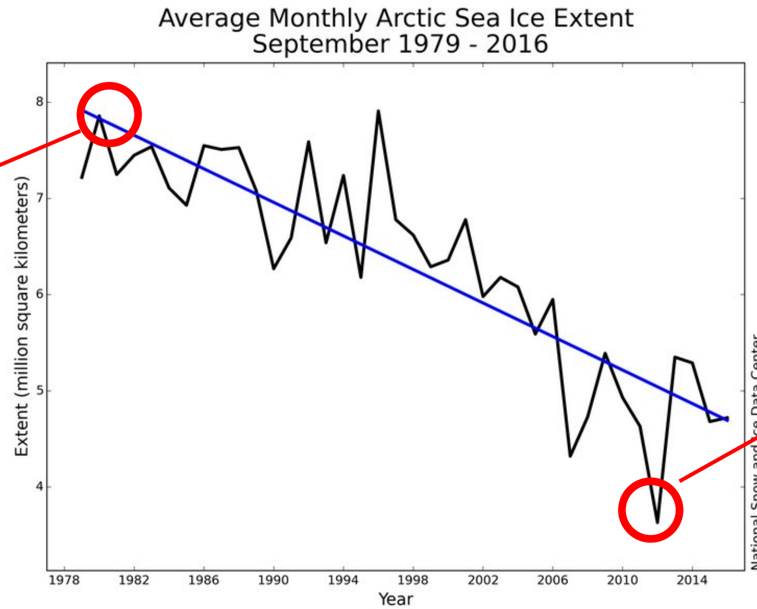
Outline:

- Why care about forecasting sea ice 1-12 months ahead?
- Potential sources of sea ice predictability
- Tools used to predict sea ice
- Forecast skill quantification
- Some recent progress (CanSISE)

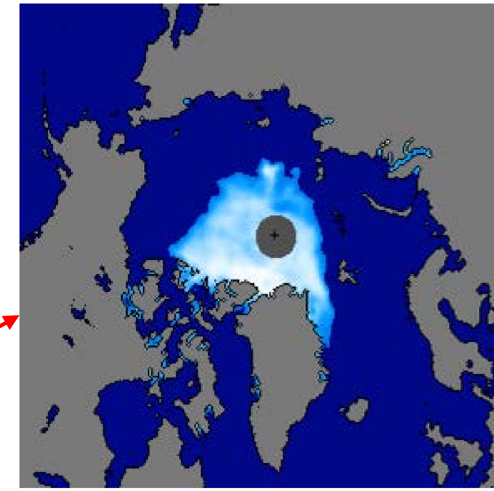
Increased marine accessibility

Sept. 1980

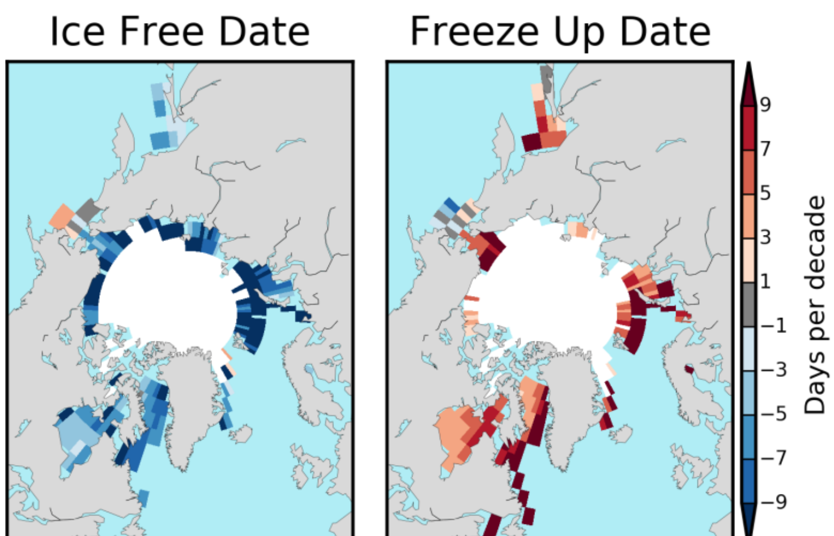




Sept. 2012



Observed trends (1979-2010)



Top: nsidc.org
Bottom: Sigmond et al. 2016, Geophys. Res. Lett.

Who might benefit from skillful forecasts?

Transport companies

Northern communities (resupply)

Tourism

National Coast Guards

Top right: http://www.cbc.ca/news/canada/north/resupply-ships-stuck-in-frobisher-bay-due-to-ice-conditions-1.1217970
Bottom left: http://www.cbc.ca/news/canada/north/massive-cruise-ship-brings-new-era-of-arctic-tourism-to-cambridge-bay-1.3739491

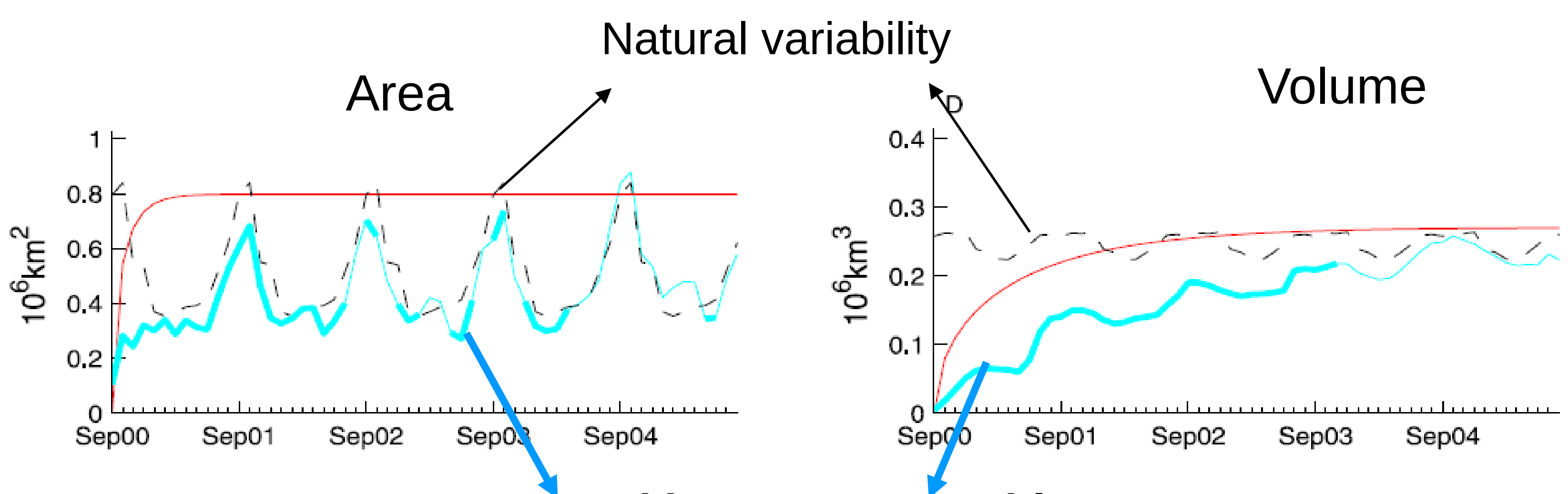
Is sea ice predictable on seasonal timescales (1-12 months) ?

