

**Noisier Waters: Multi-Model Insights on the Internal Variability of the Changing
Upper Arctic Ocean**

By

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The University of Wisconsin–Madison occupies ancestral Ho-Chunk land, a place their nation has called Teejop (day-ȝOPE) since time immemorial. In an 1832 treaty, the Ho-Chunk were forced to cede this territory. Decades of ethnic cleansing followed when both the federal and state government repeatedly, but unsuccessfully, sought to forcibly remove the Ho-Chunk from Wisconsin. Today, UW–Madison respects the inherent sovereignty of the Ho-Chunk Nation, along with the eleven other First Nations of Wisconsin.

Legacies of violent colonization continue to shape our planet and inform our shared future of collaboration and stewardship. A more just and equitable existence for all demands us to recognize and confront this truth here and everywhere.

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Abstract

The Arctic is currently bearing the brunt of human-induced climate change. Among its most robust consequences for this region are the warming and freshening of the upper ocean and the perennial decline of sea ice. These trends are complicated in part by internal variability: a critical and irreducible source of uncertainty that can enhance or mask the signal of anthropogenic forcing at all scales. While significant advances have been made to our understanding of the response of Arctic atmospheric and sea ice internal variability to forcing, substantially less consideration has been paid to the oceanic internal variability response. Moreover, it has not yet been investigated how well the current generation of climate models represent this form of intrinsic oceanic noise. Here, we diagnose trends in the recent historical (1980-2015) internal variabilities of regional and pan-Arctic upper ocean temperature and salinity and investigate their connection to sea ice decline across eleven current-generation climate model ensembles. Upper Arctic Ocean temperature internal variability is found to increase for all considered models, with seasonal intensification and spatial coherence strongly-correlated to surface warming and anti-correlated to the decline of sea ice. For the same models, upper ocean freshening is not accompanied by robust trends or trend seasonality in salinity internal variability, implying the two forms of uncertainty are driven and modulated by differing environmental processes and mean state changes which may contain differing degrees of susceptibility to model biases.

Chapter 1

Introduction

1.1 The changing Arctic and the role of internal variability

The Arctic climate awaiting at the end of the twenty-first century will be fundamentally different from the one we know today. Owing to the accelerated human burning of fossil fuels since global industrialization, the current and previous generations of climate models consistently predict a seasonally ice-free Arctic Ocean irrespective of future emissions trajectories [Stroeve et al., 2008, Stroeve & Notz, 2018, Jahn et al., 2024, Heuzé & Jahn, 2024]. This future state will accompany warmer, fresher, wetter, and windier conditions at the surface and upper ocean [Timmermans et al., 2018, Rantanen et al., 2022, Shu et al., 2018, Zanowski et al., 2021, Vavrus & Alkama, 2022, Muilwijk et al., 2024], all of which carry profound implications for broader oceanic circulation into, within, and out of the Arctic [Timmermans & Marshall, 2020]. Reconstructions and projections of these trends are complicated in part by internal variability [Hawkins & Sutton, 2009]: the climate system's

chaotic variations that arise from complex interactions between its components. Internal variability is therefore an irreducible source of uncertainty, which can either mask or enhance the signal of anthropogenic forcing at all scales [Deser et al., 2012, Swart et al., 2015, McKinnon et al., 2017, Deser et al., 2020].

Disentangling internal variability from forcing is a nontrivial task which first motivated the creation of initial condition large ensembles over a decade ago (e.g. [Kay et al., 2015]). While significant advances have been made to our understanding of Arctic atmospheric and sea ice internal variability (e.g. [Jahn et al., 2016, Deser et al., 2020]), considerably less attention has been paid to oceanic internal variability [Le Gloannec et al., 2025]. This is a substantial gap, given that there is ample evidence to suggest that internal variability exacerbated recent Arctic warming and sea ice loss [Swart et al., 2015, Sweeney et al., 2023] and can change in response to mean state environmental conditions [Rodgers et al., 2021, Le Gloannec et al., 2025]. In light of how rapidly changes in the upper Arctic Ocean have occurred and continue to occur, it is vitally necessary to expand our understanding of how the internal variability (and thus the uncertainty) of its key thermodynamic properties (i.e. temperature and salinity) are responding. Before doing so, it is helpful to first review the influences on upper ocean temperature and salinity variance which characterize the historical and present-day Arctic. These are summarized in the following section.

