Arctic sea ice variability during the Instrumental Era

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Key Points:

- Data assimilation is a skillful technique for reconstructing Arctic sea-ice extent during the satellite era.
- Reconstructed sea ice shows large decline in total Arctic sea-ice extent during the early 20th-century warming (1910–1940).
- Trends in total Arctic sea-ice extent during the satellite era are ∼33–38 % greater than during the early 20th-century warming.

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Abstract

Arctic sea-ice extent (SIE) has declined drastically in recent decades, yet its evolution prior to the satellite era is highly uncertain. Studies using SIE observations find little variability prior to the 1970s; however, these reconstructions are based on limited data, especially prior to the 1950s. We use ensemble Kalman filter data assimilation of surface air temperature observations with Last Millennium climate model simulations to create a fully gridded Arctic sea-ice concentration reconstruction from 1850–2018, and investigate the evolution of Arctic SIE during this period. We find a decline of $\sim$1.25 x10^6 km^2 during the early 20th-century warming (1910–1940). The 25-year trends during this period are $\sim$33-38% smaller than the satellite era (1979–2018) but almost twice as large as previous estimates. Additionally we find that variability of SIE on decadal timescales prior to satellite era is $\sim$40% greater than previously estimated.

Plain Language Summary

Arctic sea ice is an important part of the climate system, serving as the interface between the ocean–atmosphere system. Arctic sea ice has undergone rapid declines in recent decades, prompting the question of whether there have been changes of similar magnitude in the past. To answer such questions, a long record of sea ice is necessary, but spatially and temporally complete satellite observations are only available starting in 1979. Previous studies combining sea ice observations from various sources during the Instrumental Era (1850–2014) found little variability in sea-ice extent prior to the satellite era, but data availability is limited prior to the 1950s. Here we create an independent estimate of Arctic sea ice from 1850–2018 using a data assimilation approach that blends more abundant temperature observations with data from climate models. Our results show substantial loss of sea ice between 1910–1940, with a rate that is about $\sim$33-38% less than what has been observed in satellite observations. These results reinforce previous findings that the current trend is unprecedented in duration since 1850, but also that sea-ice variability prior to 1979 is $\sim$40% larger than previously estimated.

1 Introduction

Arctic sea ice is one of the most rapidly changing components of the climate system, affecting surface albedo and modulating ocean–atmosphere interaction through surface fluxes. Large declines in sea ice can impact local ecosystems, human communities, and the global climate system (Meier et al., 2014). Documenting and understanding decadal–centennial variability in sea ice is limited by the availability of high-quality observations, which are only spatially and temporally complete during the satellite era (1978–present) (Fetterer et al., 2017). Furthermore, given the presence of strong radiative forcing during this period, it is difficult to partition the relative role of natural variability (e.g. Ding et al. (2017); England et al. (2019)) and radiative forcing (Notz & Marotzke, 2012) on the rapid Arctic sea ice declines observed in the satellite record. In order to estimate the natural variability of sea ice, a longer record is needed. Here we introduce a novel method to reconstruct sea ice cover from 1850–present, using data assimilation (DA), numerical model data, and observations of surface air temperature (SAT).

The longest Arctic sea-ice extent (SIE) observation-based reconstruction combines various sea ice observation types, ranging from satellite data to shipping records, to extend Arctic sea ice records back to 1850 (Walsh et al., 2017). The Walsh et al. (2017) reconstruction shows little SIE variability before 1970, particularly on decadal to multi-decadal timescales. However, the fidelity of this dataset is limited by gaps in observation availability, particularly before 1953 and during winter months (see below and Supporting Information Figure S1).

Although direct observations of sea ice are limited in space and time, instrumental observations of SAT are much more abundant. Polar, hemispheric and global mean SAT, both in observations and climate models, are known to be tightly coupled to sea ice variability on annual and longer timescales (e.g. Gregory et al. (2002); Armour et al. (2011); Mahlstein and Knutti (2012); Olonscheck et al. (2019)). Observations show that global-mean SAT was relatively stable between 1850–1900 (Morice et al., 2012), which may explain low decadal sea ice variability in the Walsh et al. (2017) record. However, during the early 20th century (1900–1940), an anomalous warming event is well documented across Northern Hemisphere high latitudes (e.g. Hegerl et al. (2018)). The magnitude of this early 20th century warming (ETCW) was largest during winter months (Semenov, 2007; Overland et al., 2004) and similar in spatial structure to that observed in the late 20th century.

Interestingly, the Walsh et al. (2017) record of Arctic SIE shows much less decline during the ETCW than during the satellite record, with one period of decline of $\sim$0.5 x 10^6 km^2 between 1920-1945 followed by a recovery of $\sim$0.5 x 10^6 km^2 between 1945–1950 (see below). The peak loss in Walsh et al. (2017) also lags the period of largest ETCW temperature anomalies seen in observations, which together with the modest decline in SIE suggests a weak relationship between temperature and sea ice during the ETCW. In this paper we investigate the relationship between temperature and sea ice during the Instrumental Era using satellite observations, reanalysis, and the Walsh et al. (2017) reconstruction. Then we use a DA framework to construct a new independent Arctic sea ice reconstruction using more abundant SAT observations. We then explore the decline of sea ice during the ETCW, and compare the ETCW decline to that observed and reconstructed in the satellite era.

2 Temperature and sea ice in the Instrumental Era

We begin by analyzing the relationship between Arctic SAT derived from the HadCRUT4.6.0.0 dataset (HadCRUT, Morice et al. (2012)) and SIE from Walsh et al. (2017). We partition the analysis in two ways: by season (April–August and September–March) and by time period (pre- and post-1953 for Walsh et al. (2017), plus the satellite era (1979–2017)), in order to investigate the effect of observation availability on the Walsh et al. (2017) record. We find that the relationship between SAT and SIE from the Walsh et al. (2017) and satellite observations generally agree from 1953–present, but differ greatly before 1953 (Figure 1).