- Long timescales in the ocean and sea ice system

→ skillful seasonal forecasts of sea ice seems reasonable

- Potential predictability studies: area predictable up > 1 year

- Approach: run a climate model multiple times with slightly different initial conditions and examine growth of differences



Spread between ensemble members in a climate model

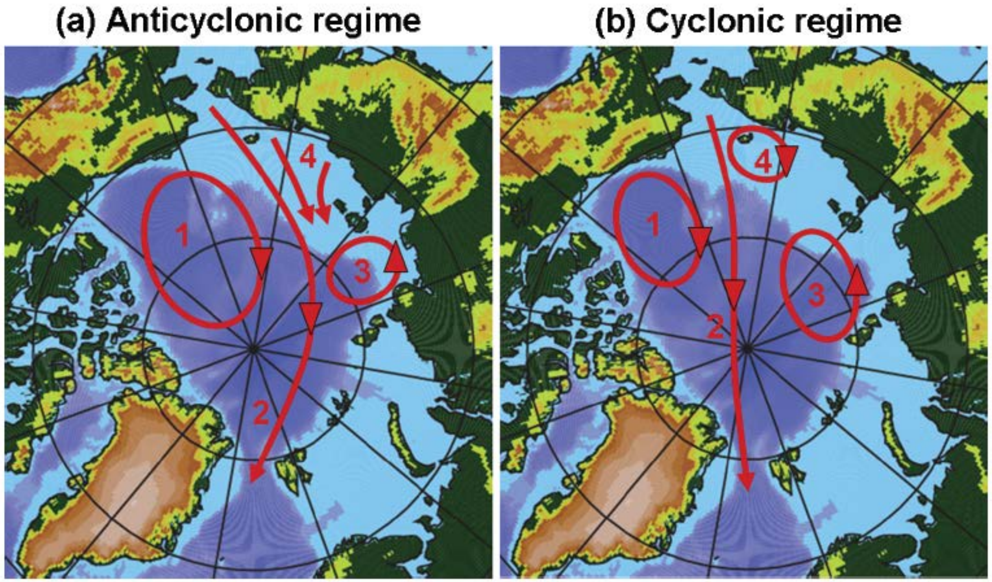
Blanchard-Wrigglesworth et al. , 2011, J. Clim.

Potential sources of predictability:

1) Long term trend due to external forcings

2) Persistence of sea ice anomalies (~months)

3) Advection (mean circulation)



1) Beaufort gyre
2) Transpolar Drift Stream
3) Laptev Sea Gyre
4) East Siberian circulation

Guemas et al, 2016, Q.J.R. Meteorol. Soc.

Potential sources of predictability:

4) Atmosphere

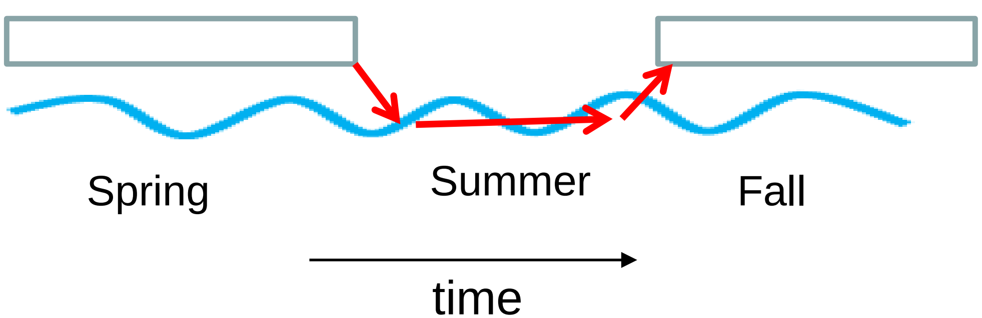
5) Ocean heat transport (e.g., through Bering Strait)

6) Re-emergence of sea ice anomalies:

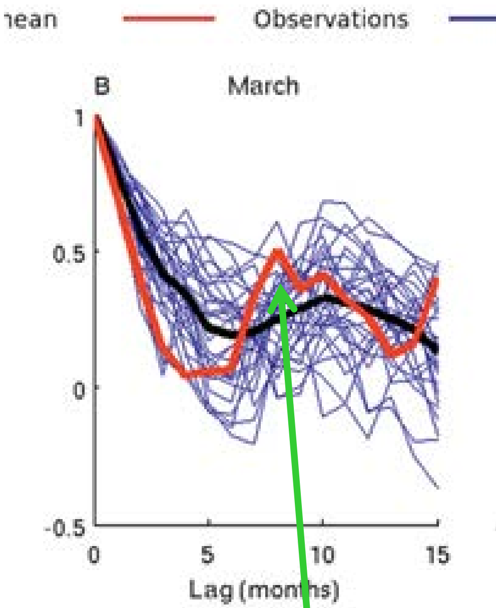
- *Increase of lag correlation after initial drop-off*

- *Summer to summer re-emergence (Thickness)*

- *Melt-to-growth season re-emergence*



Area lag correlation



're-emergence'

Blanchard-Wrigglesworth et al. , 2011, J. Clim.