1.2 Competing seasonal influences on upper Arctic

Ocean temperature and salinity variance

While changes to the thermodynamic mean state and variance in the Arctic Ocean occur on all time scales [Frankignoul & Hasselmann, 1977], upper ocean temperature and salinity variance are dominated by the seasonal cycle. Primarily owing to vast differences in surface solar insolation (i.e. 24 hours of continuous sunlight in the summer, $\sim 150 \text{ W m}^{-2}$ shortwave vs. 0 hours in winter, $\sim 0 \text{ W m}^{-2}$), Arctic sea ice area varies by around nine million square kilometers over the course of a year [Serreze et al., 2007, DiGirolamo et al., 2022, Fetterer et al., 2025, Stewart et al., 2025]. This massive seasonal variation (equivalent to growing and melting a United States-sized amount of sea ice every twelve months) imposes substantial radiative and mechanical imprints on upper Arctic Ocean temperature and salinity variance depending on the region and time of year. In the summer and fall, solar and atmospheric warming drive land and sea ice melt, releasing freshwater to the sea surface. This influx of cool, light water reduces surface salinity and forms a seasonal freshwater layer [Peralta-Ferriz & Woodgate, 2015, Randelhoff et al., 2017], which increases upper ocean stratification (i.e. shoaling of the mixed layer). This configuration reduces the efficacy of wind-driven mixing across the pycnocline, dampening temperature and salinity variance. At the same time, however, reduced summertime sea ice cover in the marginal seas facilitates stronger coupling of the ocean to the atmosphere [Rainville & Woodgate, 2009, Rainville et al., 2011], which can enhance variance by promoting air-sea heat fluxes, regional precipitative freshwater input, and vertical mixing via internal wave generation [D’Asaro & Morison, 1992]. Moreover, the greater absorption of solar radiation by the open sea surface induces warming which increases horizontal temperature gradients close to the sea ice edge [Le Gloannec et al., 2025], further enhancing temperature variance.

From mid-fall to early spring, decreased solar radiation cools the atmosphere and sea surface, which drives sea ice formation. As surface waters freeze, salt is released as brine (i.e. brine rejection), increasing upper ocean salinity and densifying surface waters. This input weakens upper ocean stratification and deepens the mixed layer [Peralta-Ferriz & Woodgate, 2015, Timmermans & Marshall, 2020], which amplifies the efficacy of vertical wind and ice-driven mixing in regions with looser ice packs. Concurrently, upper ocean mixing is also increased in these regions by the seasonal intensification of surface winds in the late fall and early winter compared to the summer [Spreen et al., 2011, Stegall & Zhang, 2012, Jakobson et al., 2019], further enhancing temperature and salinity variance. This is in contrast to regions with more complete sea ice cover, which largely insulates the upper ocean from solar and atmospheric fluxes of radiant energy, latent and sensible heat, and mechanical wind energy, reducing temperature variance [Muilwijk et al., 2024].

1.3 Synthesis and research questions

Upper Arctic Ocean temperature and salinity variance are in summary characterized both by opposing seasonal signals and the superposition of competing sub-seasonal influences. As demonstrated by [Rodgers et al., 2021] and [DeRepentigny et al., 2020], Arctic atmospheric internal variability can depend strongly on mean state conditions. With large observed mean state changes already occurring in the Arctic [Serreze et al., 2009, Jahn & Laiho, 2020, Landrum & Holland, 2020, Vavrus & Alkama, 2022], an investigation into the response of the internal variability of the upper-ocean thermodynamic state is needed. Furthermore, to date, there has not yet been an investigation into how this oceanic internal variability response is depicted by our current generation of climate models. A multi-model perspective is critical

to employ in this context, given how substantially they've been shown to differ in their depictions of the changing Arctic climate by previous studies [Watts et al., 2021, Zanowski et al., 2021, Wang et al., 2022, Khosravi et al., 2022]. As such, the contents of this thesis are devoted to answering the following research questions:

1. How have the internal variabilities of upper Arctic Ocean temperature and salinity responded to the recent historical decline of sea ice?
2. How are these responses depicted across the current generation of climate model ensembles?

