Detection and Attribution of Arctic Climate Change

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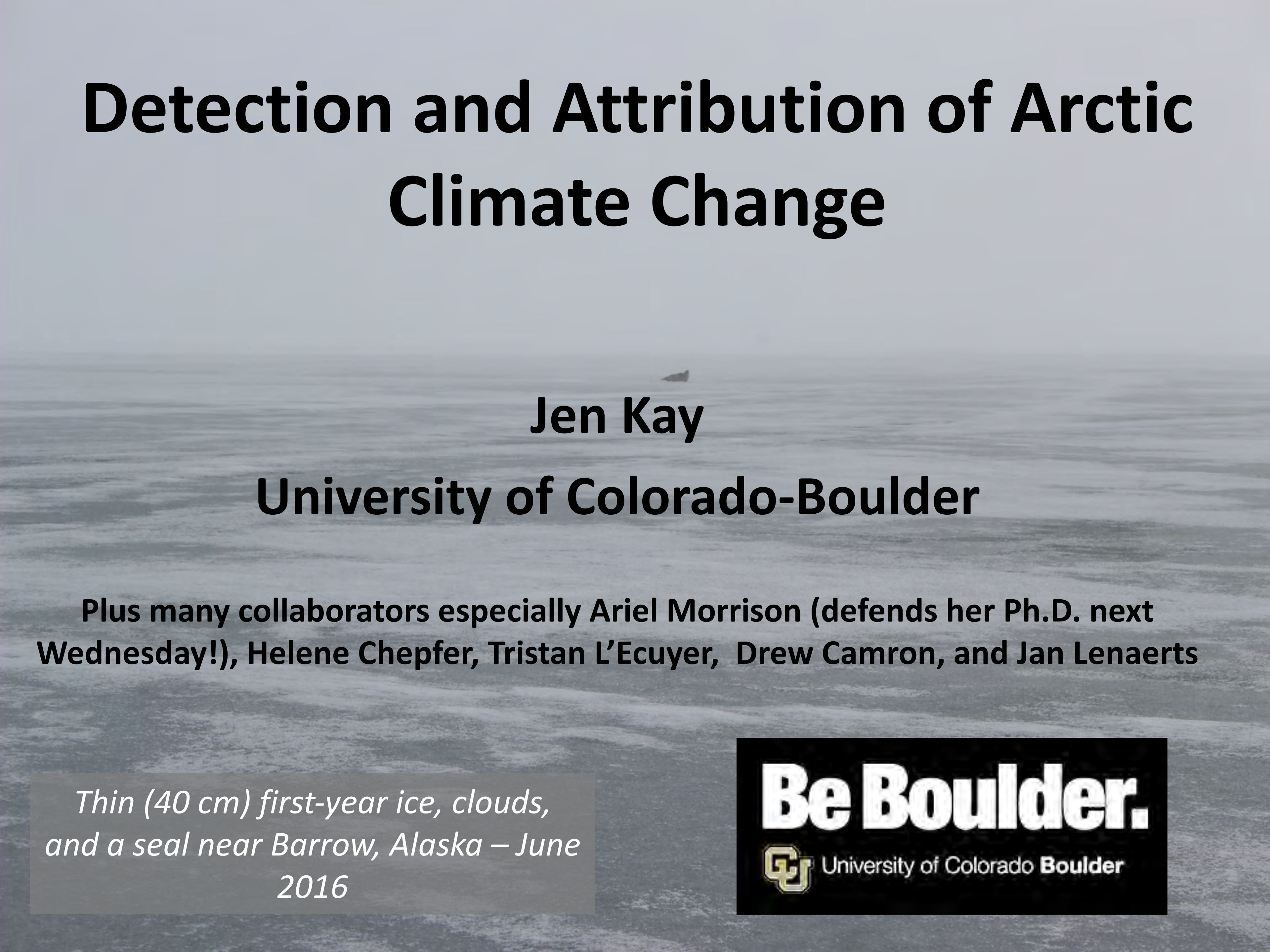
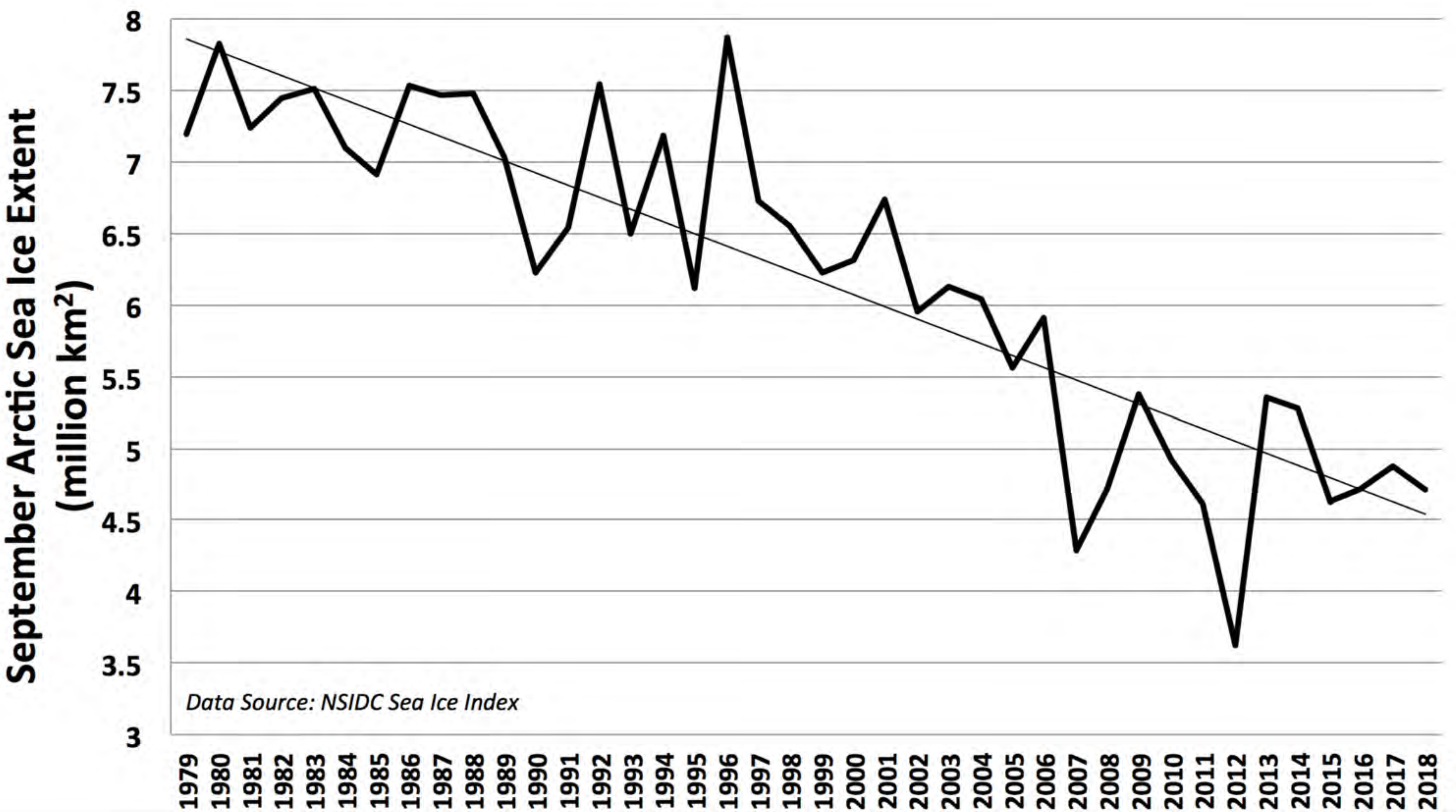
Plus many collaborators especially Ariel Morrison (defends her Ph.D. next Wednesday!), Helene Chepfer, Tristan L'Ecuyer, Drew Camron, and Jan Lenaerts



Thin (40 cm) first-year ice, clouds, and a seal near Barrow, Alaska – June 2016

Be Boulder.
University of Colorado Boulder

Observed Arctic Sea Ice Loss



Summer absorbed shortwave radiation is increasing.

Summer Arctic sea ice concentrations are decreasing.

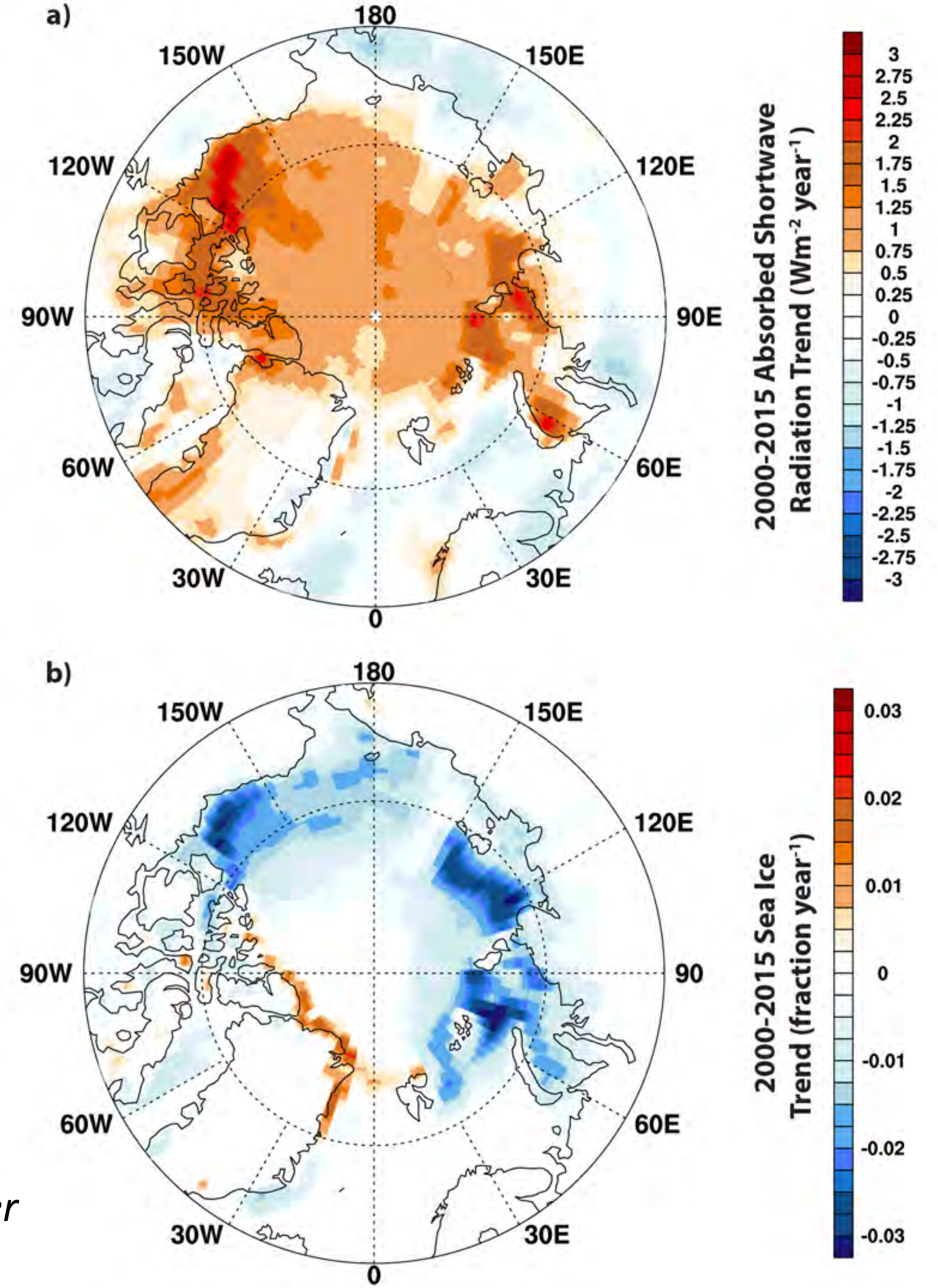
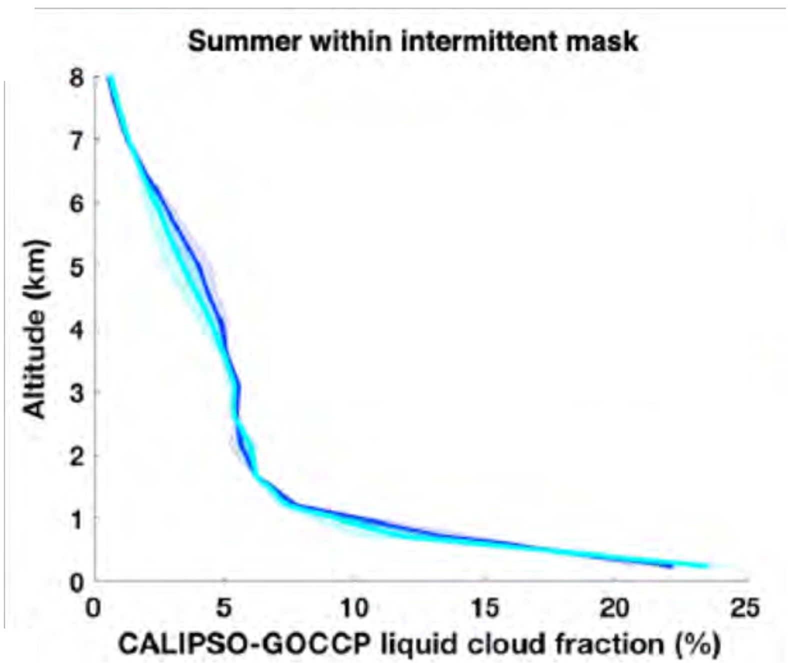
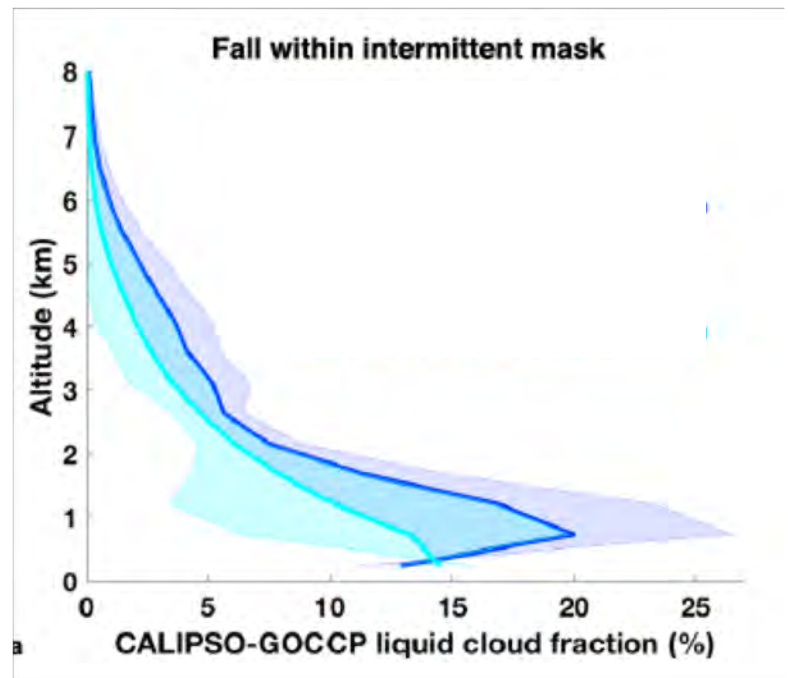