Tools/methods used to produce forecasts:

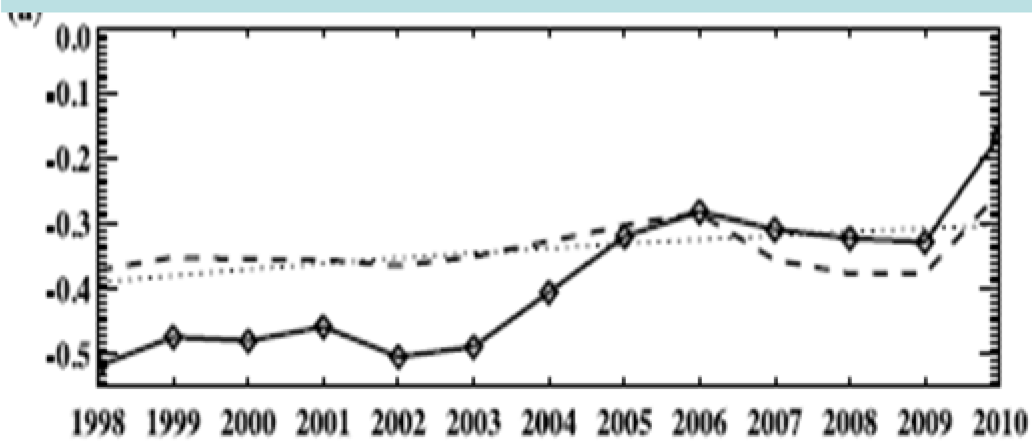
1) Analog year method

- *look for year with similar conditions like freeze-up date, ice thickness, summer air temperature outlook*
- *Ran out of analog years by 2007*

2) Statistical models (Multi Linear Regression models)

- *Built upon statistical relationships derived from historical observations*
- *May not be valid today (future) because of rapidly changing Arctic*

Correlation AO winter and SIE in September



Begin year: 1979

Dynamical models:

- Global climate models (numerical models that represent interactions between atmosphere, ocean, sea ice)

- Initialized with observed climate state

- Aspects of weather forecasting (initial value problem) and long-term climate projections (boundary value problem, interactive ocean)

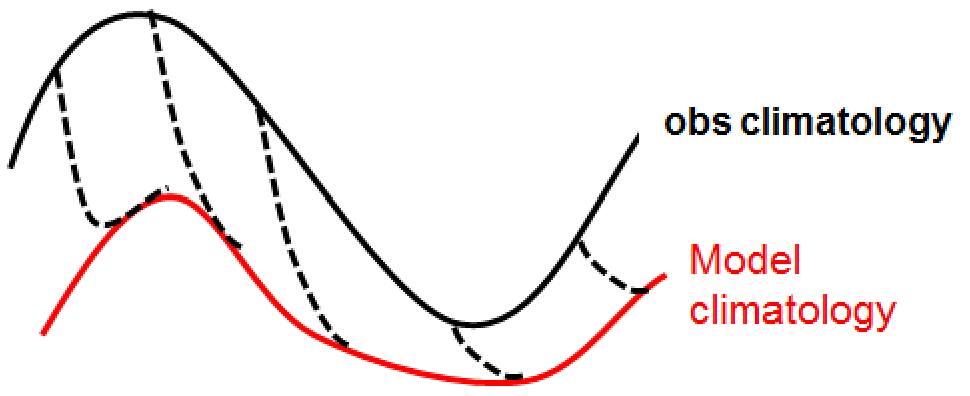
- Dynamical models used for seasonal forecasting (temperature, precipitation) since ~1990s, but not suitable for sea ice forecasts (not interactive)

Canadian Season to Inter-annual prediction System (CanSIPS)

- ECCC's operational seasonal forecasting system since Dec 2011
- One of the first to include interactive sea ice
- Based on 2 global climate models (CanCM3/4, cancellation of errors→ improved skill)
- Seasonal forecasting is a probablistic problem → run multiple realizations (10 for each model) with slightly different initial conditions

Hindcast dataset - a key ingredient

- Purposes of Hindcasts (re-forecasts of past):
  1) Skill quantification
  2) Statistical bias correction (mean, distribution)



- CanSIPS: hindcasts initialized at start of each month since 1979 (forecast range: 12 months)

Verification metrics:

O_t: observation, F_t: Forecast (e.g. Sept sea ice area)

Mean square error:

$$MSE = \frac{\sum_{t=1}^{N}(F_t - O_t)^2}{N}$$

$$SS = 1 - {}^{MSE}/_{MSE_{ref}}$$ (SS=1: perfect forecast,

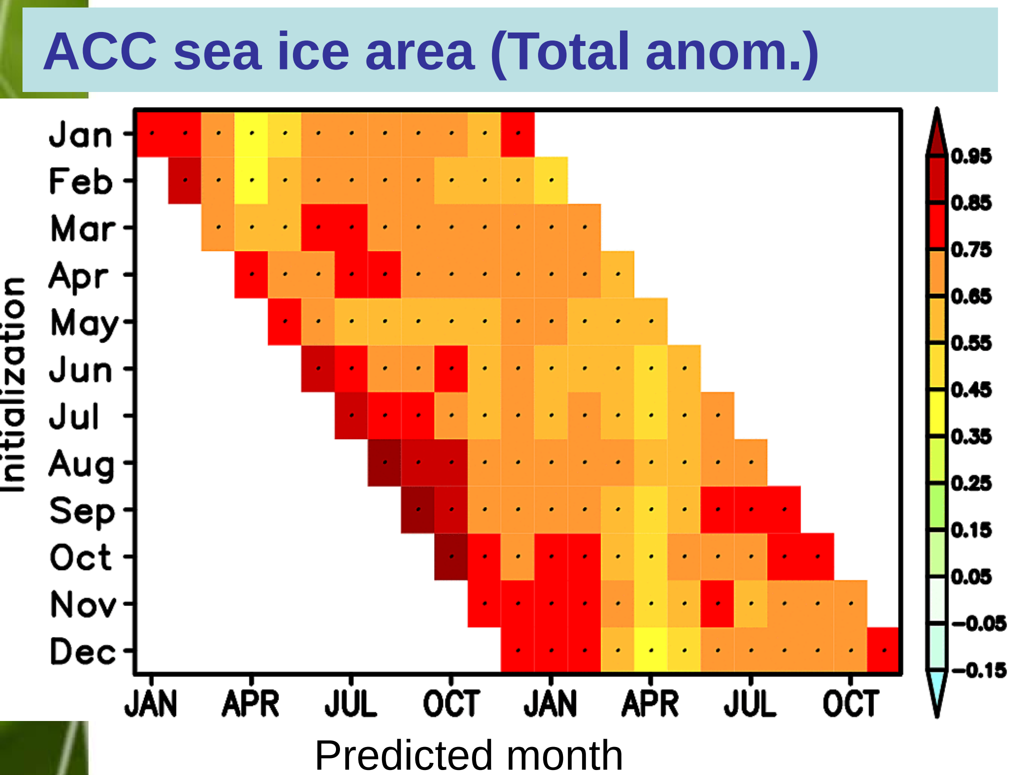
SS<0: worse than ref.)

Anomaly correlation coefficient:

$$ACC = \frac{1}{N}\sum_{t=1}^{N}(F'_t O'_t) \Big/ \sqrt{Var(F_t)Var(O_t)}$$

And many other metrics to verify probablistic forecasts (Brier Skill Score, Ranked probability Score)

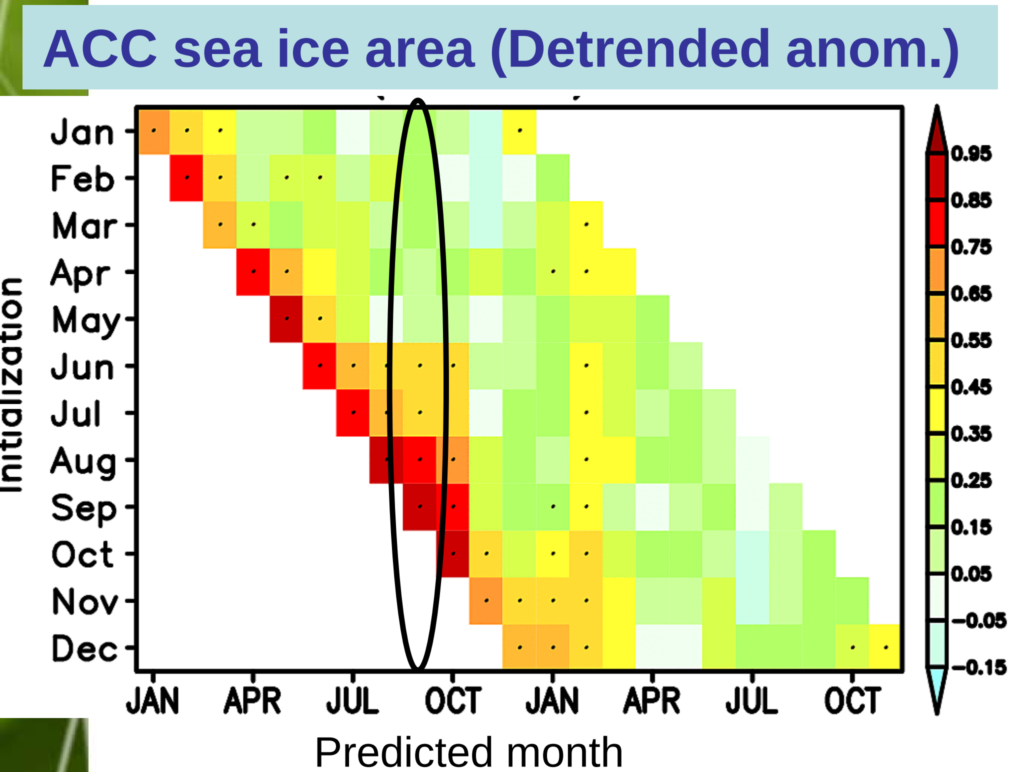
CanSIPS skill of sea ice area forecasts



- Significant skill up to a year ahead
- Skill at longer lead times mostly stems from model's ability to reproduce long-term trend

Sigmond et al, 2013, Geophys. Res. Lett.