Figure 1 shows that the relationship between SAT and SIE is linear in the satellite record in both seasons, with R^2=0.76 (September–March) and 0.85 (April–August). The Walsh et al. (2017) record also shows a linear relationship for both seasons between 1953–2013, with a similar slope during winter (Figure 1b) and a slightly steeper slope during summer (Figure 1a), both not statistically different from the slope determined with satellite observations at the 95% confidence level. In contrast, the earlier part of the Walsh et al. (2017) record, between 1850–1952, exhibits a much lower SIE–SAT sensitivity in summer relative to the satellite era (Figure 1a) and almost no SIE–SAT sensitivity in winter (Figure 1b). Since SAT is a primary driver of sea ice variability (Olonscheck et al., 2019), the inconsistent relationship between these two time periods in the Walsh et al. (2017) record suggests either a strong nonlinearity in this relationship during the ETCW, or that the reconstruction underestimates SIE-SAT sensitivity.

There are at least two possible hypothesis for the reduced sensitivity of SIE-SAT in Walsh et al. (2017) before 1953. Firstly, the sensitivity of sea ice to temperature may be mean-state dependent, such that in colder, thicker, sea-ice regimes (which may have existed in the Arctic during the late 19th and early 20th century) sea ice may be less sensitive to changes in temperature. However, model simulations of sea-ice sensitivity to temperature for different mean states (Armour et al., 2011; Mahlstein & Knutti, 2012) do

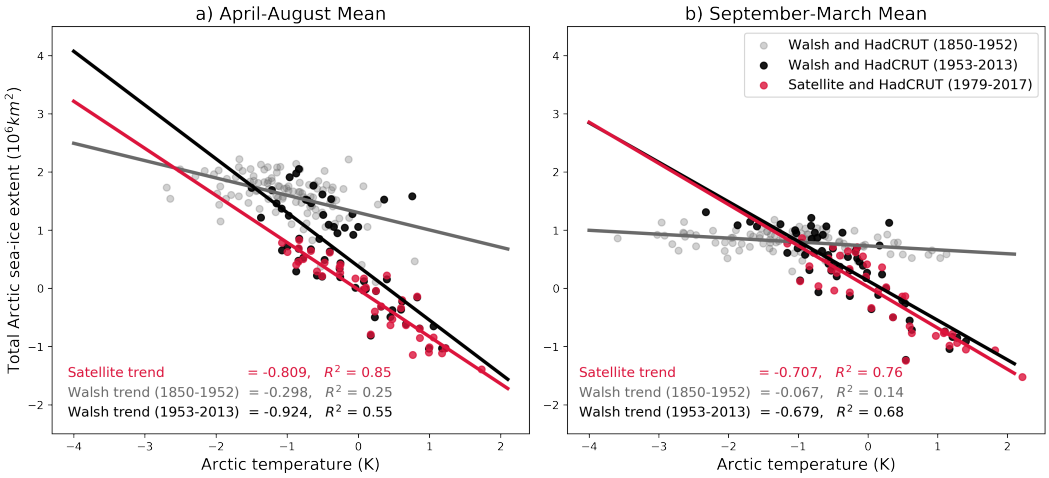

Figure 1. Arctic SAT (averaged north of $65°N$, derived from HadCRUT) and total SIE in both the satellite data between 1979-2017 (in red) and the Walsh et al. (2017) data set between 1850 to 1952 (in gray) and 1953 to 2013 (in black). Anomalies are relative to 1979-2013.

not support this hypothesis. A second hypothesis is that the reduced sensitivity of sea ice to temperature may simply be due to the fact that there are significantly fewer observations available to the Walsh et al. (2017) analysis prior to 1953 (as illustrated in Supporting Information Figure S1).

The fidelity of sea-ice reconstructions has broader implications, as they are used for boundary conditions in reanalysis products. The widely-used sea surface temperature and sea ice concentration HadISST2 product (Titchner & Rayner, 2014) incorporates an earlier version of the Walsh et al. (2017) sea-ice reconstruction (Walsh & Chapman, 2001), which is based largely on climatology for the first half of the 20th century. Atmospheric reanalysis during the 20th century such as ERA-20C (Poli et al., 2016) commonly use HadISST2 as a boundary condition. Figure 2 shows temperature trends in ERA-20C and the station-based HadCRUT (which uses no infill or interpolation). While HadCRUT shows the large magnitudes and spatial extent of SAT trends during the ETCW, in some locations comparable to the that during the recent satellite-era warming, ERA-20C shows minimal trends across the Arctic. The NOAA/CIRES 20th Century reanalysis (Compo et al., 2011) shows even larger biases than ERA-20C (see Supporting Information Figure S2).

We postulate that these atmospheric reanalysis biases in simulating the ETCW are strongly influenced by the small inter-annual sea-ice variability in Walsh and Chapman (2001) that serve as boundary conditions. This hypothesis is consistent with Semenov and Latif (2012), who find that the ETCW cannot be simulated with an atmospheric model forced with HadISST1.1 (Rayner, 2003) boundary conditions, which show little sea-ice variability prior to 1950. Thus improving sea-ice reconstructions has broad implications, especially for studying high latitude climate variability.

To this end, we exploit the linear relationship between SAT and Arctic SIE evident in Figure 1 and in the literature (Mahlstein & Knutti, 2012) to reconstruct sea ice using a DA approach. Other approaches have exploited this relationship to reconstruct sea ice in the 20th century using linear regression models. For example, Connolly et al. (2017) use pre-satellite temperature trends to re-calibrate sea-ice data sources from three regions in the Arctic and find that sea ice retreated after the 1910s and advanced after the mid 1940s, though the magnitude of these changes are small relative to the satellite