Figure from Kay et al. 2016 Review Paper
DOI: 10.1007/s40641-016-0051-9

Observations show small impact of cloud-sea ice feedbacks on observed warming



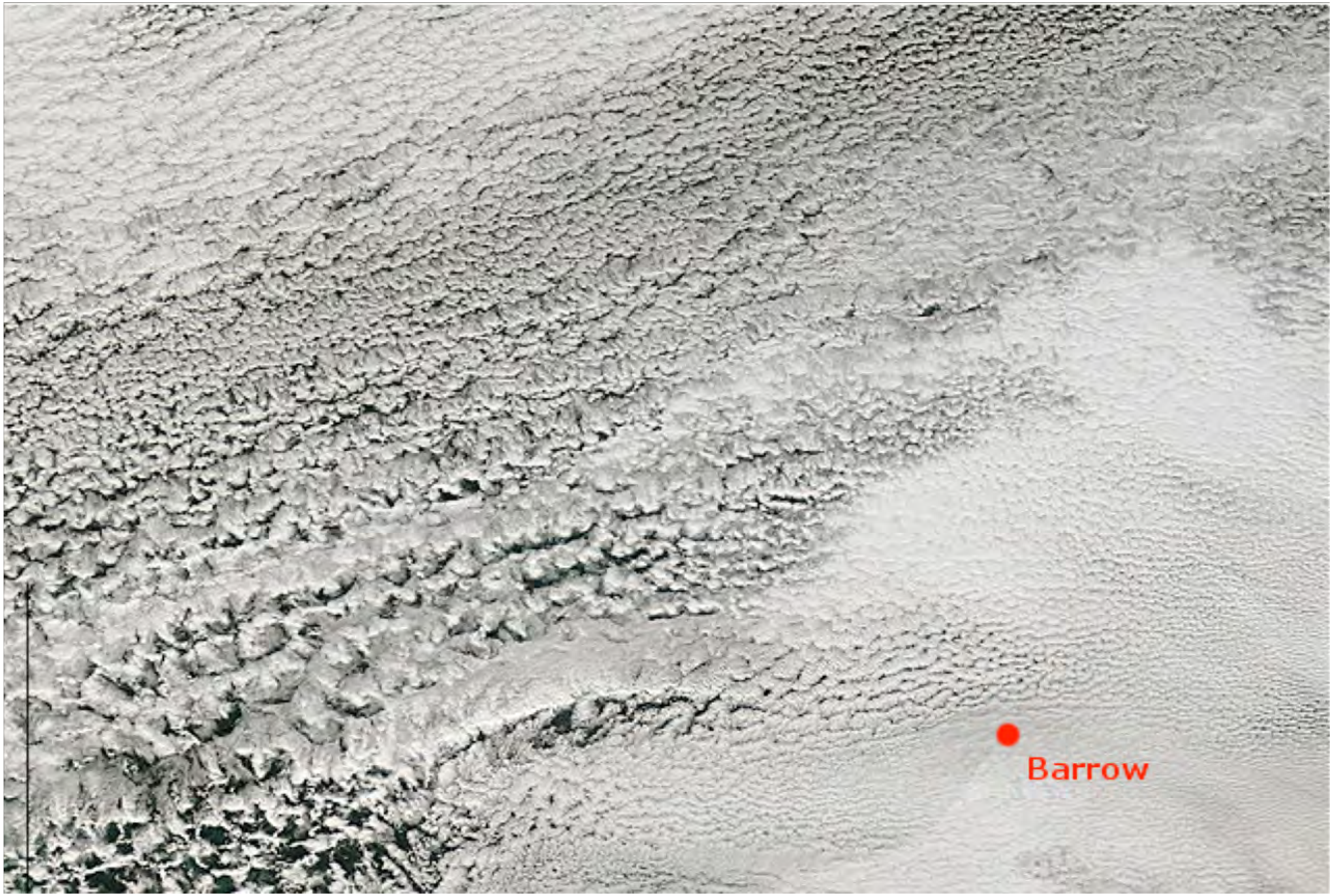
No evidence for summer cloud-sea ice feedback



Weak cloud-sea ice feedback in Fall – shortwave and longwave compensate.

Morrison et al. 2018 - JGR

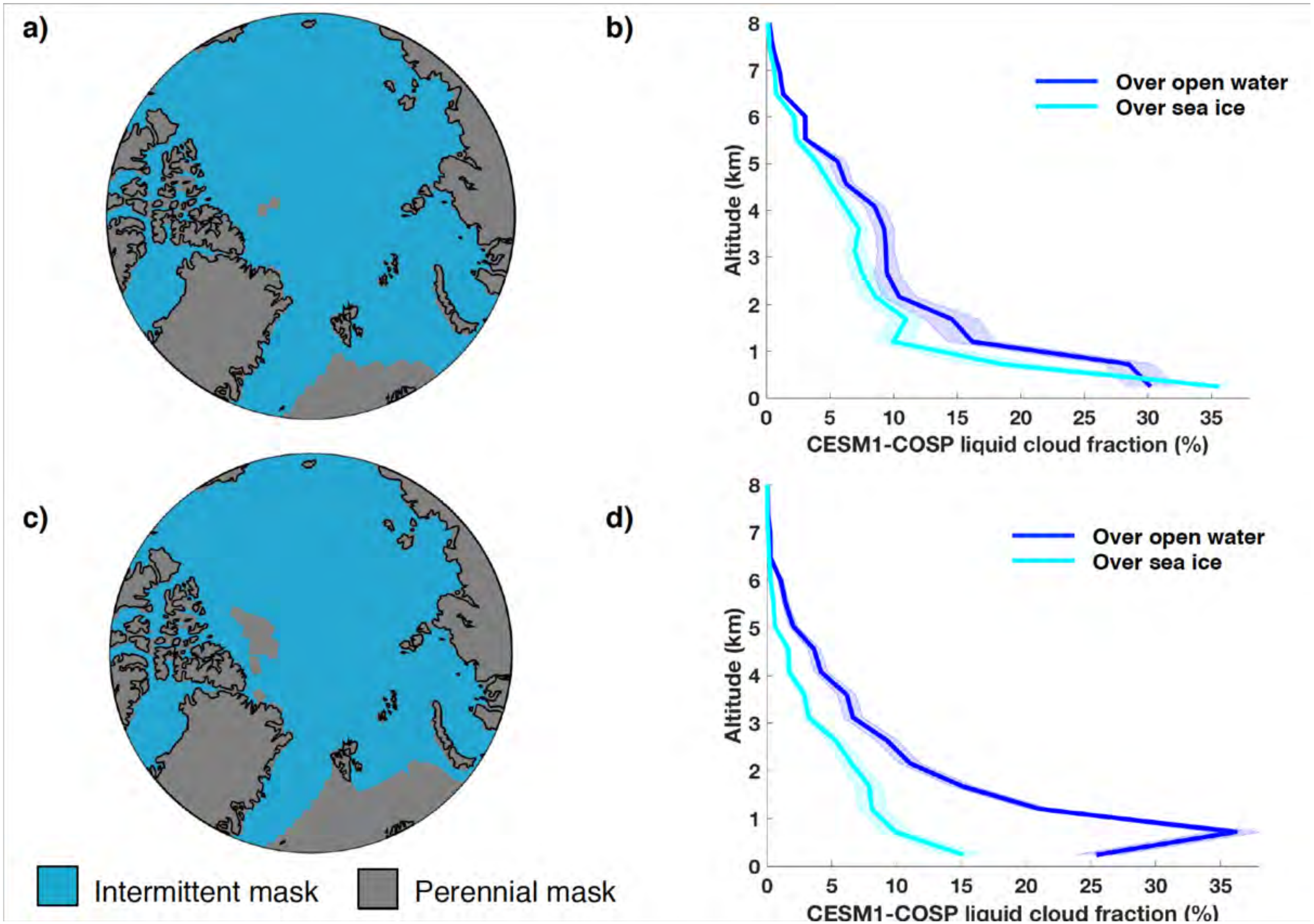
MODIS Visible Image September 30, 2007



CESM1 matches observations: no change in summer, more clouds over open water than over sea ice in fall

Summer

Fall



Morrison et al. (in review)

What tools are best for Detection and Attribution of human-caused Arctic change?

THE COMMUNITY EARTH SYSTEM MODEL (CESM) LARGE ENSEMBLE PROJECT

A Community Resource for Studying Climate Change in the Presence of Internal Climate Variability

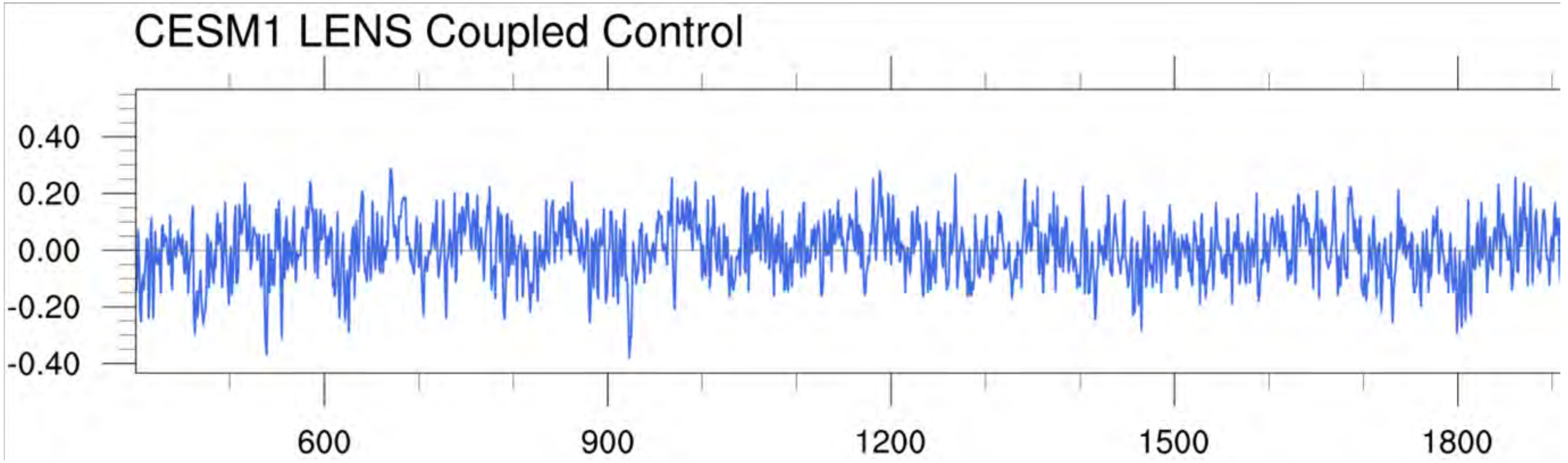
BY J. E. KAY, C. DESER, A. PHILLIPS, A. MAI, C. HANNAY, G. STRAND, J. M. ARBLASTER, S. C. BATES, G. DANABASOGLU, J. EDWARDS, M. HOLLAND, P. KUSHNER, J.-F. LAMARQUE, D. LAWRENCE, K. LINDSAY, A. MIDDLETON, E. MUNOZ, R. NEALE, K. OLESON, L. POLVANI, AND M. VERTENSTEIN