CanSIPS skill of sea ice area forecasts

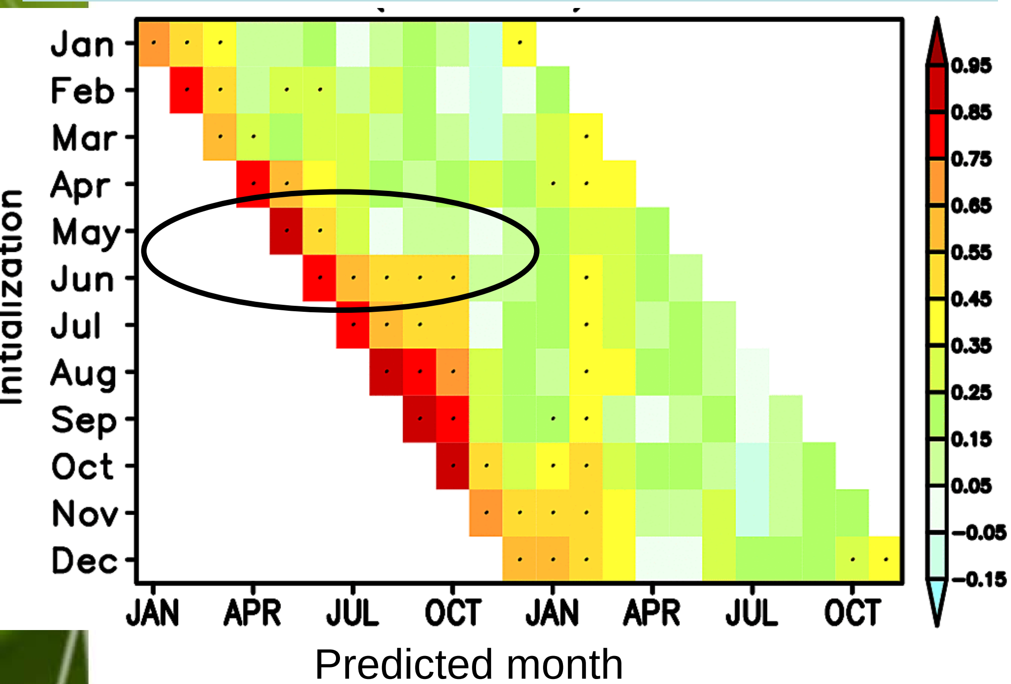


- Detrended Sept. SIA skillfully predicted from June

Sigmond et al, 2013, Geophys. Res. Lett.

CanSIPS skill of sea ice area forecasts

ACC sea ice area (Detrended anom.)



- Detrended Sept. SIA skillfully predicted from June
- Strong dependency of skill on initialization month

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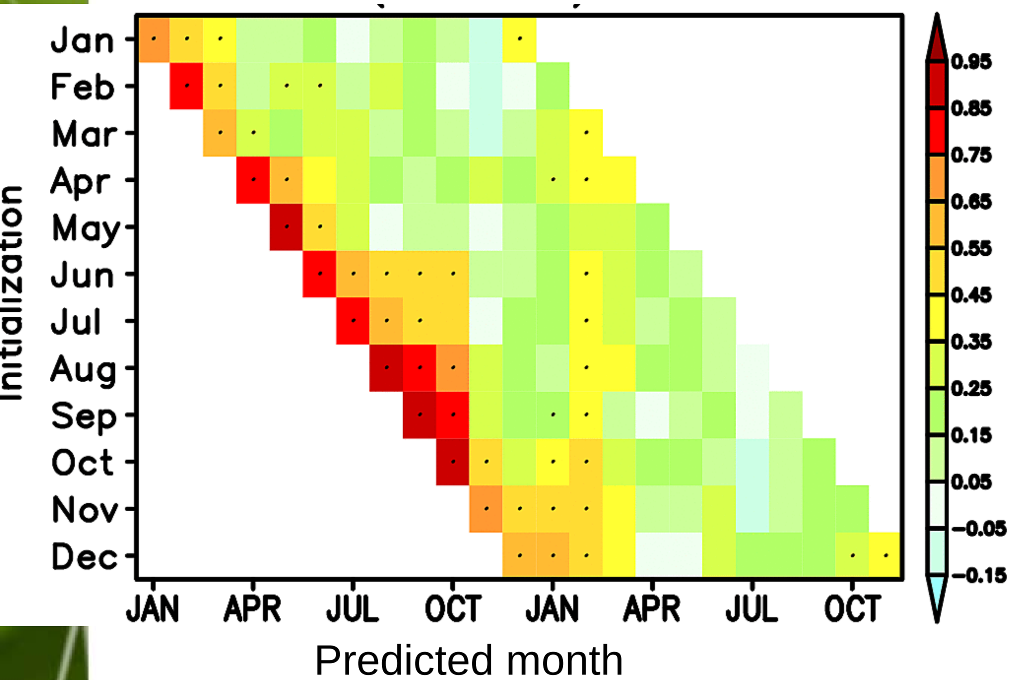

- Detrended Sept. SIA skillfully predicted from June
- Strong dependency of skill on initialization month
- Substantial skill at long lead times for winter predictions
- Model beats persistence

Sigmond et al, 2013, Geophys. Res. Lett.

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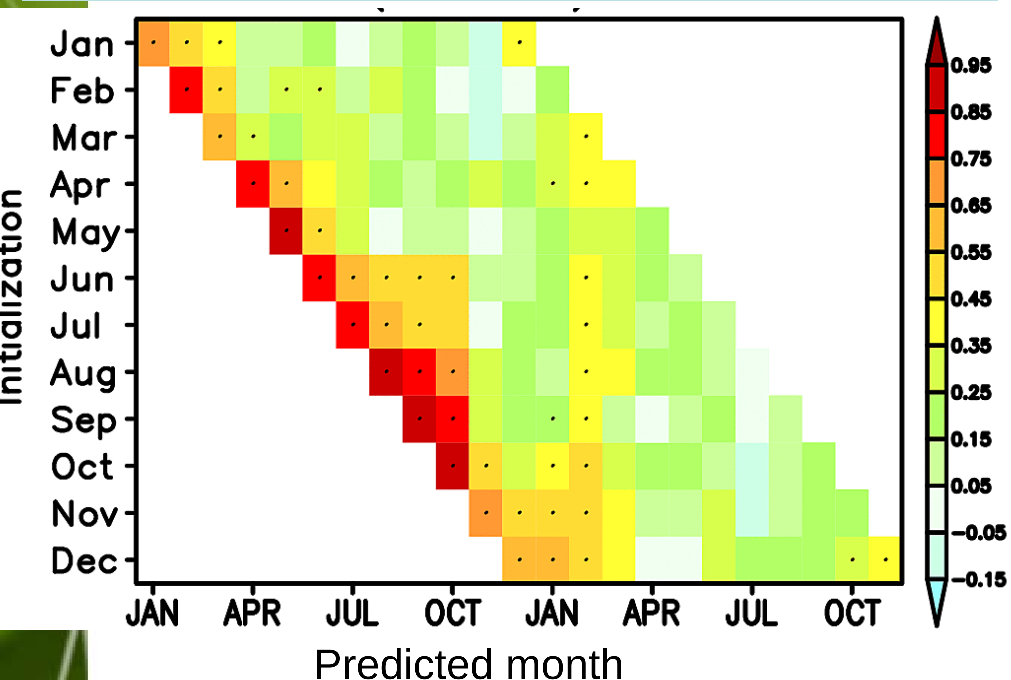