The remaining contents of this thesis are organized as follows: Chapter 2 details the data and methods chosen to answer the above questions, Chapter 3 presents the thesis's key findings, Chapter 4 justifies and places the results within our current scientific understanding of Arctic Ocean internal variability, and Chapter 5 summarizes the prior contents and presents possible directions for future research.

Chapter 2

Data & Methods

2.1 Models & output

2.1.1 Historical CMIP6

This study uses historical (1850-2015) monthly output from eleven fully coupled climate models published in the Coupled Model Intercomparison Project phase 6 archive (CMIP6) [Eyring et al., 2016]. The models used in the study as well as their specifications are provided in **Tables 1 & 2**. These models were selected both for the diversity of their constructions and for the size of their ensembles, offering at minimum ten realizations of the Earth’s climate from which its forced response and internal variability may be estimated. For each model, the first ten ensemble members with identical initializations, physics, and forcing schemes were used (e.g., r#i1p1f1, or r#i1p1f2 when the former was not available, as was the case for CNRM-ESM2-1 and UKESM1-0-LL). Upper ocean temperature and salinity data were provided by their corresponding standard CMIP6 output variables, ‘thetao’ and ‘so’, evaluated at grid cells closest to fifteen meters of depth in each model’s respective ocean

component. This depth was chosen to allow for consistent analysis between ice-covered and ice-free regions of the Arctic Ocean. In ice-covered regions, grid cells closest to the sea ice bottom ($z \leq 5$ m depth) are held closely to the freezing point of saline water, which in turn dampens their temperature variance [Timmermans & Marshall, 2020, Athanase et al., 2026]. In order to assess how internal variability has responded to changes in the upper Arctic Ocean, selecting a uniform depth of the polar mixed layer (a depth that's assuredly removed from the sea ice bottom) lessens the influence of temperature damping from the ice-ocean interface, which could otherwise occur when averaging over the upper 15 m or selecting only the top-most oceanic layer. Further analyses (not shown) confirm the results are insensitive to the choice of depth above the halocline, implying that the internal variability trends of the aforementioned thermodynamic properties are consistent throughout the polar mixed layer. For simplicity, upper ocean temperature and salinity are denoted by θ_{sfc} and S_{sfc} , respectively. Monthly sea ice concentration (SIC) data were provided by the standard CMIP6 output variable, 'siconc' ('siconca' for GISS-E2-1-H).

All model analyses were computed on their respective native ocean component grids before interpolating via a nearest source-to-destination algorithm to a common half-degree resolution for ease of model inter-comparison between basins. The region masks used to partition trends by basin/marginal seas are shown in Fig. 2.1. When calculating spatial averages, all data were weighted by their respective model's ocean grid cell area variable, 'areacello'.

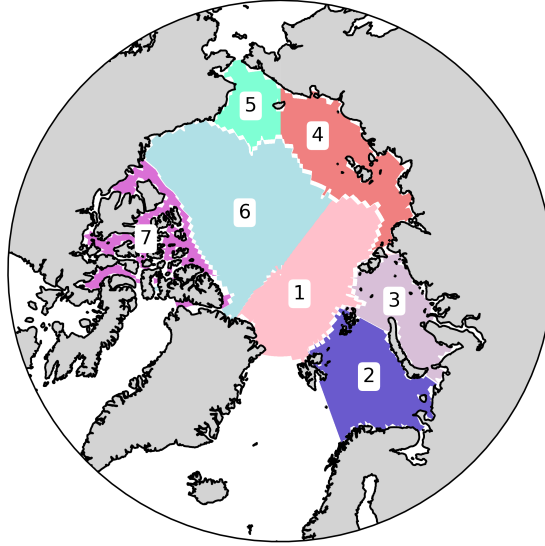


Figure 2.1: Arctic basin masks used in spatial averaging. [1] Eurasian Basin, [2] Barents Sea, [3] Kara Sea, [4] Siberian Seas, [5] Chukchi Sea, [6] Canadian Basin, [7] Canadian Arctic Archipelago.