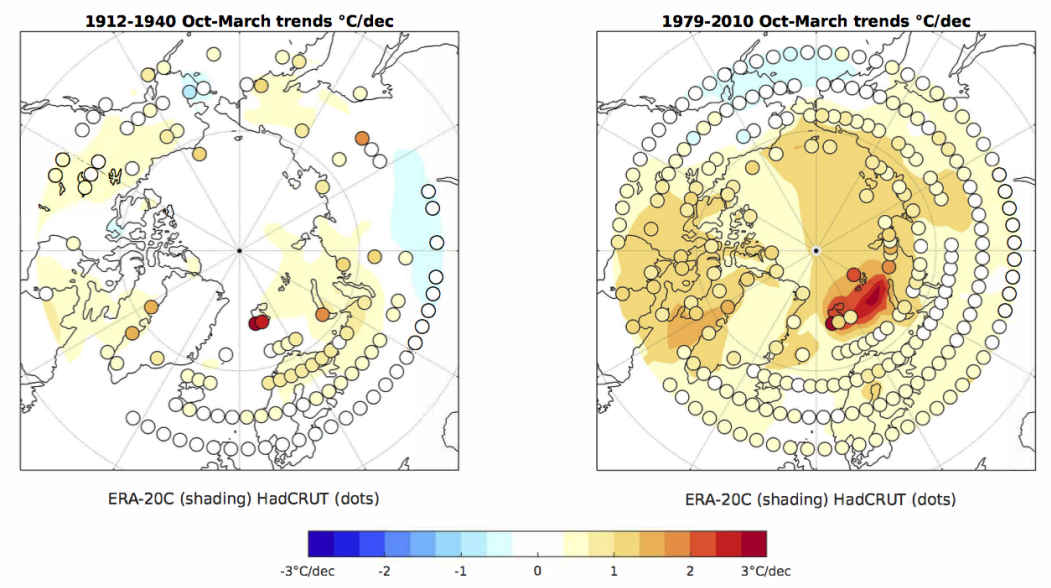

Figure 2. Temperature trends from ERA-20C are shown in shading and that from HadCRUT overlaid as shaded dots for both the early 20th century (1912–1940, left) and satellite era (1979–2010, right).

era. Alekseev et al. (2016) use the relationship between summer SAT and SIE to reconstruct total Arctic SIE with a linear regression model, finding a decline of total Arctic SIE of $\sim$2 x 10^6 km^2 between 1900–1940 followed by a recovery that peaked around 1970. The main benefit of the DA approach described here is the use of high quality 2 mair temperature observations with a robust framework for uncertainty quantification (see Section 3). Moreover, the results provide fully-gridded, spatially consistent climate fields that can be used as boundary conditions for models and to probe the dynamics associated with sea-ice variability.

3 A new sea-ice reconstruction using data assimilation

3.1 Data Assimilation approach

DA aims to optimally combine spatial data with noisy and sparse observations, resulting in a better estimate of climate fields. Generally, DA updates a prior estimate, an initial 'best guess', of the climate state with new information from observations. DA allows point-wise observations of temperature to influence broader spatial regions of other climate variables, like sea ice, based on the covariance relationships derived from the prior. The prior estimate and observations are weighted based on their relative uncertainty, yielding continuous fields.

To reconstruct Arctic sea ice we use an offline (Oke et al., 2002) ensemble Kalman filter approach to combine Last Millennium climate model simulations (Schmidt et al., 2011; Taylor et al., 2012) with temperature observations. The prior, $\mathbf{x}^b$, is an ensemble of 200 random years drawn from these Last Millennium simulations (more details are provided in Section 3.2). The update to this prior estimate uses annually averaged temperature observations, $\mathbf{y}$, weighted as $\mathbf{y} - \mathbf{H}\mathbf{x}^b$ (the 'innovation'),

$$\mathbf{x}^a = \mathbf{x}^b + \mathbf{K}(\mathbf{y} - \mathbf{H}\mathbf{x}^b). \tag{1}$$

The innovation weight that results in the analysis, $\mathbf{x^a}$, is given by the Kalman gain,

$$\mathbf{K} = \mathbf{B}\mathbf{H}^{\mathrm{T}}(\mathbf{H}\mathbf{B}\mathbf{H}^{\mathrm{T}} + \mathbf{R})^{-1}, \tag{2}$$

where $\mathbf{B}$ is the error covariance matrix of the prior, $\mathbf{R}$ is the error covariance matrix of the observations, and T is the transpose operator. Matrix $\mathbf{H}$ maps the prior to the observations by selecting grid-point data in the prior nearest to the observations. The Kalman gain spreads the new information from temperature observations both spatially and to other climate variables, weighted by the relative uncertainty of each. We sample temperature observations from instrumental datasets every 10° latitude and longitude, chosen to ensure the observation errors are uncorrelated and therefore $\mathbf{R}$ is diagonal. This assumption allows us to use serial observation processing, which assimilates observations one at a time, simplifying implementation of spatial covariance localization as described below.

To solve (1), we employ a square-root ensemble Kalman filter (Whitaker & Hamill, 2002), which updates the ensemble mean and the perturbations from the ensemble mean separately. The Kalman gain used in the update equation for the ensemble perturbations ($\tilde{\mathbf{K}}$) is adjusted by a constant α to yield the correct posterior covariance matrix. Therefore, $\tilde{\mathbf{K}} = \alpha\mathbf{K}$, where, for a single observation, i,

$$\alpha = \left(1 + \sqrt{\frac{\mathbf{R}_{ii}}{\mathbf{H}\mathbf{B}\mathbf{H}^{T}{}_{ii} + \mathbf{R}_{ii}}}\right)^{-1}, \tag{3}$$

where ii denotes the matrix diagonal entry in the ith row and column.

As is standard practice in ensemble DA, we reduce the effect of spurious long-distance covariances using covariance localization (e.g. Hamill et al. (2001)), applying the Gaspari-Cohn fifth order polynomial function (Gaspari & Cohn, 1999) with a localization radius (the distance from observations set to zero influence) of 15,000 km.

Kalman filter methods rely on the covariance in the prior ensemble between temperature and the variables of interest (here, sea ice concentration, SIC). Climate models tend to underestimate the sensitivity of Arctic sea-ice loss to temperature (Rosenblum & Eisenman, 2017; Winton, 2011; Stroeve et al., 2007). To address this low-sensitivity bias, we inflate the sea-ice perturbations from the prior ensemble-means for the simulations used here, MPI and CCSM4 Last Millennium simulations (see Section 3.2), by a factor of 1.8 and 2.6, respectively. The inflation factors are determined empirically by goodness of fit to the observed sea-ice trend during the satellite era. Sensitivity of the results to the localization radius and inflation factor is explored below and in the Supporting Information (see figures S4 and S5).