- Detrended Sept. SIA skillfully predicted from June
- Strong dependency of skill on initialization month
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- These features appeared to be robust for other systems (*CFSv2:* Wang et al. 2013, *MetOffice:* Peterson et al. 2014, *GFDL:* Msadek et al 2014)
- But **not clear** if dynamical model provide skillful seasonal forecasts of **user-relevant sea ice quantities**

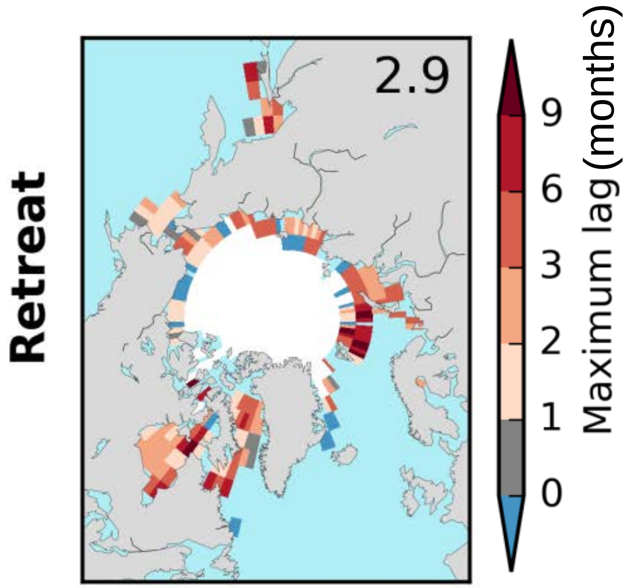
CanSIPS skill of retreat and advance dates

- Retreat date: First calendar day with SIC < 50%
- Advance date: First calendar day with SIC > 50%
- Maximum lead time with skill:

  [climatological date] – [earliest initialization month with skill]

ACC>0.3 (*p*=0.05)

CanSIPS skill of retreat and advance dates

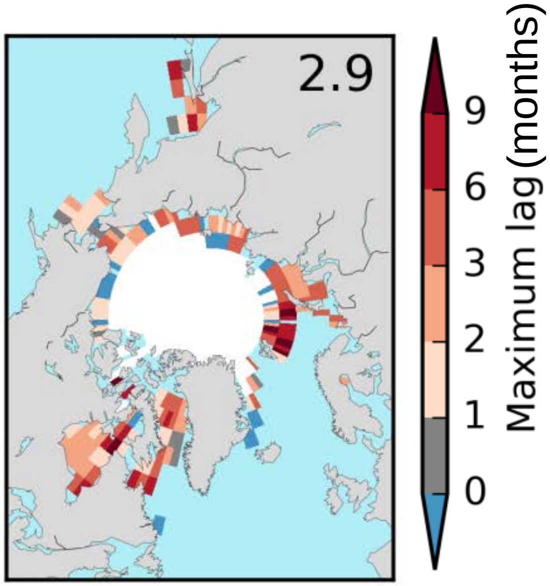


- Retreat date forecasts skillful at 3 month lead
- Drops to 2.2 month for detrended anomalies
- Main source skill: persistence
- Model beats persistence-based forecast

Sigmond et al, 2016, Geophys. Res. Lett.

CanSIPS skill of retreat and advance dates

Retreat



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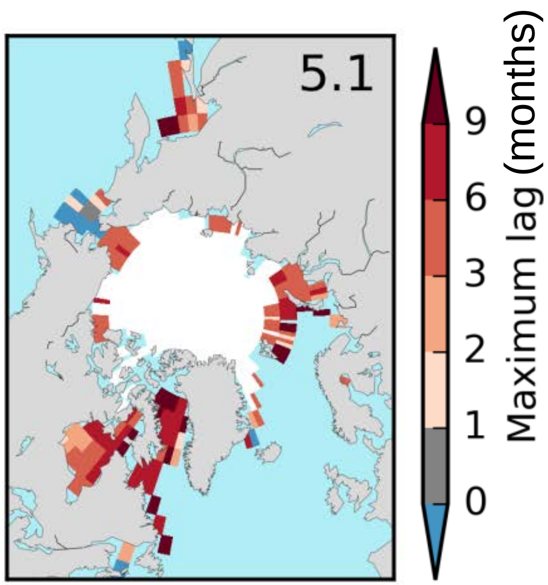
Advance

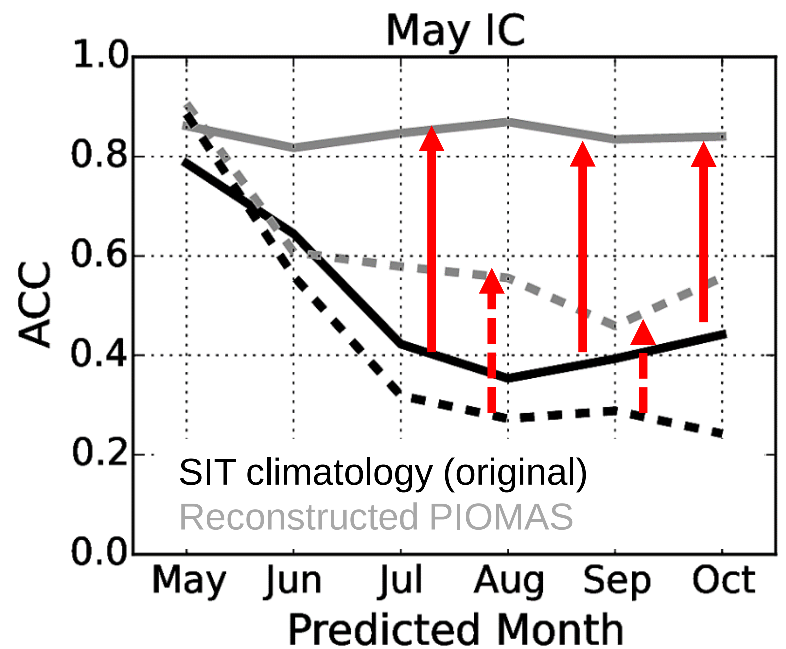


- Advance date forecasts skillful at 5 month lead
- Drops to 3.3 months for detrended anomalies
- Sea ice persistence provides no skill
- Model skill at longer lead times stems from skillful SST predictions

Sigmond et al, 2016, Geophys. Res. Lett.