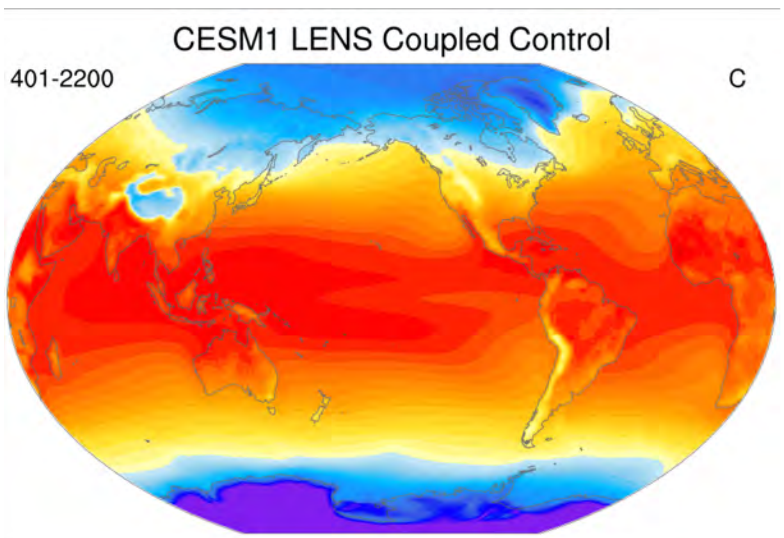
By simulating climate trajectories over the period 1920–2100 multiple times with small atmospheric initialization differences, but using the same model and external forcing, this community project provides a comprehensive resource for studying climate change in the presence of internal climate variability.

https://journals.ametsoc.org/doi/10.1175/BAMS-D-13-00255.1

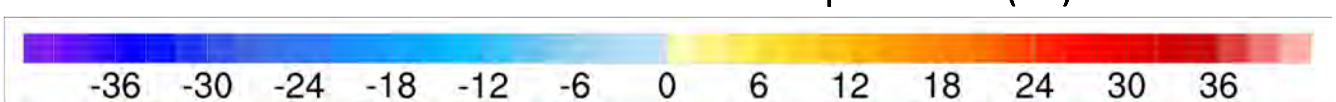
Introduce CESM1 1850 control run

Global mean surface air temperature anomaly (°C)





Annual mean surface air temperature (°C)



CESM Large Ensemble

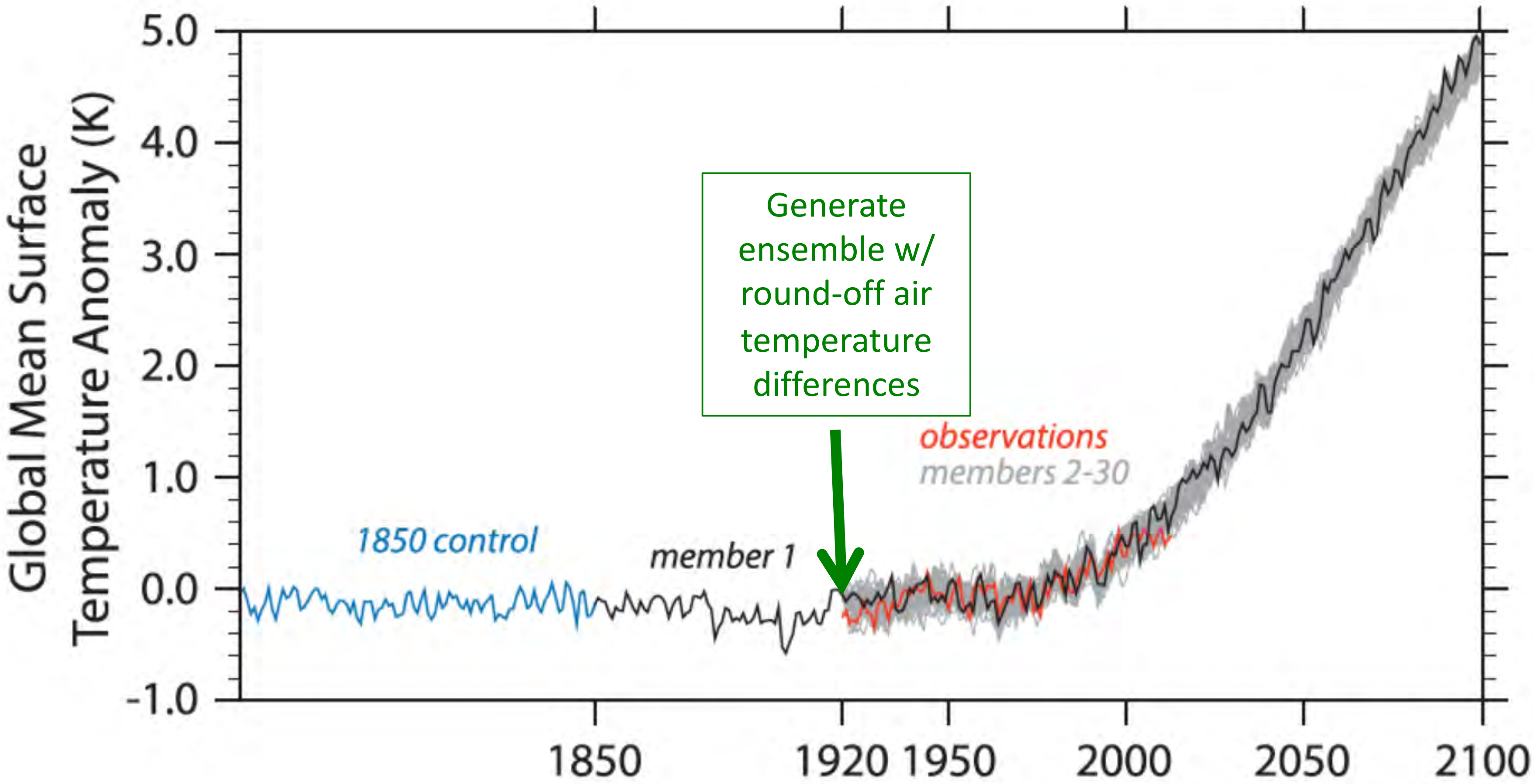


FIG. 2. Global surface temperature anomaly (1961–90 base period) for the 1850 control, individual ensemble members, and observations (HadCRUT4; Morice et al. 2012).

Figure from Kay et al. 2015 (BAMS), a « hot » paper cited 520+ times

Let's use climate models to understand Arctic sea ice trends

Assumption: Climate models represent the key processes affecting sea ice trends.

Modeled vs. Observed September sea ice trends

1. Observed sea ice loss cannot be explained by natural variability alone.

2. Individual climate model simulations can reproduce the observed ice loss, but the ensemble spread is large.

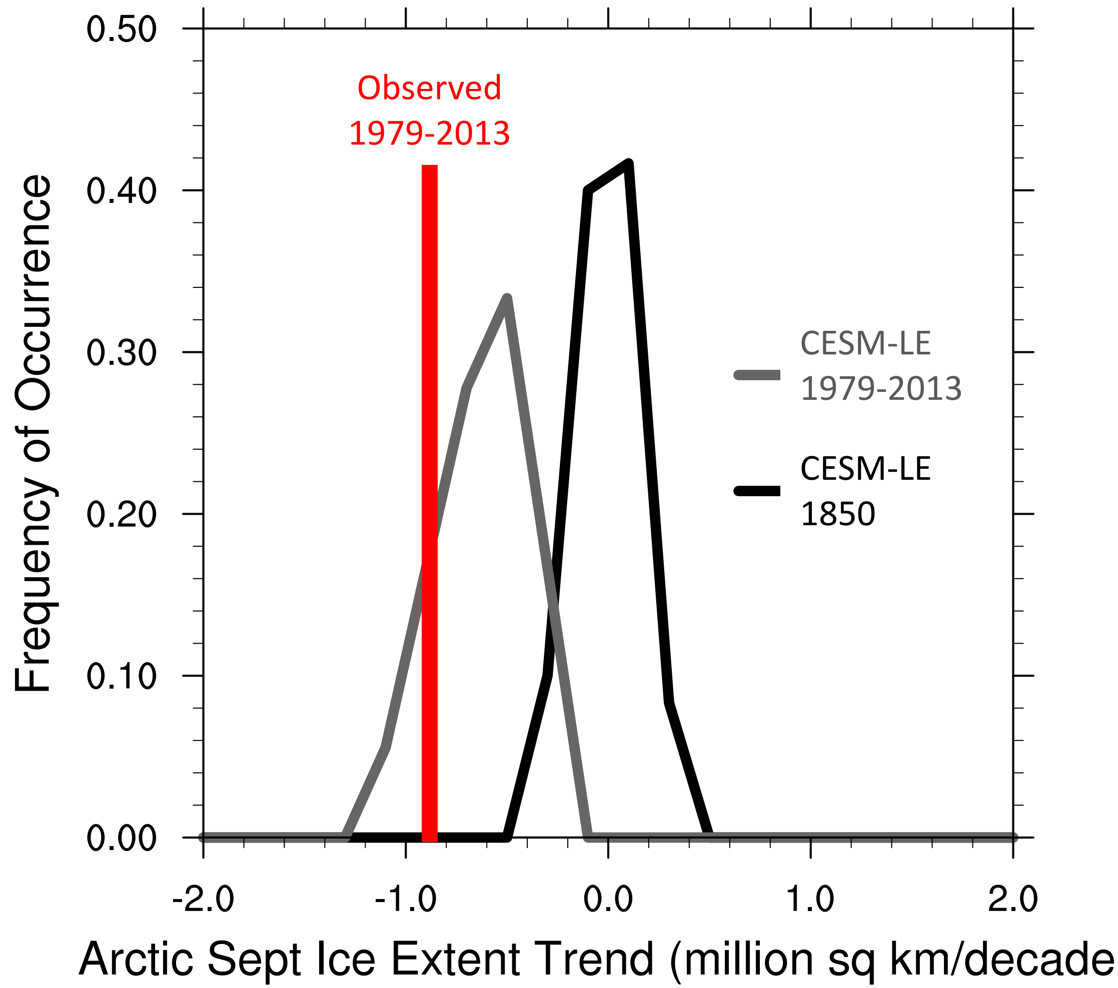
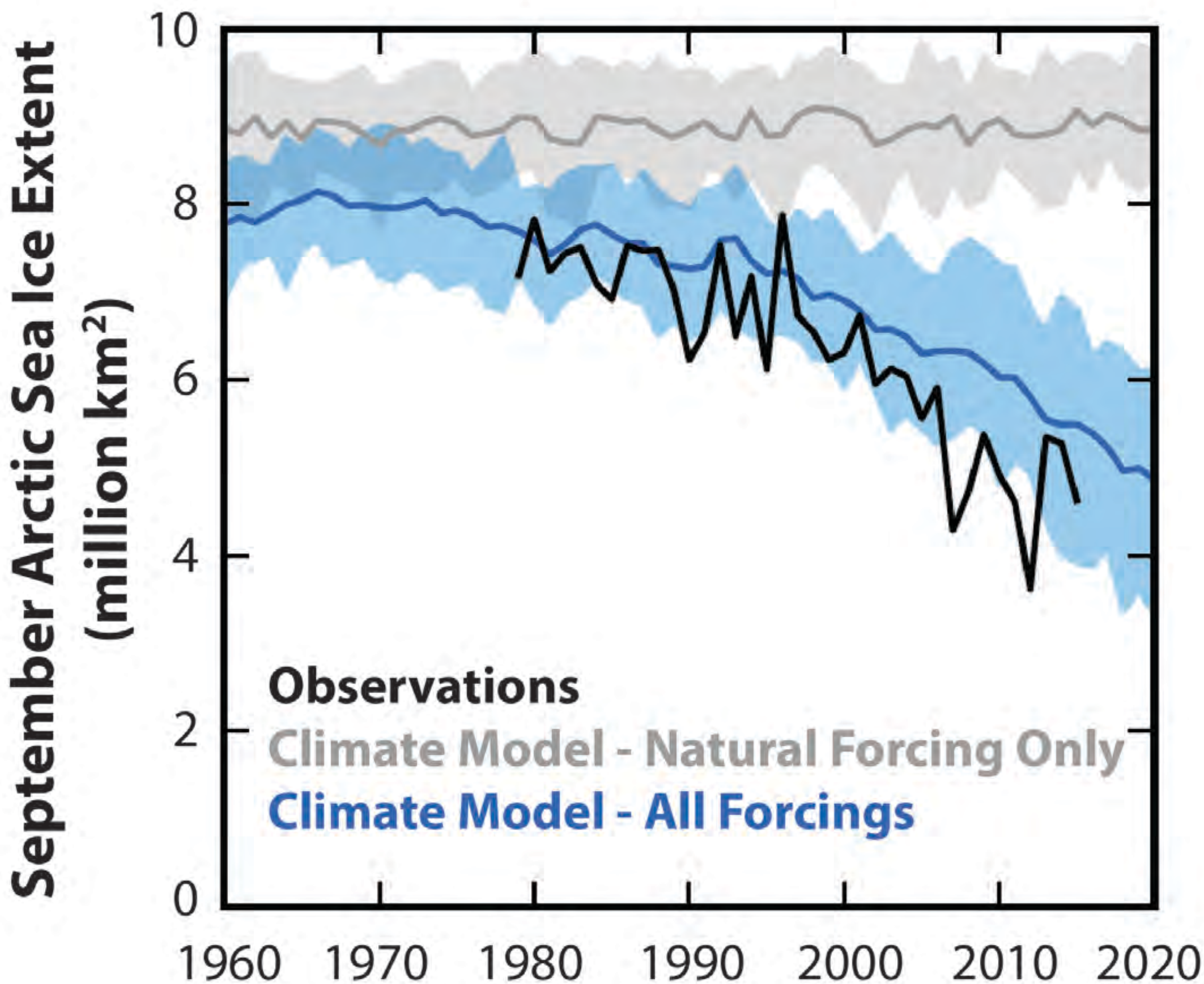