2.1.2 Comparison with state estimate

The mean states and trends of simulated Arctic θ_{sfc} and S_{sfc} are compared with those obtained from the monthly output from the ECCOv4r4 State Estimate [ECCO Consortium et al., 2021]. ECCOv4r4 is a global one-degree resolution ocean state estimate which provides hourly, daily, and monthly data spanning 1992-2017 for key upper-ocean and surface-layer atmospheric variables. The state estimate assimilates multiple sources of observational data into the initial conditions, parameterizations, and atmospheric boundary conditions of a global ocean model. The benefit of using this approach is that it provides an estimation of the observational record that satisfies the thermodynamic laws of mass and energy conservation. This is in contrast to traditional ocean reanalyses, which rely on non-physical data

assimilation of simulated state variables to match observations. Since the internal variability of the upper Arctic Ocean’s physical properties is intrinsically connected to their energetic state, it is more suitable for this study to examine data which more closely obey the laws of physics. Therefore, we employed the state estimate as a proxy for true observations of upper Arctic Ocean temperature and salinity, assessed at fifteen meters of depth.

There are known biases which cause the estimation of the Arctic Ocean to differ from observationally-derived data in multiple ECCO products, including v4r4. In particular, discrepancies in sea ice concentration, sea surface temperature, salinity, and upper ocean stratification have been documented in the subpolar North Atlantic, the North Atlantic-Arctic sector, and the Beaufort Gyre [Carton et al., 2019, Castagno et al., 2023, Heiser et al., 2026]. These biases result in underestimations of liquid freshwater storage and the subsurface intrusion of warm Atlantic water, which can influence temperature and salinity trends in the upper ocean. So, while we employed ECCOv4r4 as a reference state for CMIP6 model comparison, it is not necessarily a one-to-one stand-in for the true historical record.

2.2 Estimation of internal variability

The main objective of this thesis is to compare long-term trends (abbreviated dec^{-1}) in the modeled recent historical internal variability of the upper Arctic Ocean’s key thermodynamic properties: upper ocean temperature and salinity, and their respective links to declining sea ice. To this aim, internal variability is defined as the standard deviation across ensemble members from each model (i.e. ensemble spread), denoted by σ [Deser et al., 2012, Kay et al., 2015, McKinnon et al., 2017]. We take an additional step of removing the residual influence of atmospheric forcing on σ by subtracting the ensemble mean prior to calculating the standard

deviation, following [Leroux et al., 2018, Le Gloannec et al., 2025, Hogg et al., 2022], though further analyses confirm the results are insensitive to this choice (not shown). For geospatial data, these computations yield time series of the internal variability ($\sigma(t)$) at each grid cell from which pan-Arctic and sub-basin-scale analyses were performed. Trends (denoted by Δ) in the mean state and internal variability were estimated by a linear least-squares regression over the last 35 years of the historical period (1980-2015). This period was chosen to align with the onset of the prolonged Arctic surface warming, freshening, and sea ice melt which defines the tail-end of the historical period in observations and simulations [Serreze et al., 2009, Jahn & Laiho, 2020, Zanowski et al., 2021, Rantanen et al., 2022].

2.3 Correlation to sea ice decline

To investigate the physical relationship in each model between upper ocean temperature and salinity internal variability and the decline of the Arctic’s sea ice cover, pattern correlations between $\Delta(\sigma)$ and $\Delta(\text{SIC})$ were calculated according to a Pearson correlation statistic (**Equation 2.1**). Multi-model mean pattern correlations (r_{MMM}) were constructed by first taking the average of all 1980-2015 trend maps in σ and SIC and then calculating r . The statistical significance of all pattern correlations and trends were assessed at the 95% confidence level via a two-tailed Student’s t-test.

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (2.1)$$

2.1: Pearson correlation statistic between two samples of size n . The independent variable, x , is the 1980-2015 linear trend in SIC calculated at every grid cell poleward of 60°N. The dependent variable, y , is the same trend calculated for $\sigma(\theta_{\text{sfc}})$ and $\sigma(S_{\text{sfc}})$.