Since the Kalman filter method assumes Gaussian distributions, and SIC has a range of 0–100%, unphysical values of $\mathbf{x^a}$ outside this range may occur. Therefore, SIC values outside the lower and upper end of this range are adjusted to 0% and 100%, respectively.

3.2 Data Sources

A 200-member prior ensemble of both SAT and SIC fields are randomly drawn from fully forced Last Millennium model simulations spanning the years 850–1849 CE (Schmidt et al., 2011; Taylor et al., 2012) (tests with a 1000-member prior ensemble revealed small differences in Arctic SIE reconstructions, R^2 >0.97, from the less computationally expensive case with a 200 member prior ensemble). Results using the Community Climate System Model version 4 (CCSM4, Last Millennium simulation (Landrum et al., 2013)) and Max Planck Institute for Meteorology (MPI-ESM-P, Last Millennium simulation (Taylor et al., 2012)) models are used to determine the sensitivity of the sea-ice reconstructions to climate-model prior, and thus the sensitivity of the results to model physics and sea-ice–temperature covariance structure. All model output is regridded to a $\sim 2°$x$2°$ grid.

Sensitivity to the choice of instrumental temperature record is tested using three different products: HadCRUT, Berkeley Earth (BE, (Rohde et al., 2013)), and NASA Goddard Institute for Space Studies (GISTEMP, (Hansen et al., 2010)). An estimate of the uncertainty in these observations is required when using an ensemble Kalman filter approach (i.e., **R** in Equations 2 and 3), and HadCRUT is the only product that provides uncertainty estimates. Various ways of calculating **R** were tested, (see Supporting Information), but in order to use all three products, and for simplicity, we use an uncertainty estimate of 0.4 K^2, which is the area-weighted mean error variance provided by HadCRUT.

4 Arctic sea-ice reconstructions

We first reconstruct annual Arctic SIC for 1850–2018 by assimilating HadCRUT SAT with a prior ensemble drawn from the MPI Last Millennium simulation. Figure 3 shows annual Arctic SIE (total area with SIC greater than or equal to 15%) derived from the gridded SIC reconstructions. The timeseries is the mean of 5 independent iterations that each use a different 200 member prior ensemble, in order to take into account the uncertainty due to sampling error. Our reconstruction compares well with satellite observations (Figure 3) with R^2 value of 0.89, detrended R^2 value of 0.43, and coefficient of efficiency (see Supporting Information Equation 1) of 0.89 between 1979–2017. The trend during this period is well captured in the reconstructions with a value of -0.052 ± 0.012 x 10^6 km^2/year compared to -0.055 x 10^6 km^2/year in satellite observations. Inter-annual variability is overestimated, with a detrended standard deviation of 0.21 x 10^6 km^2 in the satellite observations and 0.28 x 10^6 km^2 in the reconstruction during 1979–2017.

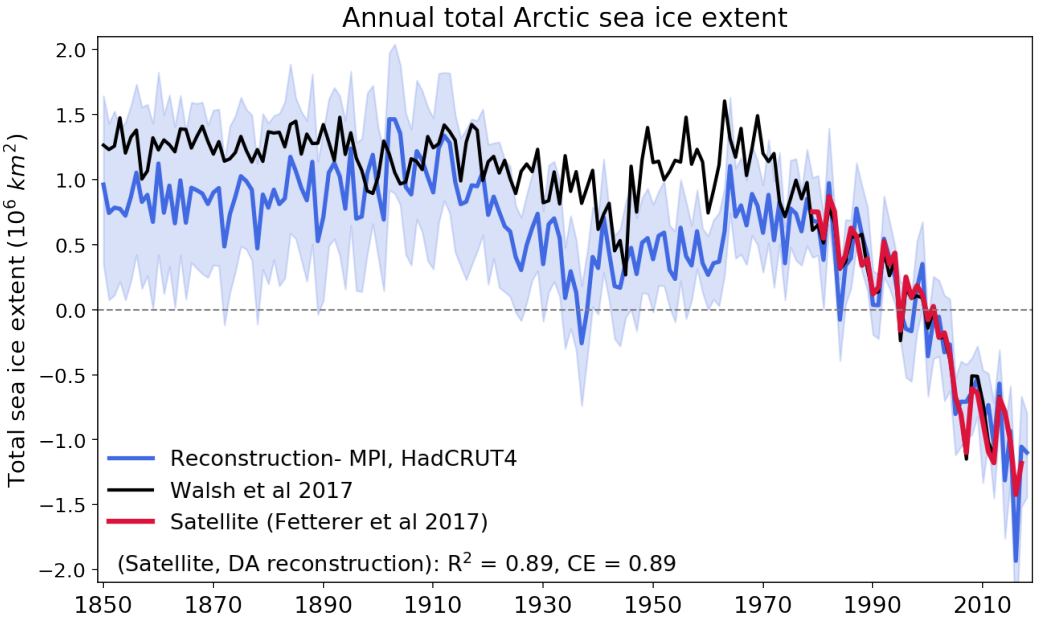

Figure 3. Reconstructed Arctic SIE from DA (blue), Walsh et al. (2017) (black), and satellite observations (red). For our reconstructions annually averaged HadCRUT temperature data was assimilated with a prior ensemble drawn from the MPI Last Millennium simulation. Anomalies are centered about 1979–2013.

The most notable feature of our reconstruction before the satellite era is the SIE decline during the ETCW, with a total loss of about 1.25 x 10^6 km^2 between 1910–1940 compared to ∼2.0 x 10^6 km^2 lost between 1979–2017 in satellite observations. Between 1930–1950, our reconstruction also shows ∼0.5 x 10^6 km^2 less SIE than in the Walsh et al. (2017) SIE record (see Figure 3), and the ETCW minimum occurs approximately eight years earlier than in Walsh et al. (2017). Between 1850–1900 our reconstruction shows a slow increase in SIE, reaching a maximum just after 1900, as opposed to the Walsh et al. (2017) record which shows maximum SIE in the 1960s. Overall, prior to the satellite era our reconstruction shows greater decadal variability compared to the Walsh et al. (2017) record, which has relatively constant Arctic SIE between 1850–1970. Prior to the satellite era (1850–1979) our reconstruction has a time-series standard deviation of 310,000 km^2 whereas the Walsh et al. (2017) record has standard deviation of 220,000 km^2. Though our reconstructions are annually resolved, they generally agree with the summer reconstructions of Arctic SIE in Alekseev et al. (2016).