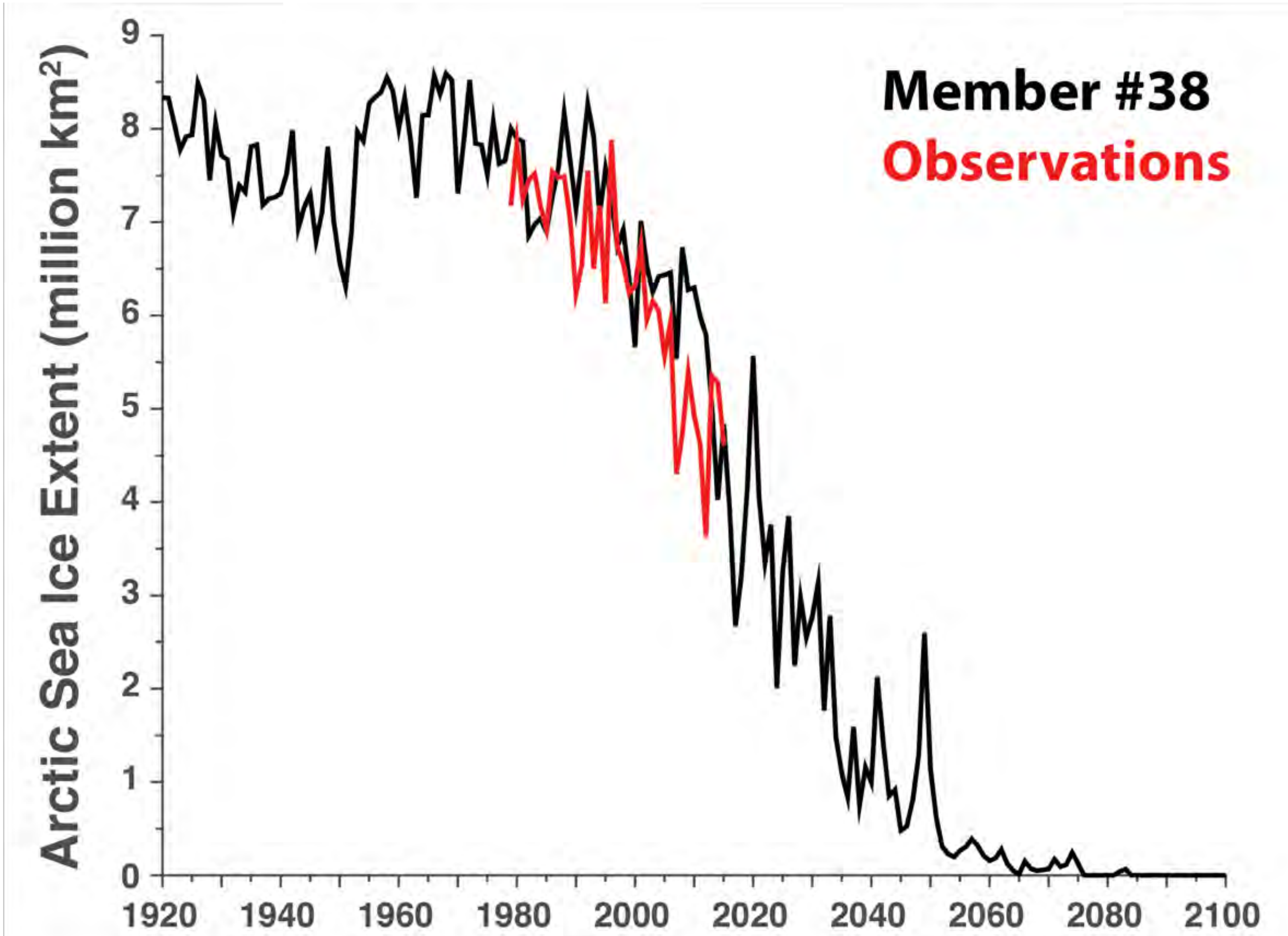
Figure from A. Jahn based on the CESM-CAM5 large ensemble. Results consistent with CCSM4 (Kay et al. 2011 GRL)

Arctic sea ice loss

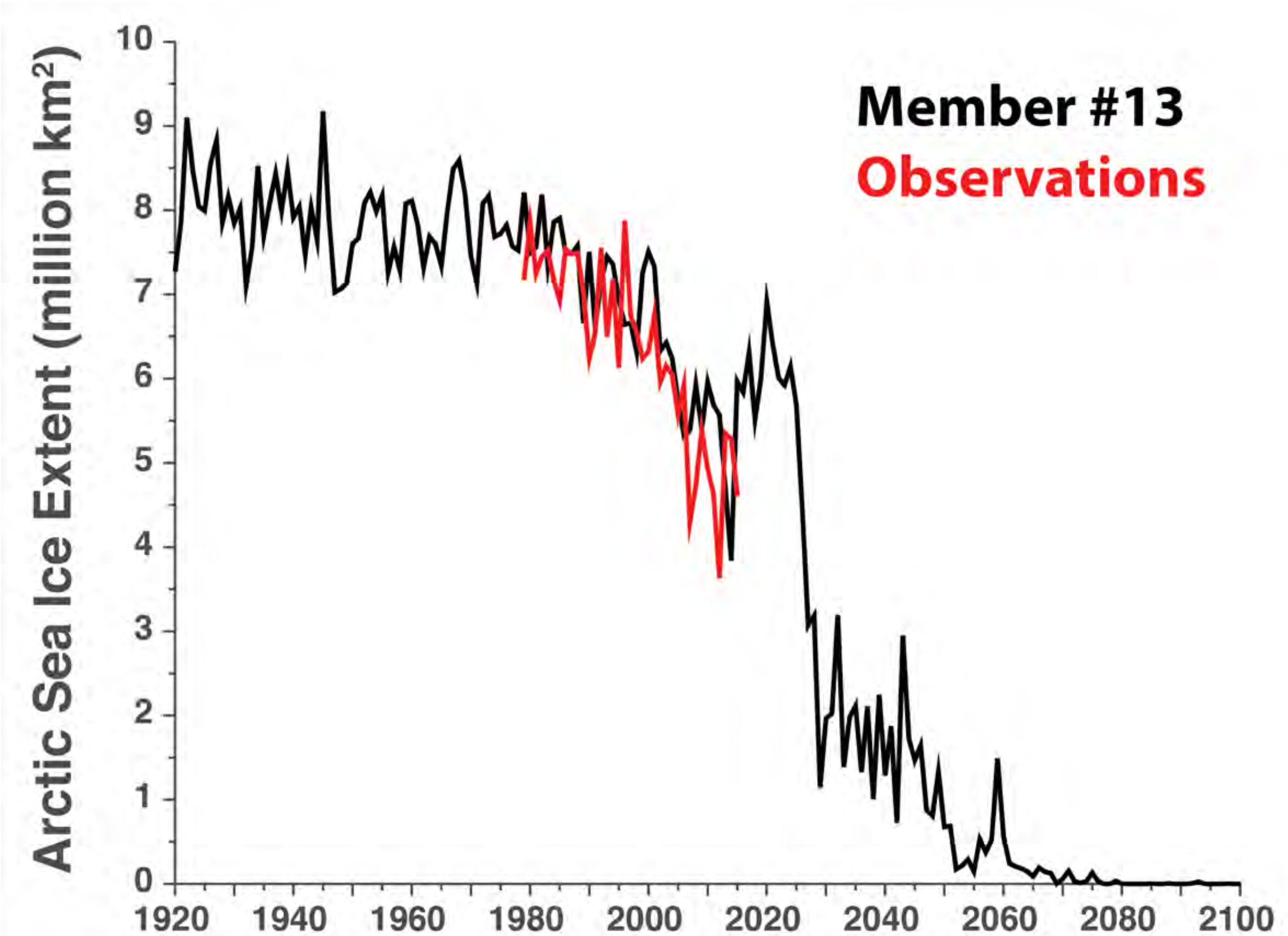


Adapted from Figure 1 Kirchmeier-Young et al. 2017

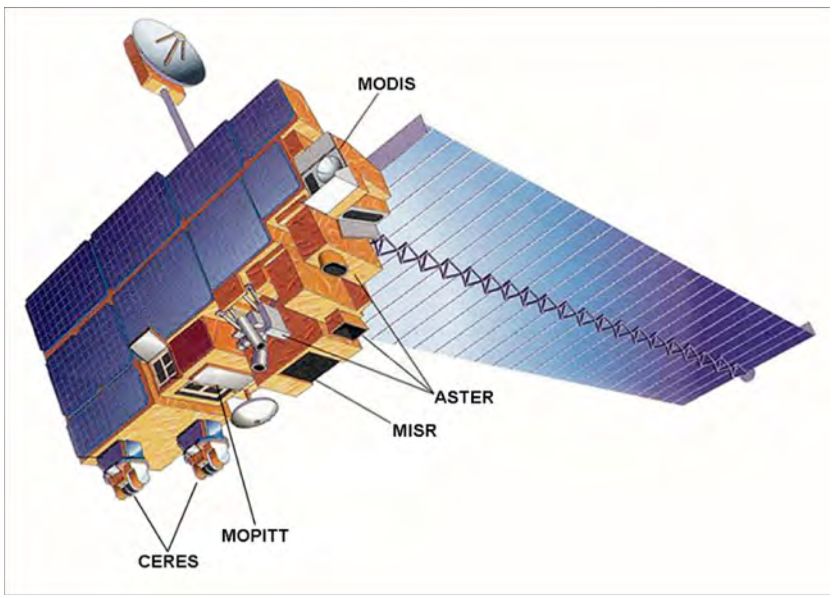
September Arctic Sea Ice Extent

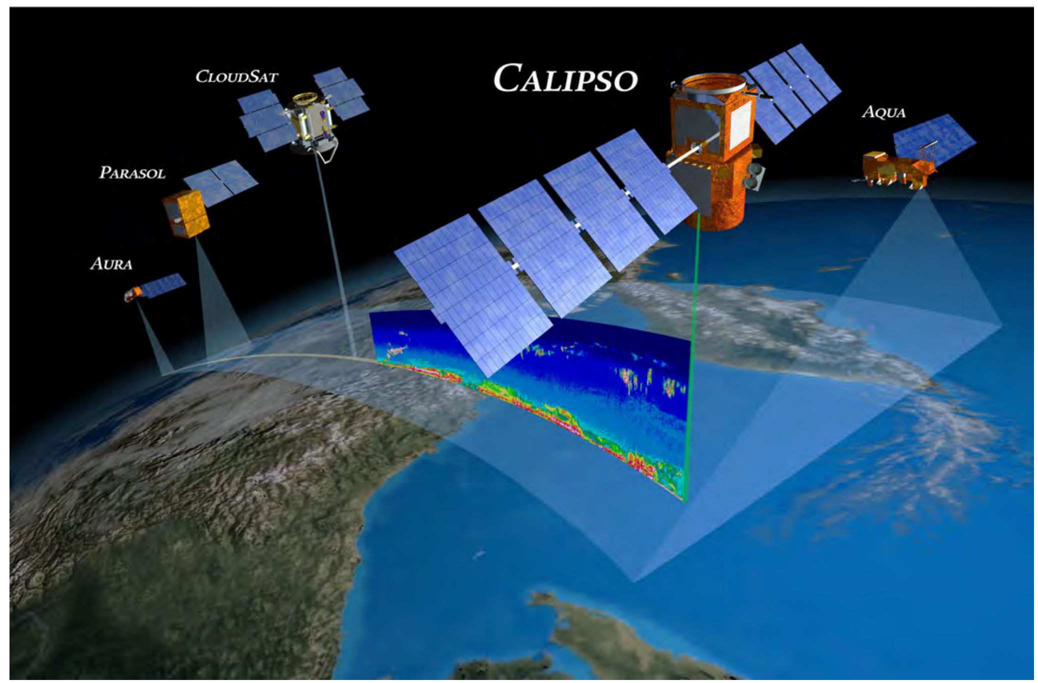


September Arctic Sea Ice Extent



Can we detect the emergence of forced change with current and future satellites?