Recent developments under CanSISE
(Dirkson, Merryfield)

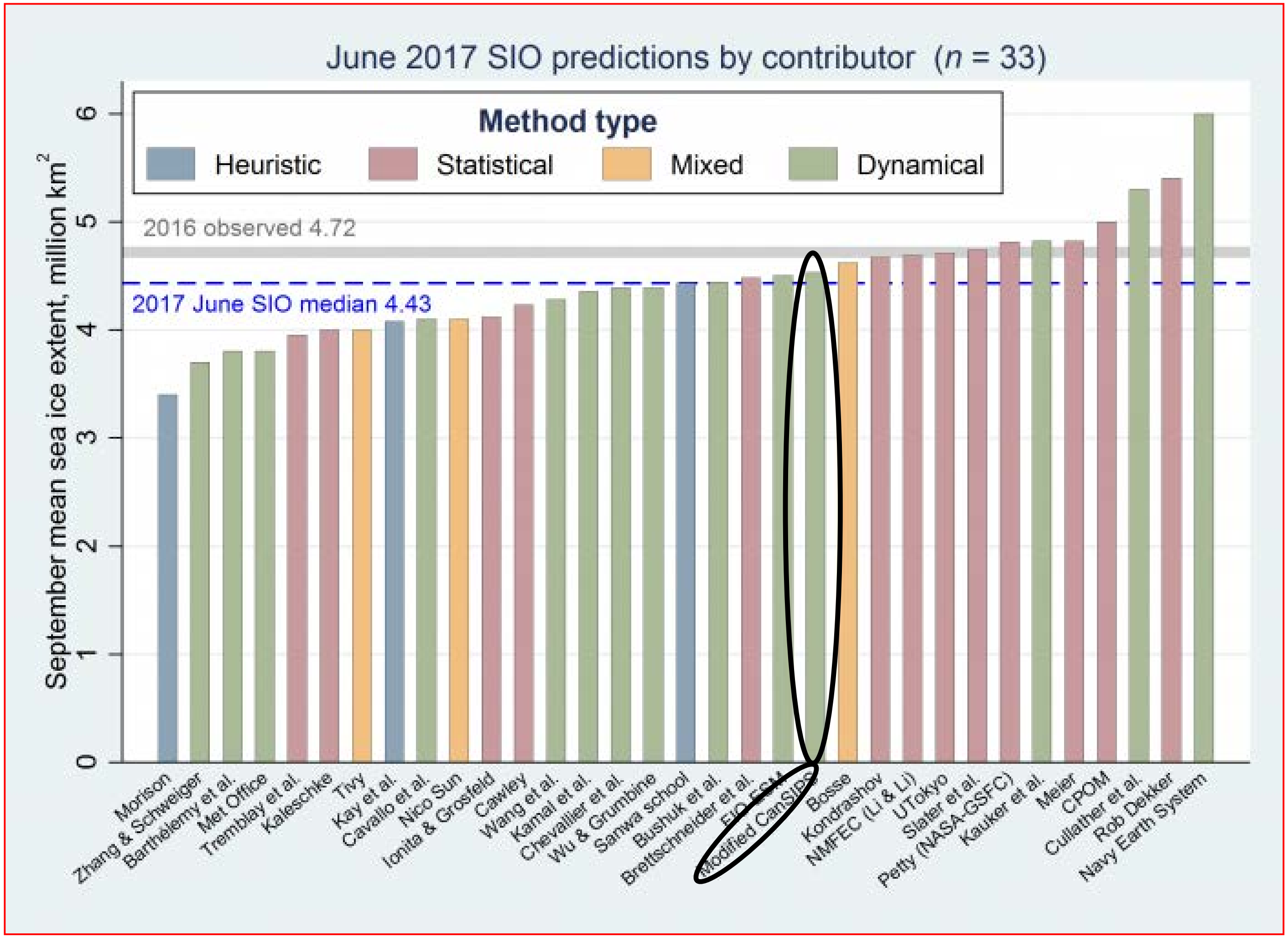
- Improved sea ice thickness initialization (time-varying instead of climatology)



- Development of methods to post-process CanSIPS output to obtain calibrated sea ice probability forecasts