4.1 Trends and variability

Next, we investigate the magnitude and significance of Arctic SIE trends during the ETCW relative to the satellite era. In our reconstructions, the SIE decline in the ETCW is shorter lived (∼25–30 years) than that in the satellite era (∼40 years), thus we investigate the distribution of 25-year trends for both the satellite era and ETCW.

Figure 4 shows the distribution of trends calculated for each ensemble member (from reconstructions using both MPI and CCSM4 model priors) for all possible 25-year segments during the satellite era (1979–2017) and the ETCW (1910–1940). The distribution of all 25-year trends between 1979–2017 for both Walsh et al. (2017) and satellite observations are also shown as boxplots below the distributions. For the Walsh et al. (2017) record, ETCW trends were calculated between 1918–1948 and are also shown as a boxplot (we use a later window for a fair comparison since the minimum SIE occurred 8 years later in Walsh et al. (2017)). The median 25-year trend found in the Walsh et al. (2017) record during the ETCW of -0.18 x 10^6 km^2/year falls at the 98th and 99th percentiles of the MPI and CCSM4 model prior reconstructions, respectively. We note that our reconstructions slightly underestimate the mean 25-year trend in the satellite era. However, when comparing these two time periods in our reconstructions, the satellite era trends are ∼33–38% greater than the ETCW trends.

4.2 Sensitivity of results

Our reconstruction of SIE depends on the gridded temperature product assimilated (and associated errors), on the climate model prior, and on sample-error mediation in the DA (localization length scale and ensemble variance inflation factor). A range of choices for these aspects have been tested, with details provided in the Supporting Information. Overall we find that the choice of observational dataset and model prior make little difference to pan-Arctic indices (see Figure S3 in Supporting Information), but that variance inflation and spatial localization have a larger affect.

With an offline DA approach, all temporal variability in the reconstruction comes from the observations. Thus, increasing the localization radius and the ensemble variance inflation of sea ice relative to temperature, both increase the influence of temperature observations, which is realized as larger temporal variability (Figure S4 and S5 in Supporting Information). The results indicate a trade-off between capturing decadal variability versus inter-annual variability. For the MPI prior assimilated with HadCRUT temperature, a localization length scale of 15,000 km leads to the best reconstructed trend for nearly all inflation factors, so we chose to use this localization length scale. Given a localization length scale of 15,000 km, the skill metrics are best for an inflation factor of 1.8. For a prior drawn from the CCSM4 Last Millennium simulation and HadCRUT

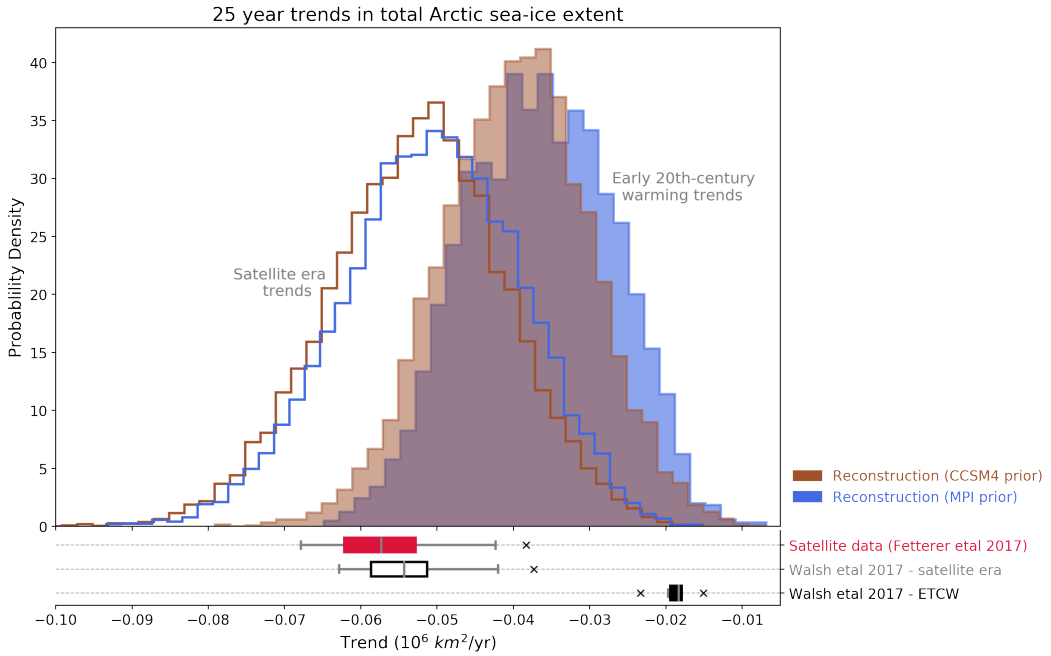

Figure 4. The distribution of all possible 25-year trends in Arctic SIE during the satellite era (1979–2017) and ETCW (1910–1940) for 5 prior iterations, each containing 200 ensemble members. The probability density functions show reconstructed SIE trends using MPI as the model prior (blue) and CCSM4 (brown). Below the histograms, the spread of trends calculated in the Walsh et al. (2017) record (black) and satellite observations (red) are displayed as box plots. The ETCW for the Walsh et al. (2017) record was calculated between 1918–1948.

observations, the same localization length scale of 15,000 km was used and an inflation factor of 2.6 gave the best skill scores. Overall, these experiments show that a range of values of localization and ensemble inflation result in skillful reconstructions relative to satellite observations, and similar reconstructions of sea ice for earlier time periods.

5 Conclusions

The relationship between SIE and SAT is linear during the satellite era in observations, but we find that this relationship is much weaker or even absent in the Walsh et al. (2017) record of SIE prior to the 1950s. This lower sensitivity of SIE to SAT in the Walsh et al. (2017) record is plausibly due to a lack of high quality sea-ice observations, especially during fall and winter and prior to 1953. We have also found that 20th century atmospheric reanalysis underestimate the magnitude of the ETCW (1910-1940) in the Arctic. Since previous versions of the Walsh et al. (2017) dataset are used as boundary conditions for 20th-century atmospheric reanalysis, we speculate that the low variability of SIE in Walsh et al. (2017) could be a reason atmospheric reanalysis do not fully capture the ETCW, but leave exploration of this hypothesis to future work.