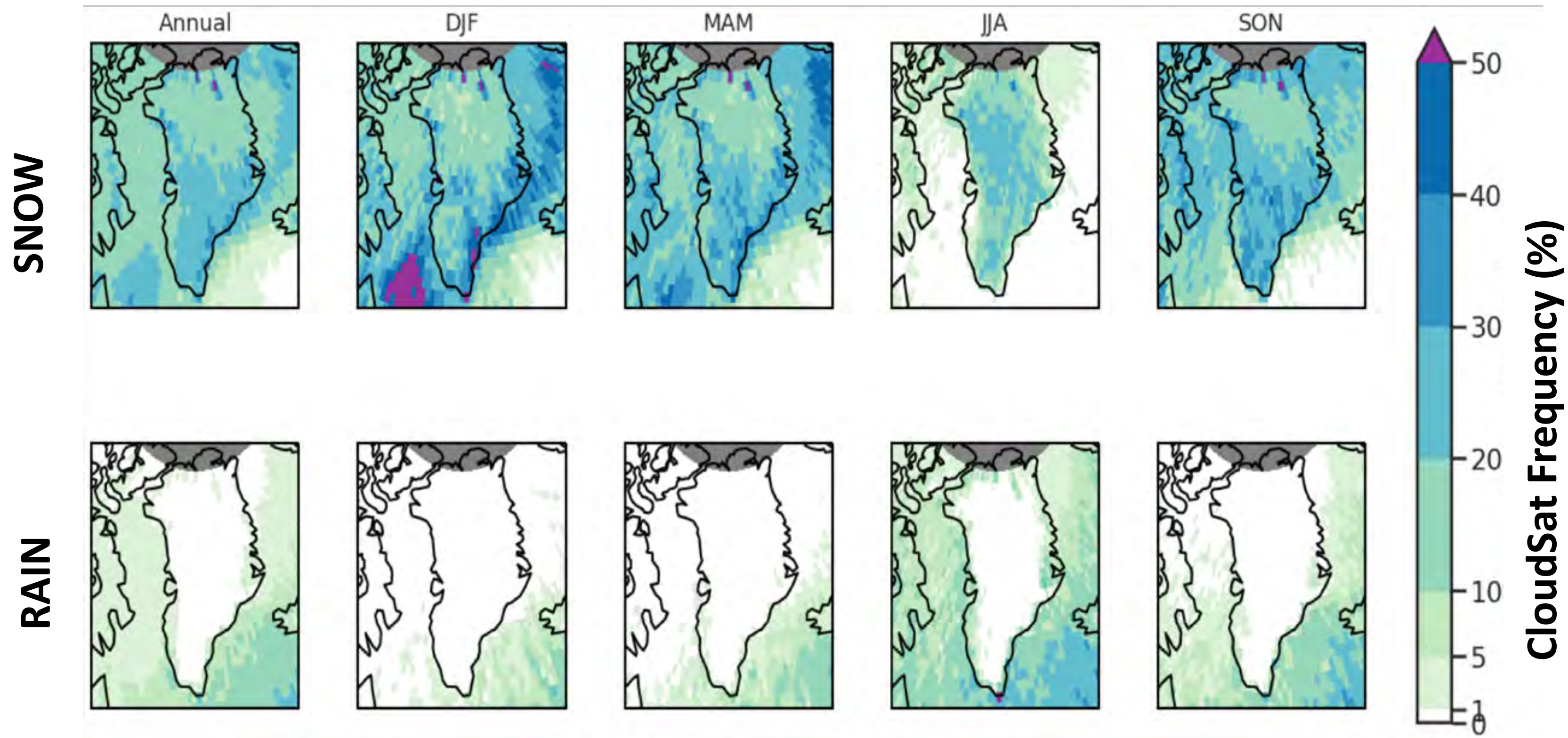




Context from the 2018 NASA Decadal Survey…

TARGETED OBSERVABLE	SCIENCE & APPLICATIONS SUMMARY	SCI/APPS PRIORITIES (MI, VI, I)	RELATED ESAS 2007 and POR	IDENTIFIED NEED/GAP	CANDIDATE MEASUREMENT APPROACH	ESAS 2017 DISPOSITION
TO-5 **Clouds, Convection, & Precipitation**	• Cloud coverage & optical properties • Solid & liquid precipitation rate • Liquid and ice water path • Convection & cloud dynamics • Diurnal cycle of clouds and precipitation	- **H-1a, 1b, 1c,** 3b, 4b - **W-1a, 2a,** W3a, **4a,** 9a, 10a - **S-1c,** 4b - **E-3a** - **C-2a,** 2g, **2h,** 3f, 5d, 7e, 8h	***ESAS 2007:*** ACE ***POR:*** CPR/EarthCARE, GPM, CloudSat, MODIS, VIIRS, SSMI, TROPICS	POR does not address diurnal cycle and does not cover precipitation after EarthCARE, GPM and SSMI, or snowfall, convection, and cloud dynamics after EarthCARE	***Similar to:*** **CloudSat, CPR/EarthCARE** • Radar(s) and multi-frequency microwave radiometer • Sampling with 1-4 km horiz & 250 m vert resolution & 0.2 mm/hr precip (rain) accuracy • Doppler for dynamics/ convection (1 m/s) • Spatial resolution ~4-10 km for global precip & snowfall; 1mm/hr snowfall accuracy	**DESIGNATED** PROGRAM ELEMENT Maximum development cost $800M; considerable synergistic value in TO-5 being coordinated in time with TO-1 and TO-2

CloudSat (radar) measures Arctic precipitation



Camron et al. (in prep)

Comparing modeled and observed clouds and precipitation is difficult…

why?

Let’s discuss!

Simulators help to reliably compare remote sensing observations to models

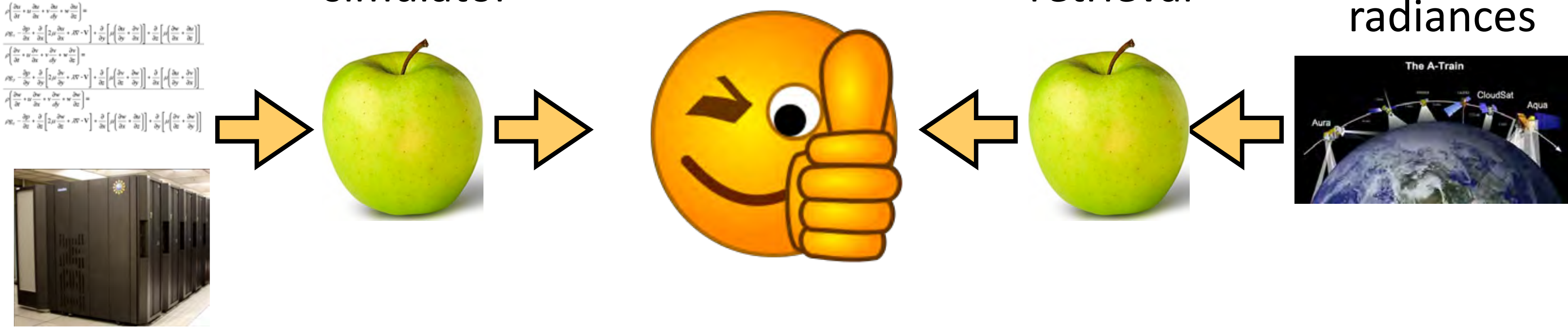
Climate Model

Satellite simulator

Trusted comparison

Satellite retrieval

Observed radiances



Take Home Message: When satellite simulators accurately mimic the observational process, they enable "apple-to-apple" comparisons between models and observations.

Established Example: Satellite simulators for clouds and precipitation ("COSP")

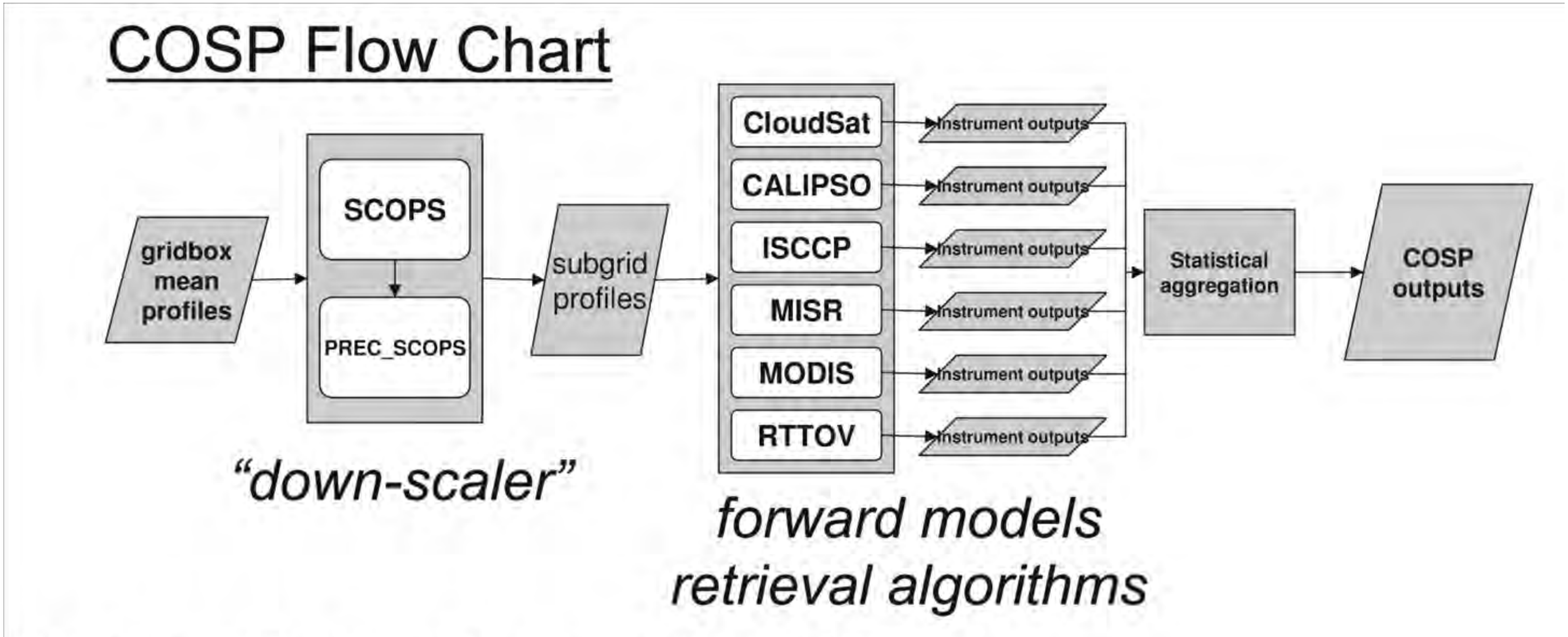


Figure credit: Jim Boyle, Alejandro Bodas-Salcedo and Stephen Klein

COSP Description Paper – Bodas-Salcedo et al. 2011
https://journals.ametsoc.org/doi/10.1175/2011BAMS2856.1