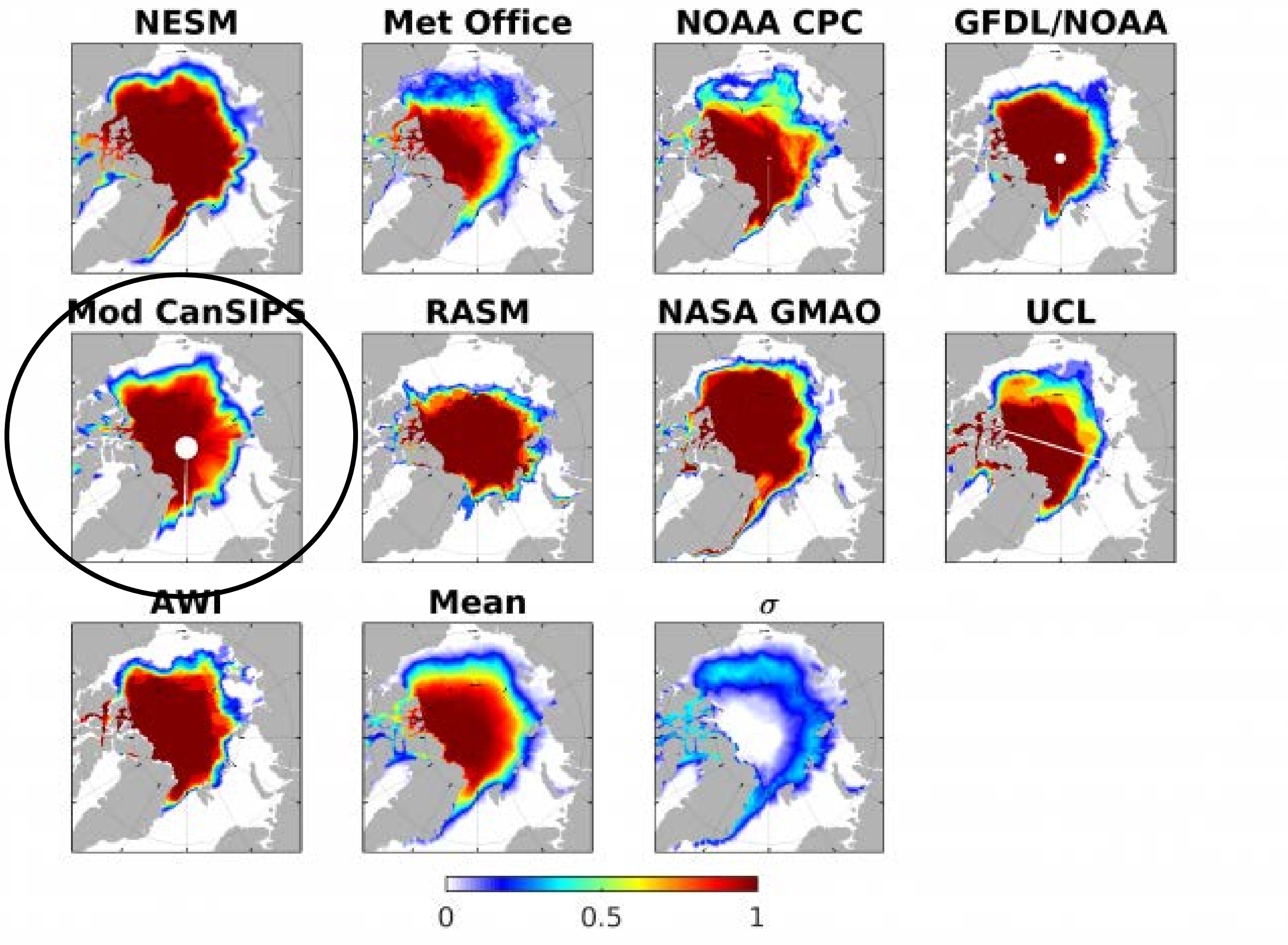
- Resolving issue with operational forecasts (inconsistency between hindcasts and operational forecasts)

Sea ice outlook (Sept sea ice area)



https://www.arcus.org/sipn/sea-ice-outlook/2017/june

Sea ice outlook (Sept sea ice probability)



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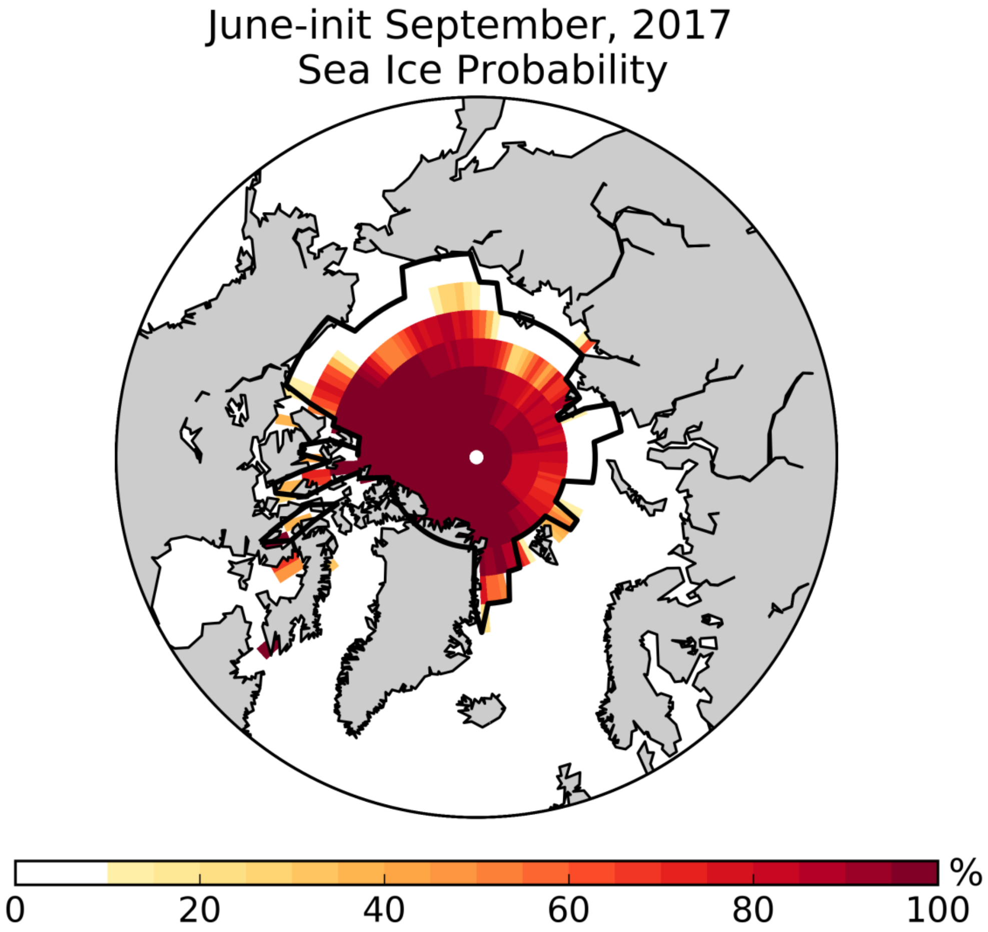
Sea ice outlook (Sept sea ice probability)



Courtesy: Arlan Dirkson, UVIC

Future developments

- Improve models (new ocean/ice model, higher resolution, better parameterization of relevant processes such as melt ponds)
- Improve observations (verification, initialization)
- Improve bias correction and calibration procedures
- Interact with end-users to come up with more user-relevant sea ice products (balance between desires and feasibility)