We exploit the relationship between SAT and SIC using an ensemble Kalman filter data assimilation approach to produce a new sea-ice reconstruction. This method optimally combines temperature observations and model data from Last Millennium simulations to yield skillful Arctic sea-ice reconstructions with annual resolution. Validation against satellite observations yields an R^2-value of 0.89 and coefficient of efficiency of 0.89. Prior to the satellite era, our reconstructions show Arctic SIE loss of ~1.25 x

10^6 km^2 during the ETCW, which is greater than the ETCW loss of ∼0.75–1.0 x 10^6 km^2 estimated in Walsh et al. (2017), yet smaller than the SIE loss during the satellite era of ∼2.0 x 10^6 km^2. The reconstructed 25-year trends of SIE indicate that the rate of sea-ice loss during the ETCW was about ∼33–38% smaller than the 25-year trends during the satellite era.

Overall, these reconstructions show more inter-annual variability in SIE than in Walsh et al. (2017) during the Instrumental Era with standard deviation ∼40% (∼90,000 km^2) greater between 1850–1979, a significant part due to the ETCW. The ETCW has been ascribed to a combination of anthropogenic forcing and strong natural variability (Fyfe et al., 2013; Delworth, 2000; Wood & Overland, 2009; Beitsch et al., 2014). Here we find that during the satellite era, Arctic sea-ice loss was larger and longer lasting than during the ETCW, which implies that the current declines likely necessitate external anthropogenic forcing, as previous results have shown (Ding et al., 2017; Kay et al., 2011; Notz & Marotzke, 2012). Future work will extend this approach to reconstructing seasonal variability and sea-ice thickness to further our understanding of sea ice during the Instrumental era.

Acknowledgments

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Figure 1.

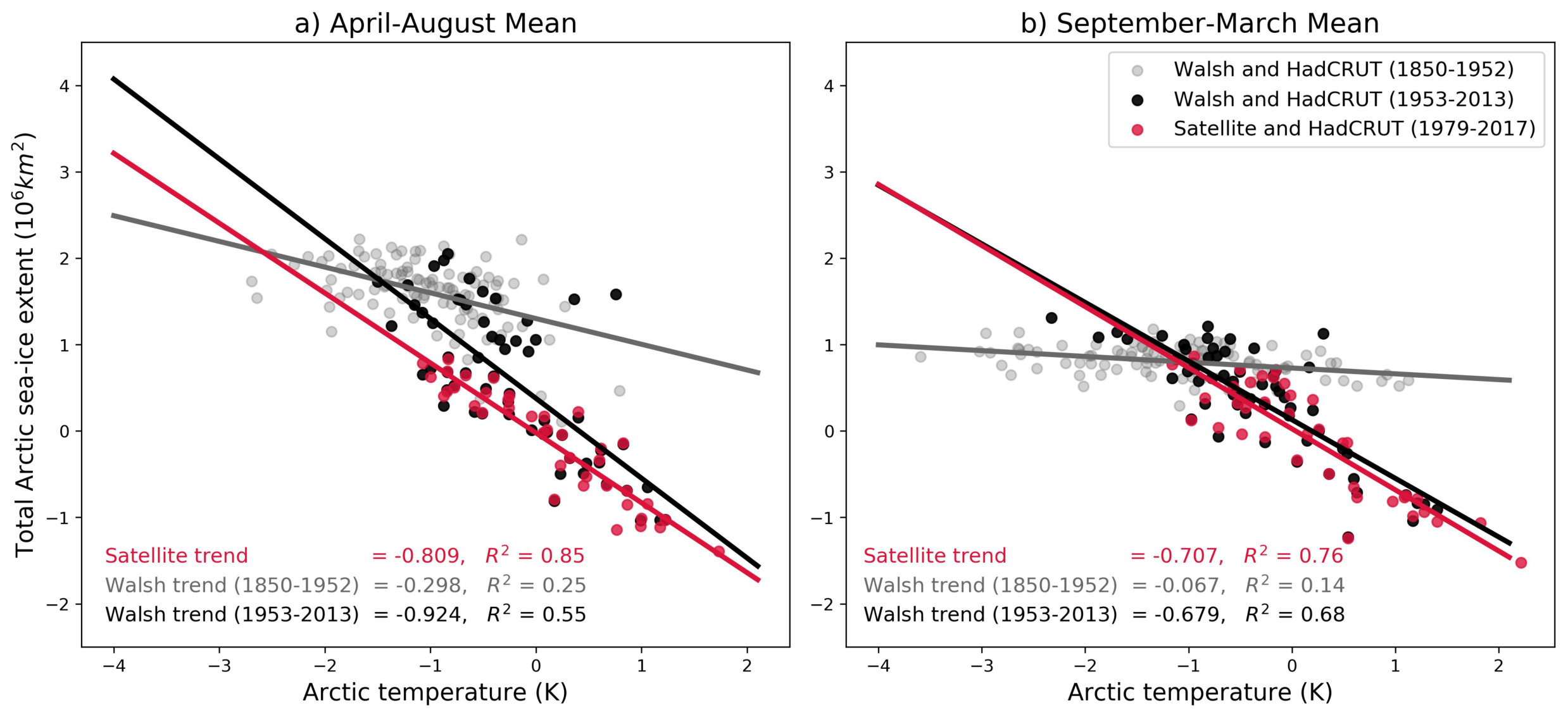
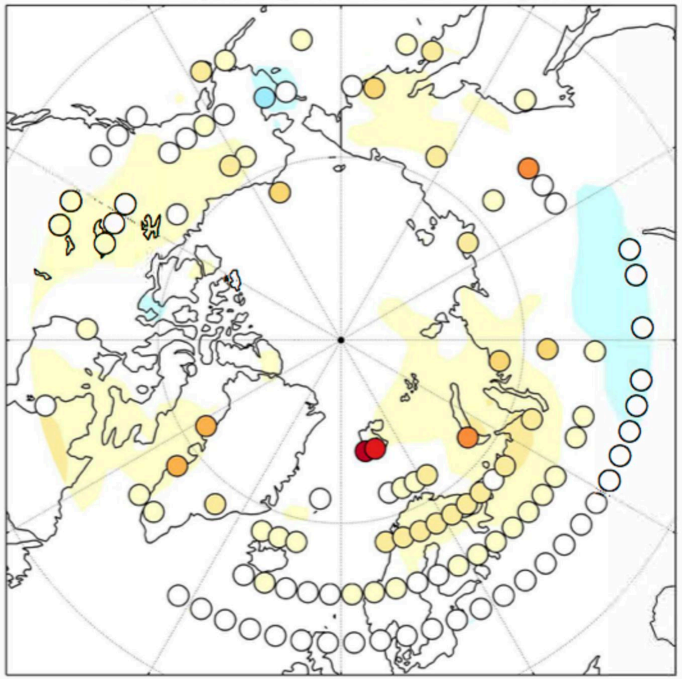
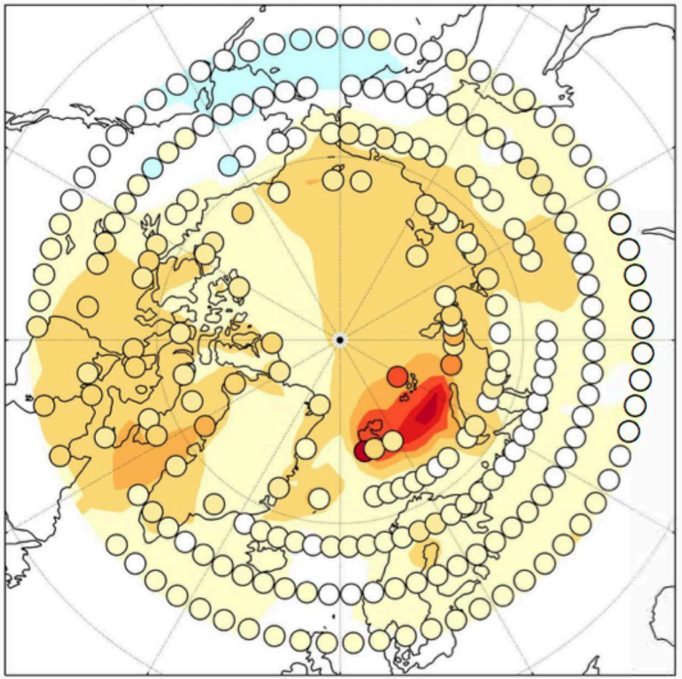