Demonstrating the importance of simulators for model evaluation

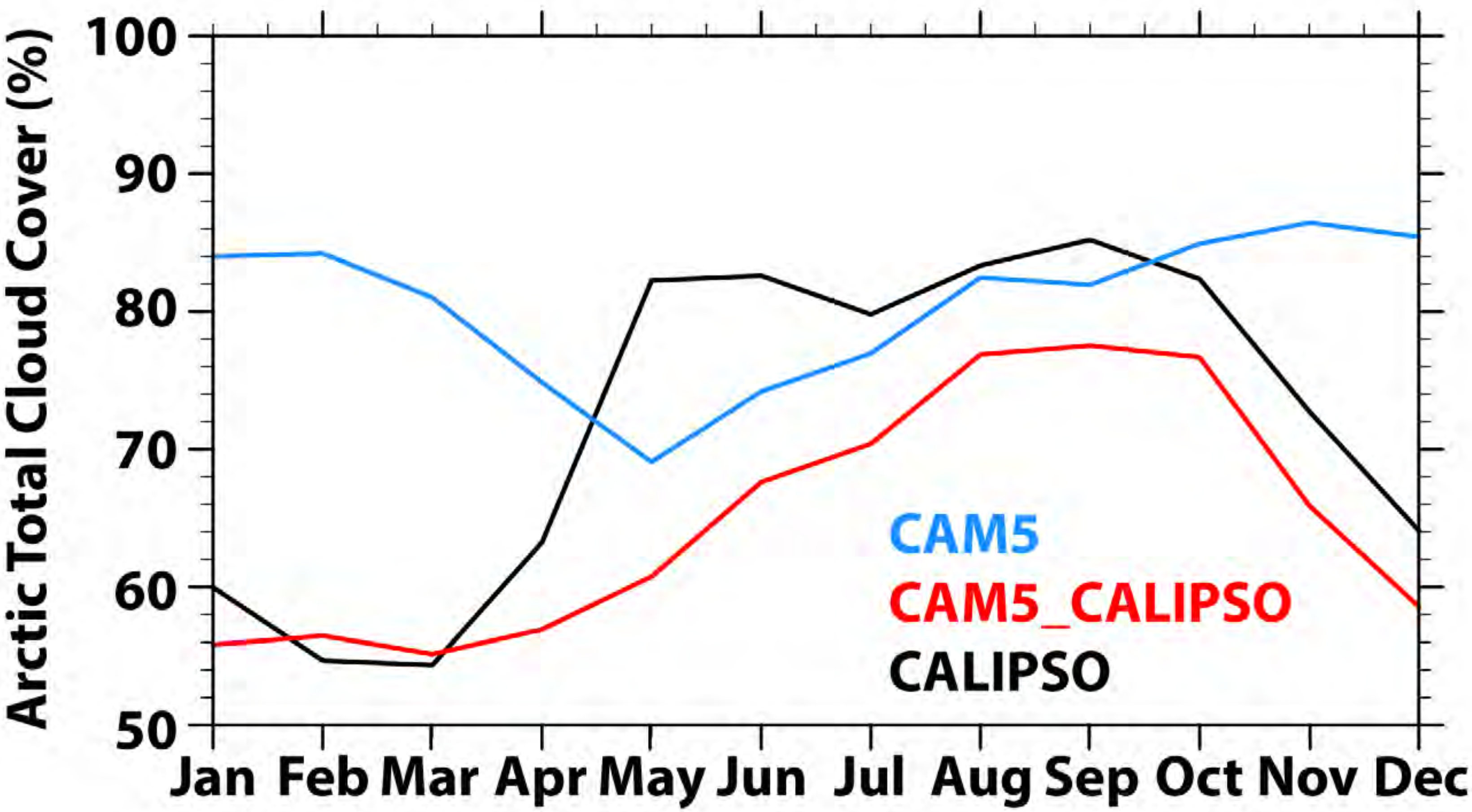
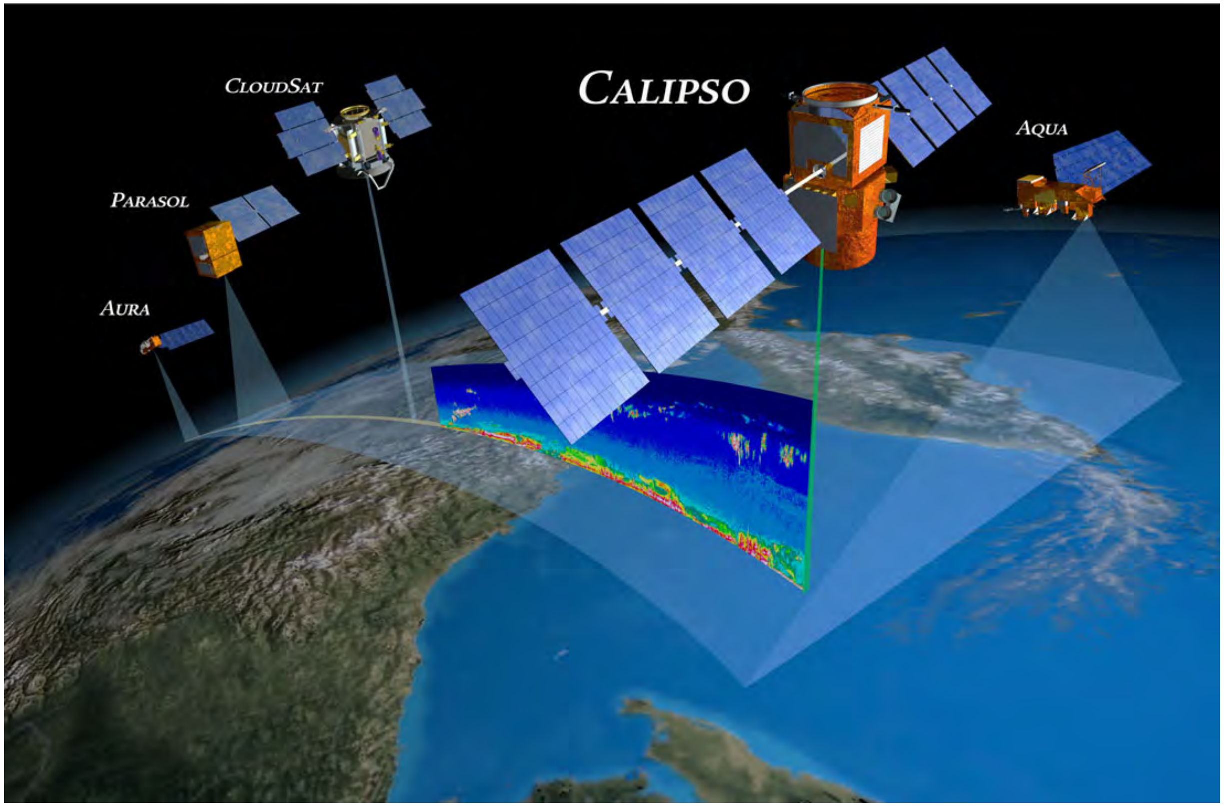
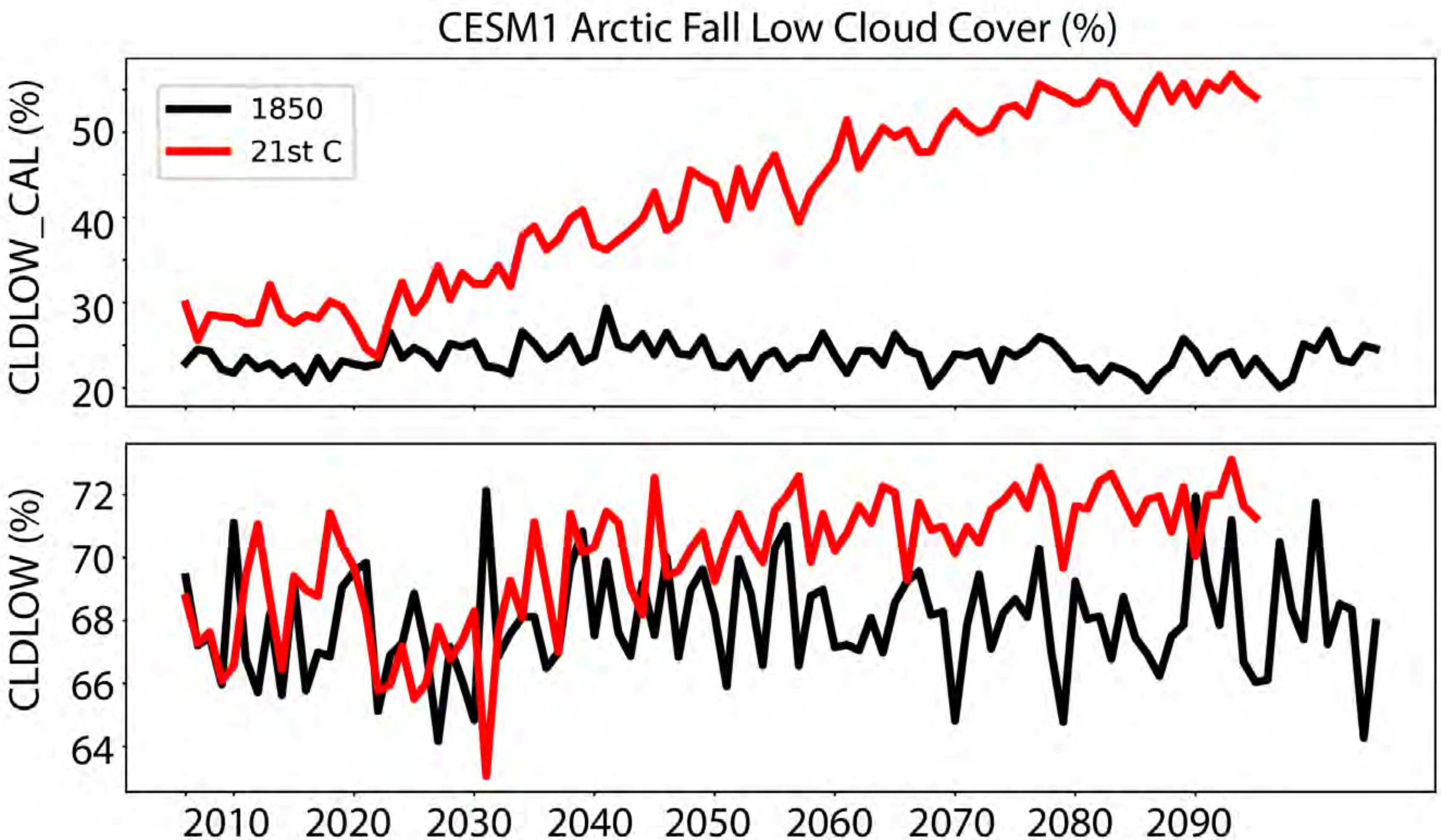


Figure from Kay et al. 2016 - DOI: 10.1007/s40641-016-0051-9

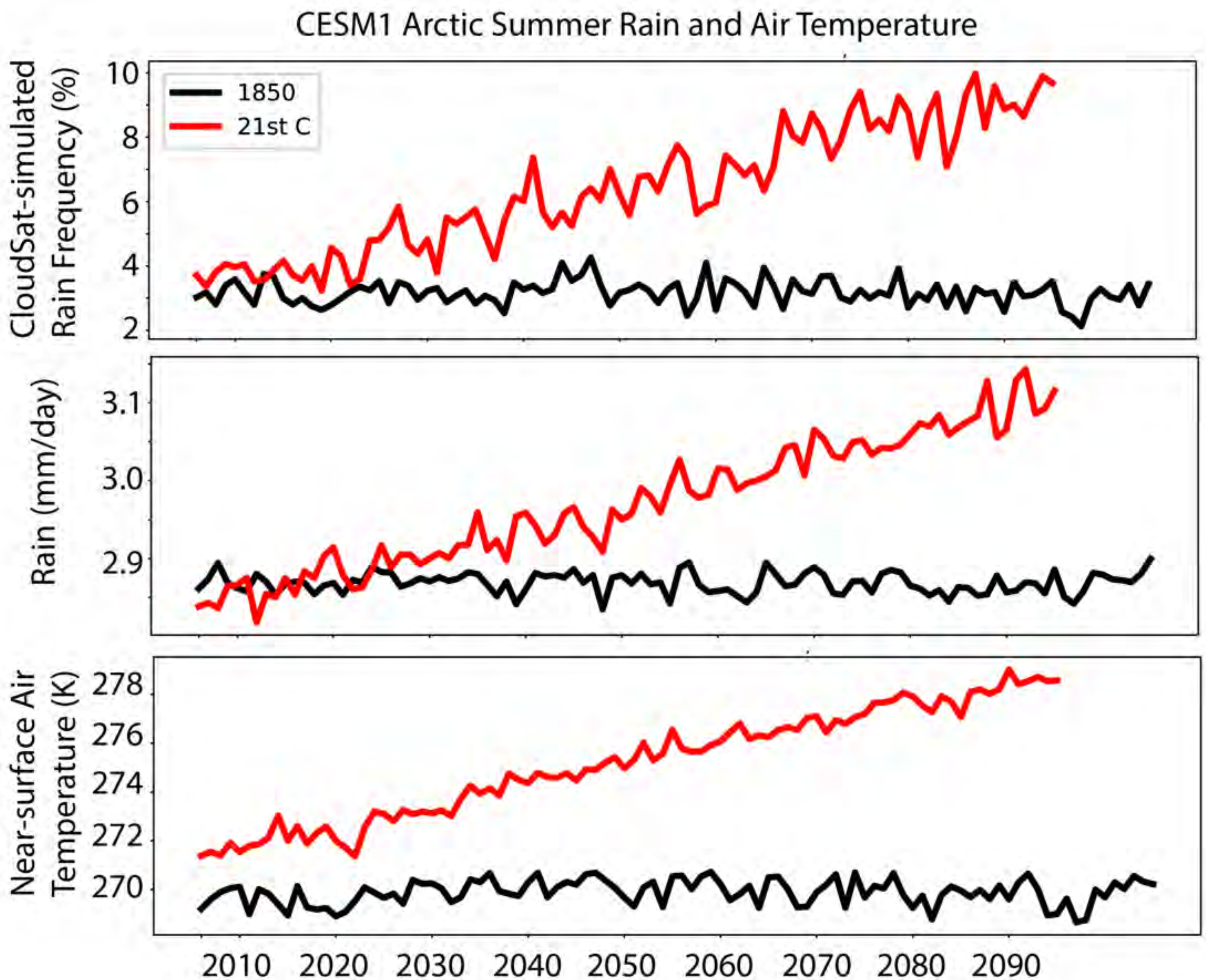
Can we detect the emergence of forced change in clouds and precipitation with current and future satellites?



Results from a single ensemble member offshoot experiment from the CESM Large Ensemble.



Also works for precipitation E.g., summer Arctic rain



Summary – Kay et al.

1) Forced Arctic climate change is currently emerging above internal climate variability. Timing depends on the metric for emergence and the physical variable under consideration.
2) Large initial condition ensembles and simulators provide essential tools for connecting models and observations to understand the emergence of forced climate change in the Arctic.

EXTRA

Notes on Variables –

Variables in red are from the satellite simulators

CLDTOT is the model total cloud cover.

CLDLOW is the model low cloud cover.