Chapter 3

Results

The contents of this chapter are presented in the following order: we first examine the mean state of Arctic θ_{sfc} , S_{sfc} , SIC and their associated internal variabilities via domain-averaged annual mean time series and their long-term trends. Across all models and the state estimate, annual mean warming and freshening of the upper Arctic Ocean is a robust feature that is accompanied by increased temperature internal variability. Substantial disagreement is found in the sign and magnitude of trends in salinity internal variability. These trends are then separated into their monthly components to investigate the seasonality of change, before comparing spatial distributions of $\Delta(\sigma(\theta_{sfc}))$, $\Delta(\sigma(S_{sfc}))$ and their correlation to $\Delta(SIC)$ during the months of sea ice maximum and minimum between models. Lastly, relative basin and marginal sea contributions to pan-Arctic variable and internal variability trends are compared to investigate their spatial consistency between models and their co-location to sea ice decline. Upper ocean temperature internal variability increases as a direct consequence of declining sea ice across all models, whereas trends in salinity internal variability exhibit comparatively lower correlation (or complete lack thereof) to $\Delta(SIC)$ depending on the time of year.

3.1 Annual pan-Arctic change

In agreement with previous studies, warming and freshening of the upper Arctic Ocean (i.e. the forced response to greenhouse gas emissions) begins around 1980 and continues for the remainder of the historical period (Fig. 3.1.i, ii; bold lines) [Stroeve et al., 2008, Carmack et al., 2015, Polyakov et al., 2017, Timmermans et al., 2018, Zanowski et al., 2021, Shu et al., 2022]. In general, the models' Arctic Oceans are biased warmer (11/12 models) and fresher (10/12 models) than the state estimate. GISS-E2-1-H exhibits the largest salinity bias, being nearly 8 g kg^{-1} fresher in the annual mean than the state estimate, which is a known bias found in its original publication [Kelley et al., 2020]. Prior to 1980, there is little to no change in the simulated annual mean temperature and salinity for each model. Comparison with the linear trends of θ_{sfc} and S_{sfc} confirm the majority of warming and freshening of the upper Arctic Ocean occurs within the last thirty five years of the historical period (Fig. 3.1). By 2015, the multi-model mean (MMM) upper Arctic Ocean warmed by $\sim 0.45^\circ\text{C}$ and freshened by $\sim 0.9 \text{ g kg}^{-1}$.

The changes to the upper Arctic Ocean are reflected in their annual mean temperature and salinity internal variability to differing degrees. For both $\sigma(\theta_{\text{sfc}})$ and $\sigma(S_{\text{sfc}})$ (Fig. 3.2), there is little to no discernible internal variability trend prior to 1980 for most models. After 1980, $\sigma(\theta_{\text{sfc}})$ increases for nine of eleven models with a multi-model mean rate of change of $\sim 0.010^\circ\text{C dec}^{-1}$. The two outliers, CNRM-CM6-1 and MIROC6, show either decreasing annual mean θ_{sfc} ensemble spread ($\sim -0.0027^\circ\text{C dec}^{-1}$) or no change ($\Delta(\sigma(\theta_{\text{sfc}})) < 0.001^\circ\text{C dec}^{-1}$), respectively. This near-consensus on increasing annual $\sigma(\theta_{\text{sfc}})$ is indicative of a robust response to the aforementioned changes in the upper Arctic Ocean. $\Delta(\sigma(S_{\text{sfc}}))$, by contrast, exhibits substantial disagreement in the direction and