a) April-August Mean
b) September-March Mean
Total Arctic sea-ice extent ($10^6 km^2$)
Arctic temperature (K)
Arctic temperature (K)
Walsh and HadCRUT (1850-1952)
Walsh and HadCRUT (1953-2013)
Satellite and HadCRUT (1979-2017)
Satellite trend = -0.809, R^2 = 0.85
Walsh trend (1850-1952) = -0.298, R^2 = 0.25
Walsh trend (1953-2013) = -0.924, R^2 = 0.55
Satellite trend = -0.707, R^2 = 0.76
Walsh trend (1850-1952) = -0.067, R^2 = 0.14
Walsh trend (1953-2013) = -0.679, R^2 = 0.68

Figure 2.


1912-1940 Oct-March trends °C/dec
ERA-20C (shading) HadCRUT (dots)


1979-2010 Oct-March trends °C/dec
ERA-20C (shading) HadCRUT (dots)

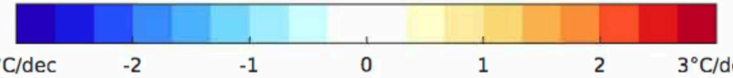

-3°C/dec
-2
-1
0
1
2
3°C/dec

Figure 3.

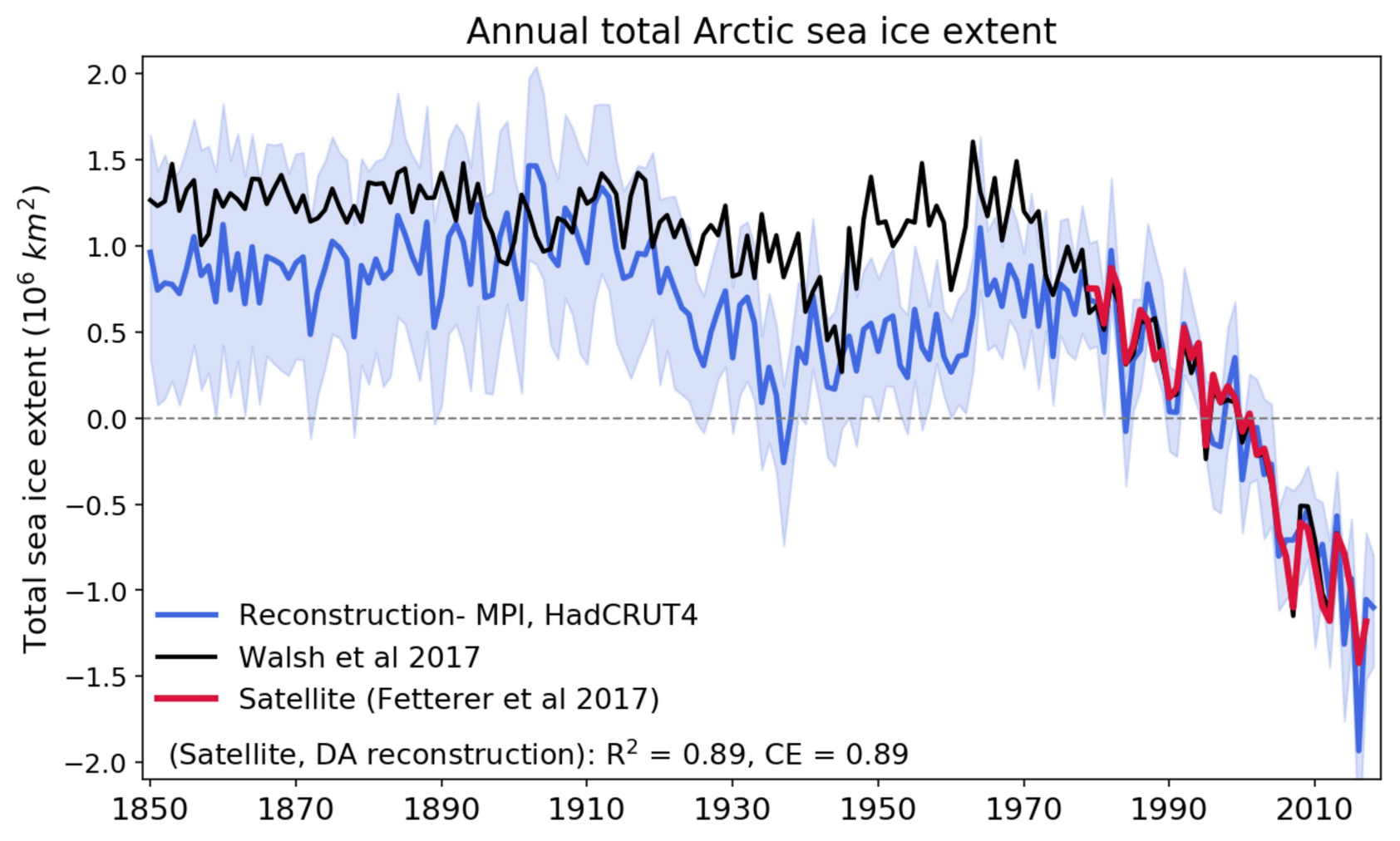
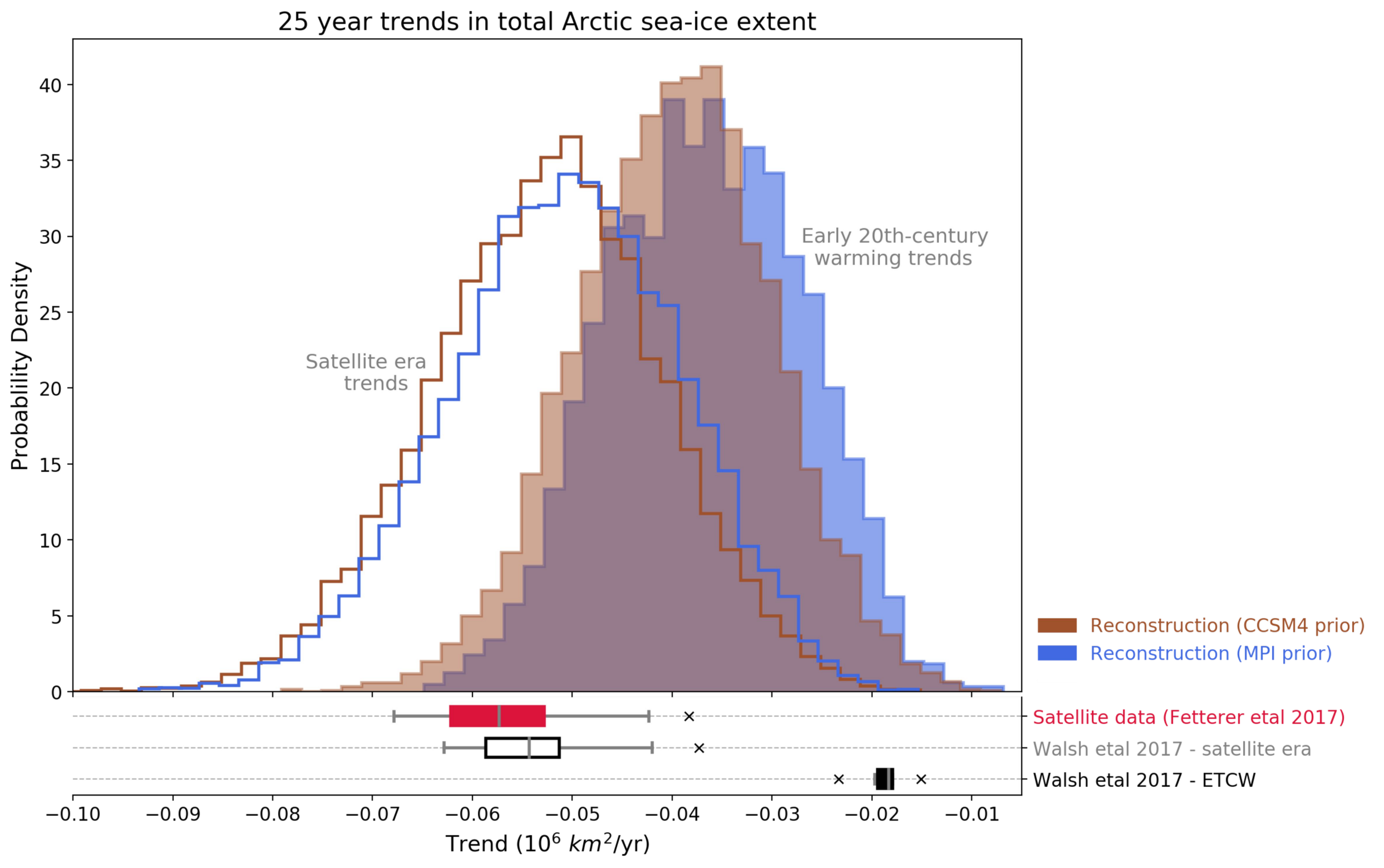

Annual total Arctic sea ice extent
Total sea ice extent (10^6 km^2)
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
1850
1870
1890
1910
1930
1950
1970
1990
2010
Reconstruction- MPI, HadCRUT4
Walsh et al 2017
Satellite (Fetterer et al 2017)
(Satellite, DA reconstruction): R^2 = 0.89, CE = 0.89

Figure 4.


25 year trends in total Arctic sea-ice extent
Probablility Density
Satellite era trends
Early 20th-century warming trends
Reconstruction (CCSM4 prior)
Reconstruction (MPI prior)
Satellite data (Fetterer etal 2017)
Walsh etal 2017 - satellite era
Walsh etal 2017 - ETCW
Trend (10^6 km^2/yr)