CLDTOT_CAL is the total cloud fraction detected by a lidar (like CALIPSO)

CLDLOW_CAL is the low cloud fraction detected by a lidar (like CALIPSO)

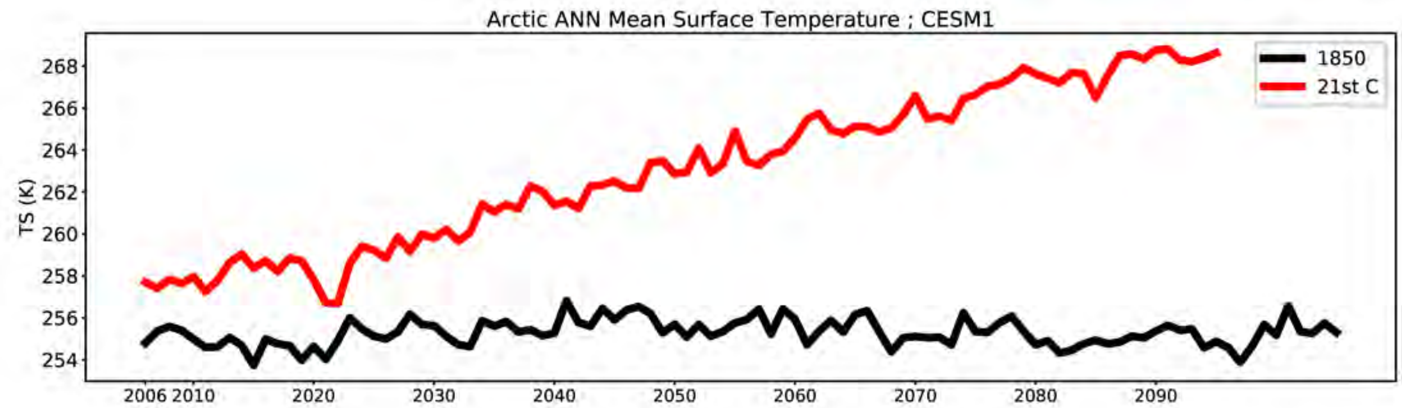
SNOW is the annual mean snow amount.

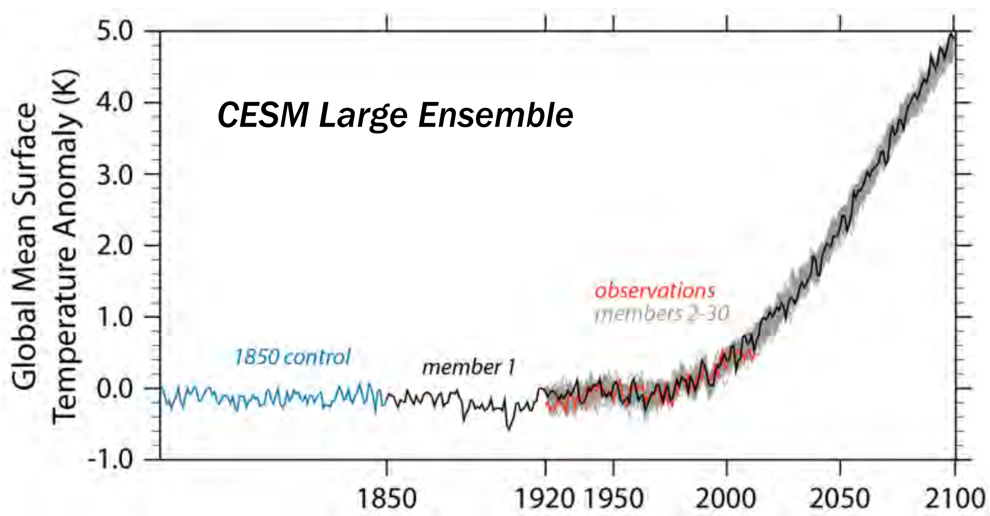
RAIN is the annual mean rain amount.

RADAR_SNOW is the average annual frequency of snow detected by a 94 GHz radar (like CloudSat).

RADAR_RAIN is the average annual frequency of rain detected by a 94 GHz radar (like CloudSat).

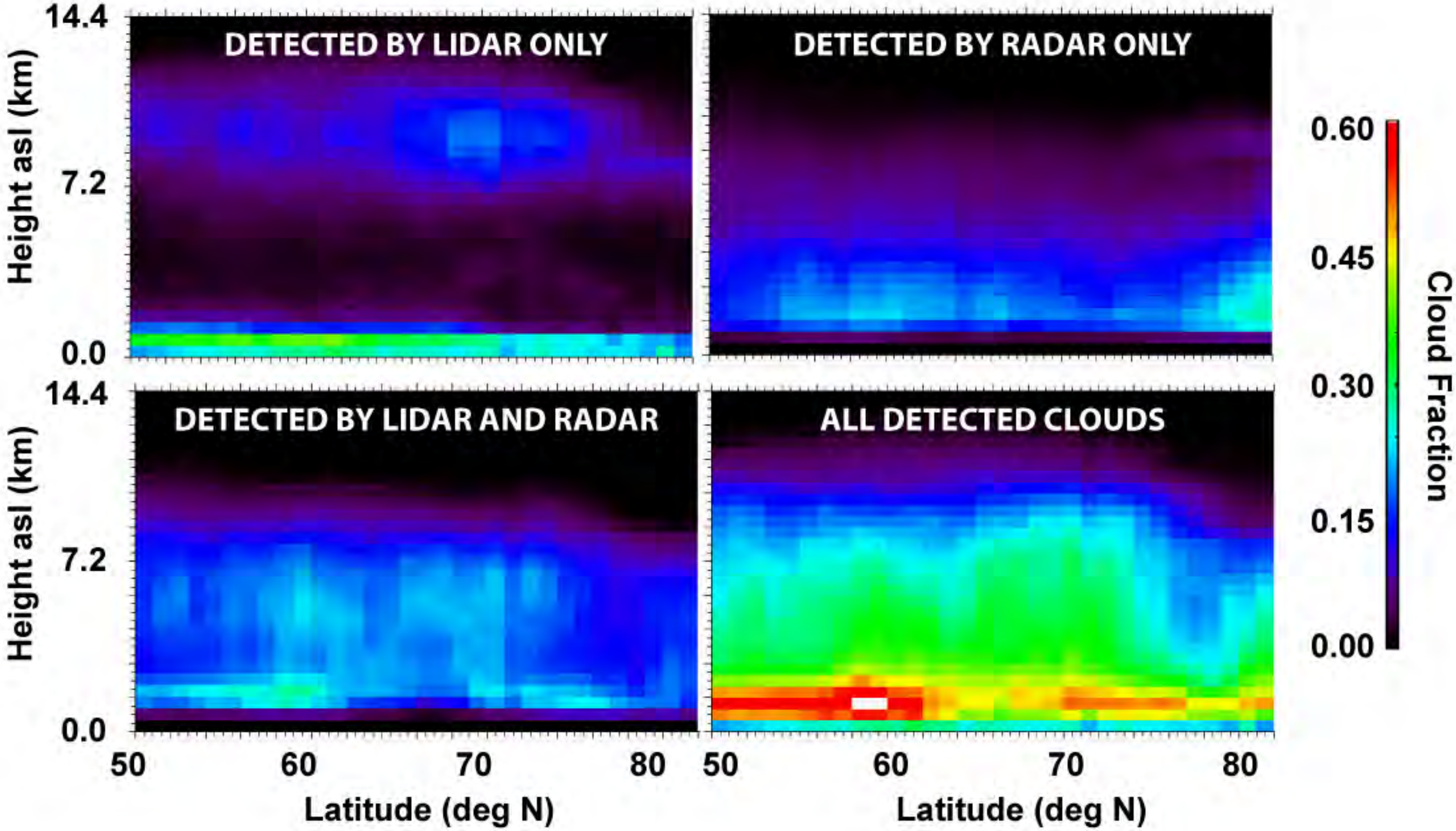
Challenge: How can you leverage a large ensemble if you only have one member with your diagnostics?





CloudSat (radar) and CALIOP (lidar) measure Arctic clouds/precipitation and their vertical structure

December 2006



Can Arctic sea ice extent increase in a warming world?

Yes.

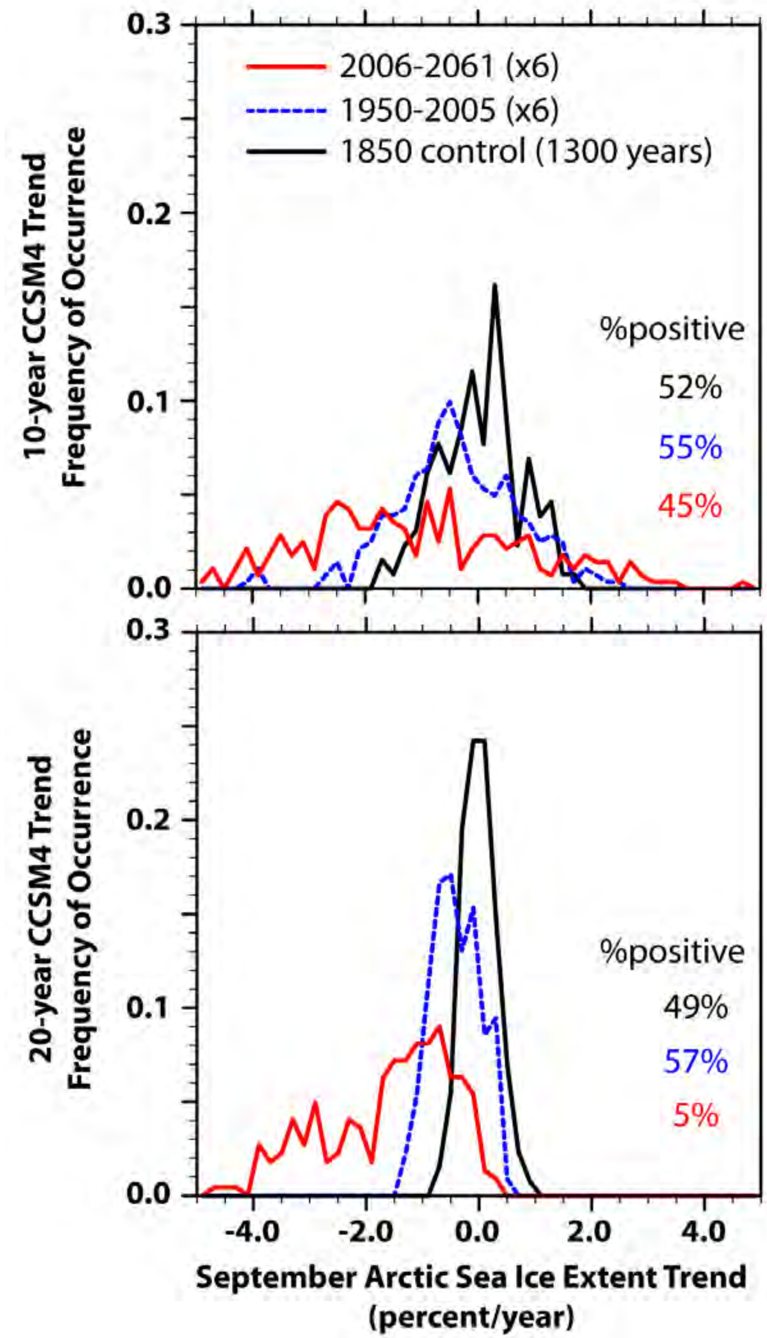
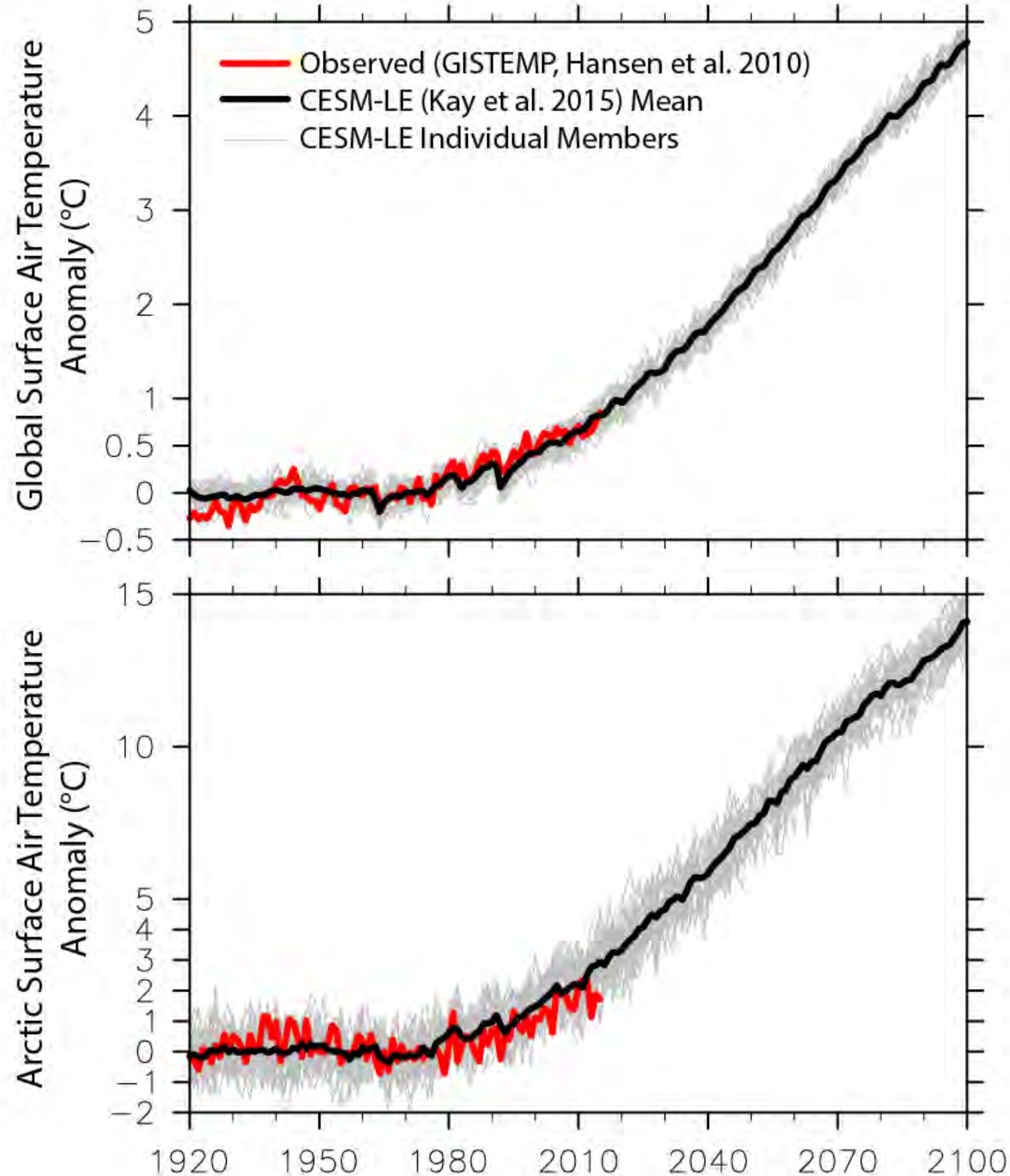
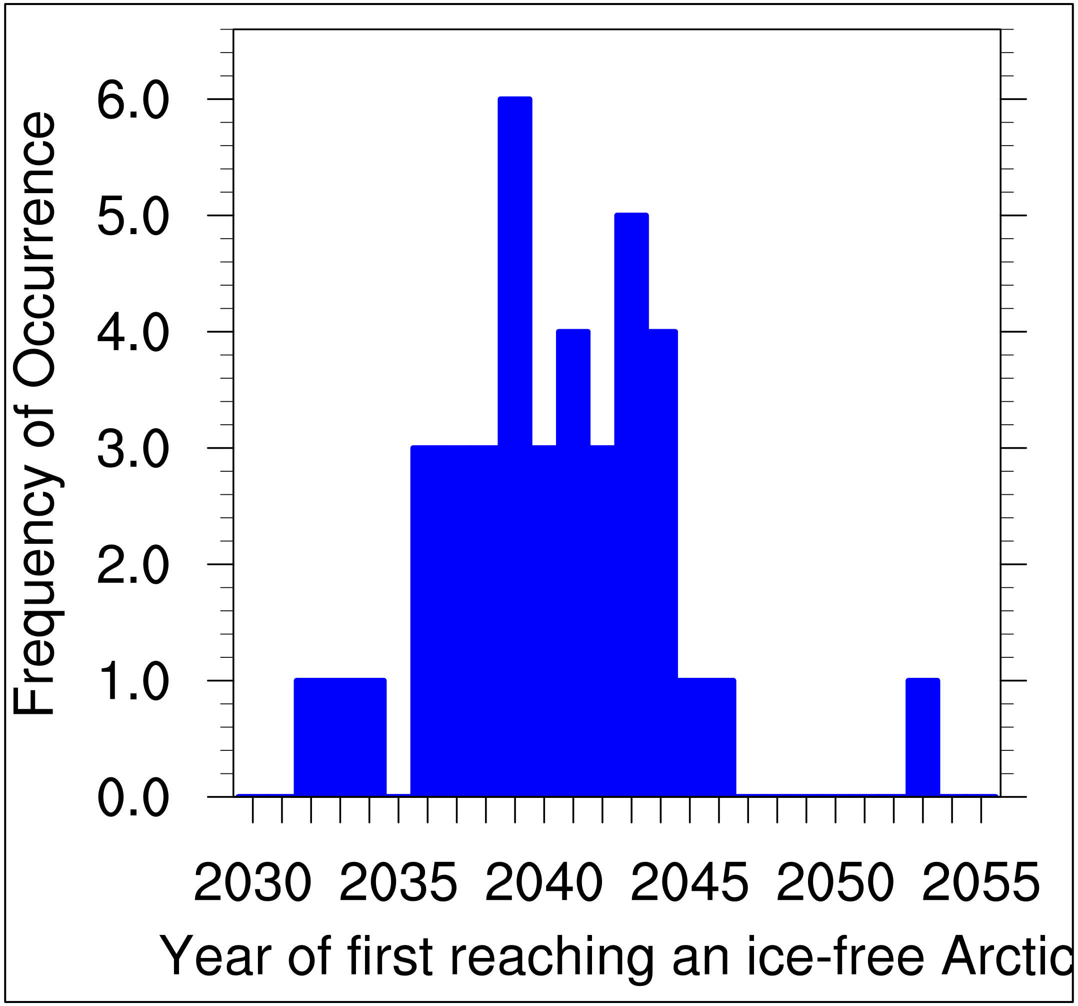