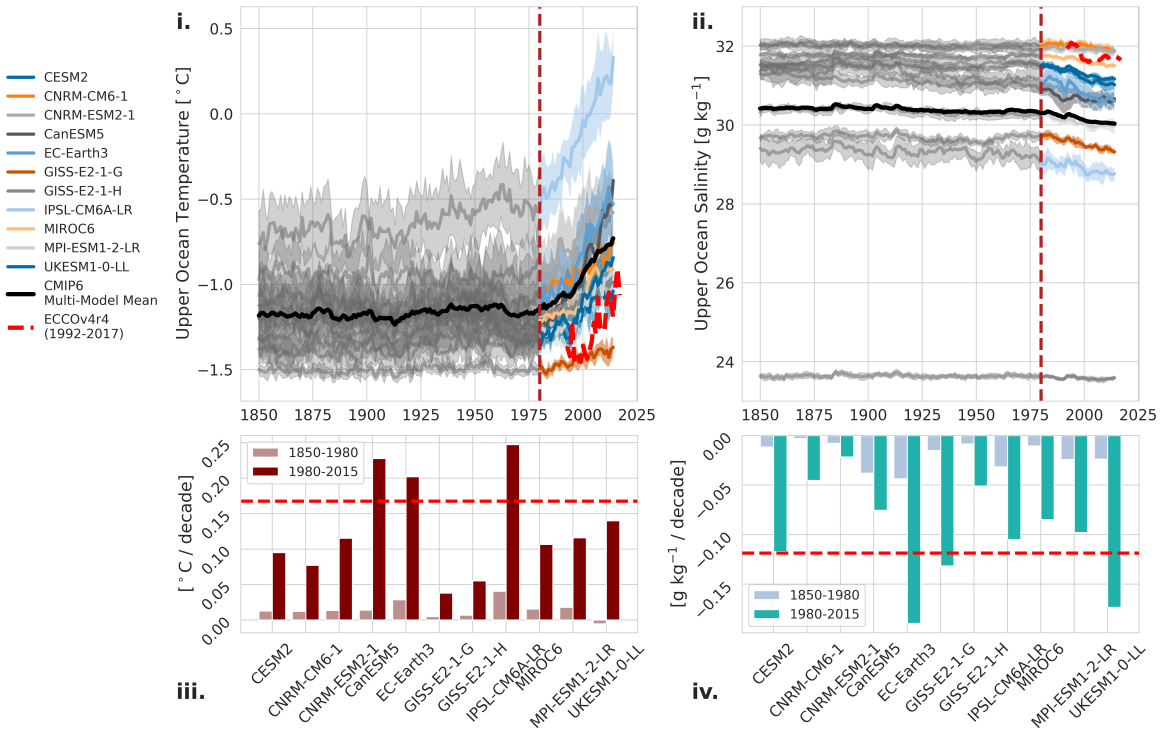


Figure 3.1: Historical (1850-2015) annual pan-Arctic mean time series of θ_{sfc} (i.) and S_{sfc} (ii.) across the considered models and state estimate. Thick, solid lines indicate the ensemble mean of each model, and shading about this line indicates the standard deviation across ensemble members. The multi-model mean is given by the thick black line. Below, linear decadal trends in θ_{sfc} (bottom left) and S_{sfc} (bottom right) are shown, calculated from the above series along with the state estimate (red dashed line). De-saturated bars are the decadal trend calculated for years prior to 1980, and saturated bars are the same calculated between 1980 and 2015.

magnitude of trends between models, and as a result, the multi-model mean shows no discernible trend in salinity internal variability ($\Delta(\sigma(S_{\text{sfc}}))_{\text{MMM}} < -0.001 \text{ g kg}^{-1} \text{ dec}^{-1}$). Opposing extrema of this set are EC-Earth3 and UKESM1-0-LL, which depict the strongest negative ($-0.035 \text{ g kg}^{-1} \text{ dec}^{-1}$) and positive ($0.018 \text{ g kg}^{-1} \text{ dec}^{-1}$) trends in salinity ensemble spread. This disagreement indicates that unlike θ_{sfc} and $\sigma(\theta_{\text{sfc}})$, the annual mean changes in upper Arctic Ocean salinity are not directly associated with changing salinity internal variability, and further suggests that the environmental factors that control changes