Figure modified from Kay, Holland, Jahn (2011)

What has happened and what will happen under large increases in greenhouse gases (1000 ppm CO2 equivalent by 2100)?



How predictable is the timing of a summer ice-free Arctic?



Internal variability introduces ~20 year uncertainty in the exact year when the Arctic goes ice-free in September.

Jahn et al. 2016 GRL

Arctic (70-90 N) Surface Air Temperature in the CESM-LE

When does a detectable forced climate change signal emerge?

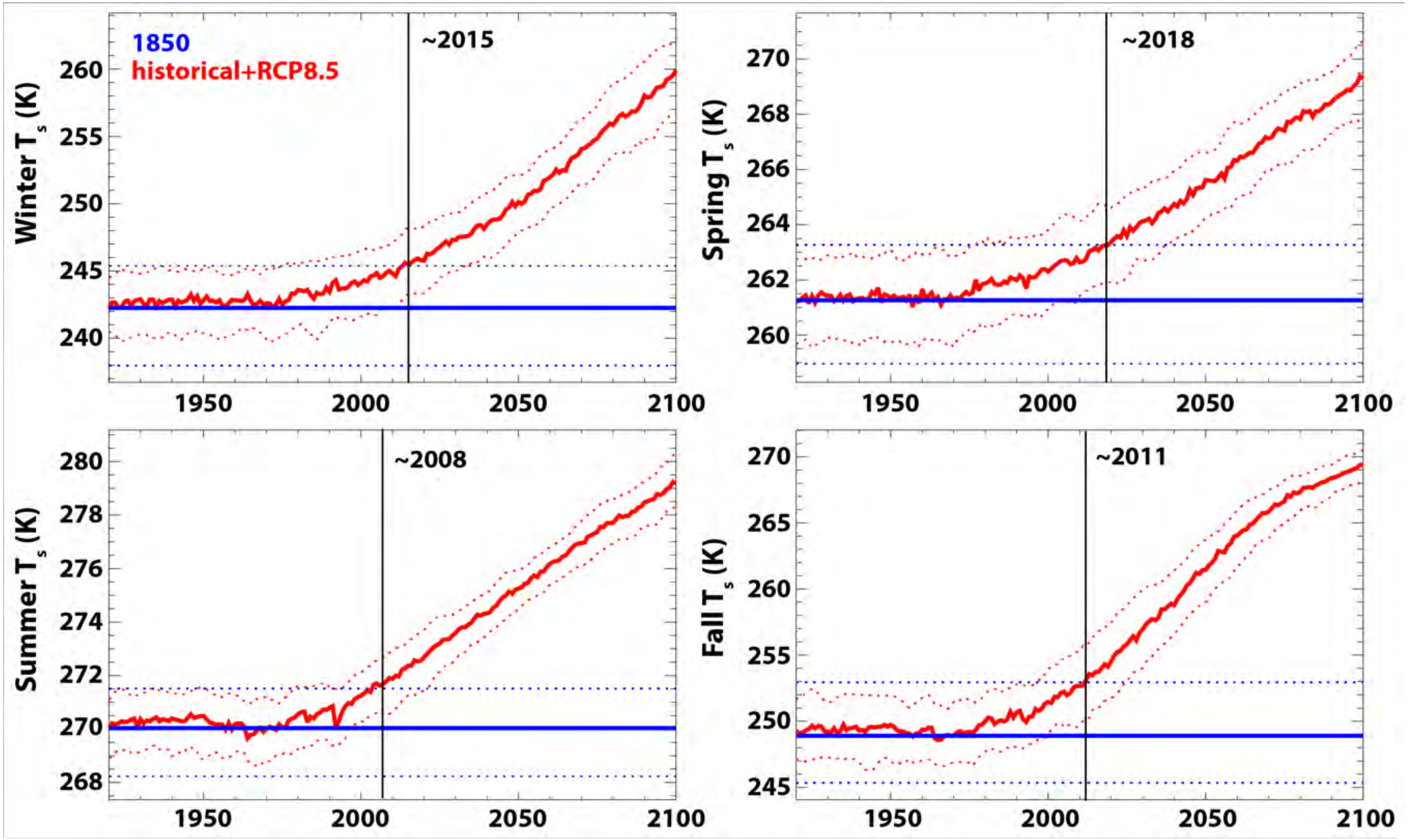


Figure courtesy Marika Holland/NSF 2018 Polar Modeling Workshop

CESM-LE Monthly Mean Arctic Surface Air Temperature

1850 histograms vs. 2006-2015 histograms

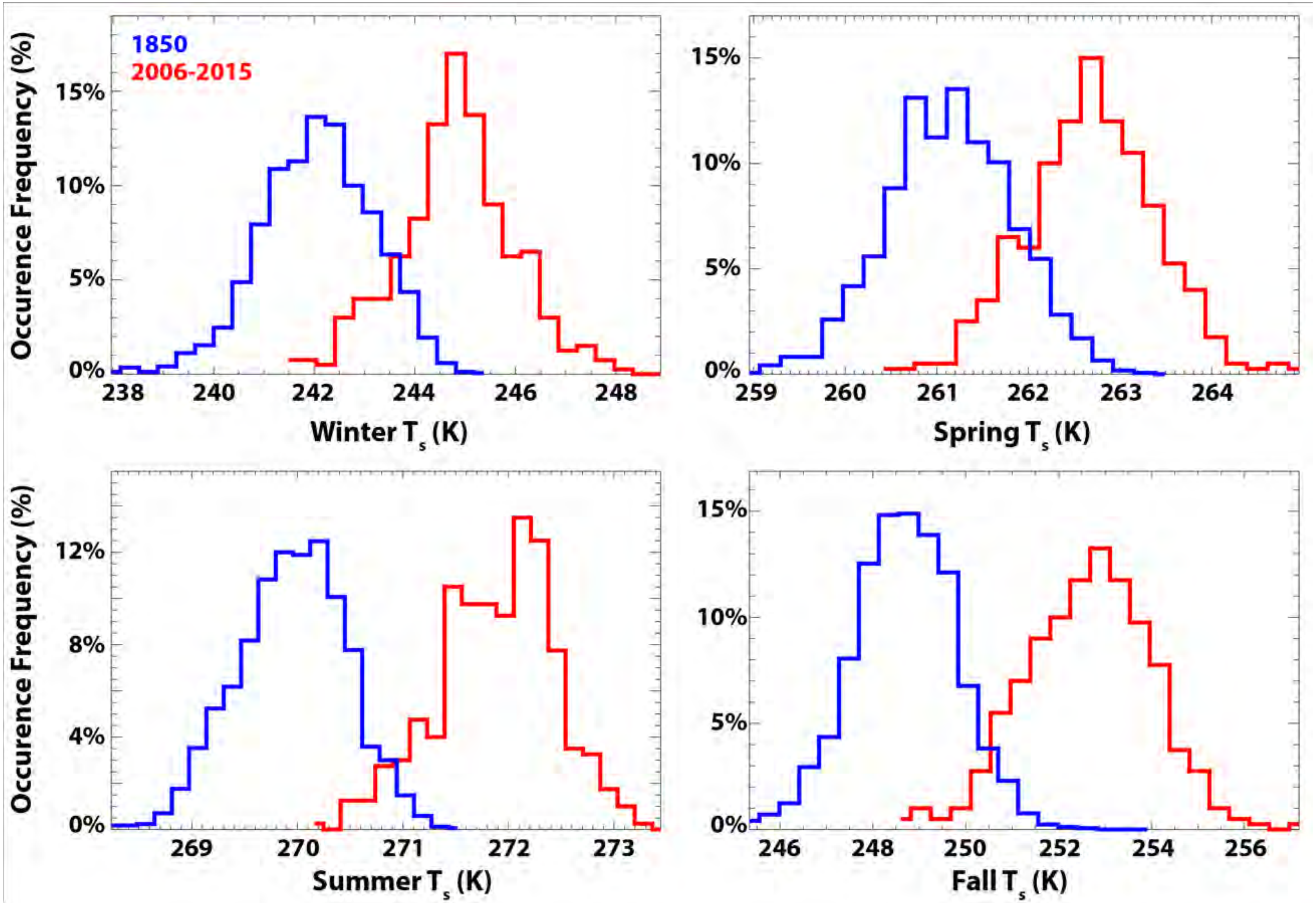


Figure courtesy Marika Holland/NSF 2018 Polar Modeling Workshop

MODIS Visible Image July 23, 2007