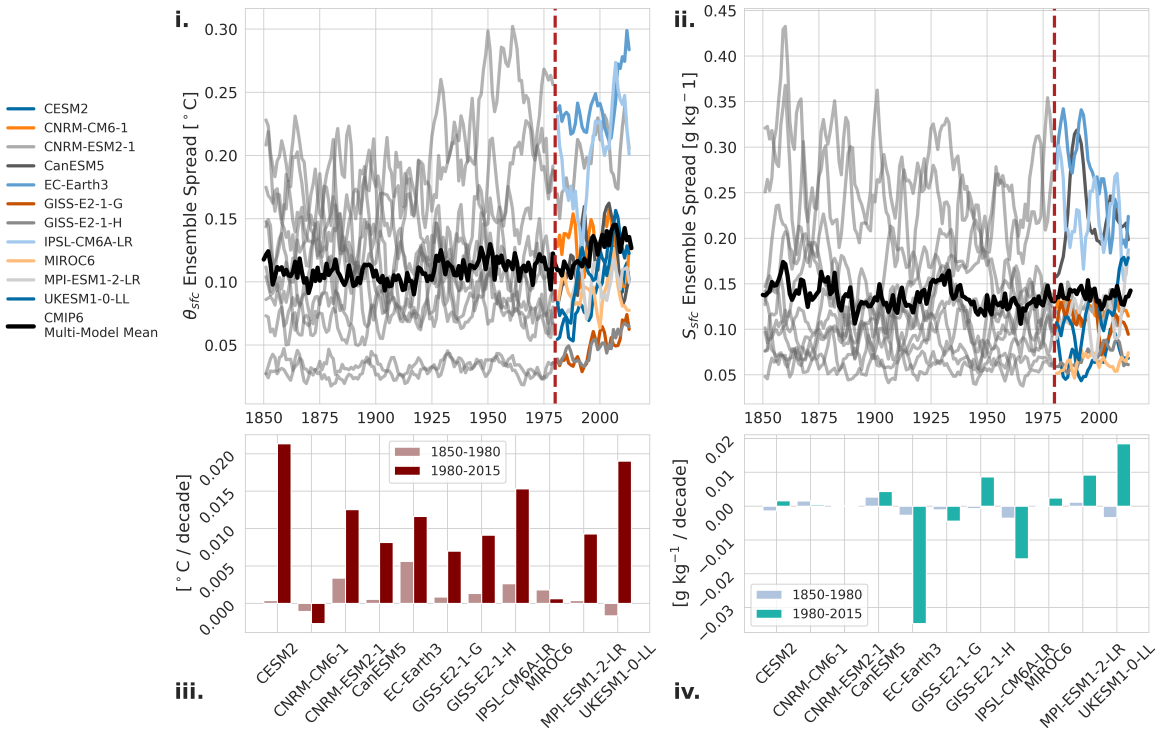


Figure 3.2: As in Figure 3.1; historical (1850-2015) annual pan-Arctic mean ensemble spread time series for θ_{sfc} (i) and S_{sfc} (ii) with a three-year running mean applied, and linear decadal trends in θ_{sfc} (iii) and S_{sfc} (iv) ensemble spread, calculated from the time series in i) and ii). The running mean is applied to make trends in the time series easier to identify visually.

in ocean temperature and salinity internal variability may differ.

As stated in Chapter 1, long-term changes in ocean temperature and salinity variance in the Arctic do not solely occur on annual time scales, but seasonal and sub-seasonal (daily-monthly) as well [Frankignoul & Hasselmann, 1977, Athanase et al., 2026]. This is of particular importance given that the Arctic climate system is dominated by the seasonal cycle [Timmermans & Marshall, 2020], which superimposes many competing influences on upper ocean temperature and salinity variance year-round. Because the annual mean flattens these seasonal and sub-seasonal signatures, the standard deviation about this mean

provides an inherently smoothed estimate of variance. To gain a sense for how the examined trends in temperature and salinity internal variability are modulated by the seasonal cycle, the previous results are separated into their monthly components in the following section.

3.2 Correlating sea ice decline to enhanced ocean temperature internal variability

3.2.1 Monthly sea ice and temperature long-term trends

Across the models, the majority of 1980-2015 pan-Arctic sea ice decline occurs in the summer (JJA) and fall (SON), with comparatively minor losses in the winter (DJF) and spring (MAM) (Fig. 3.3.i). The sharpest decline occurs in SON ($MMM_{SON} \sim -4.16 \text{ \% dec}^{-1}$), with greatest magnitude during the month of sea ice minimum, September ($MMM_{\text{September}} \sim -6.02 \text{ \% dec}^{-1}$). CESM2 and IPSL-CM6A-LR exhibit the highest rates of pan-Arctic sea ice decline of any model, with these losses most-pronounced in their central basins (Fig. 3.3.i.A, B, C) ($\Delta(SIC)_{\text{September}} \sim -12.44$ and $-10.19 \text{ \% dec}^{-1}$, respectively). The models disagree on which basin (Canadian vs. Eurasian), on average, outpaces the other in JJA/SON sea ice loss. For five of the eleven models, the Canadian Basin experiences the stronger summertime decline of sea ice, while the Eurasian Basin dominates in the remaining six. In winter and spring, sea ice loss is considerably lower ($MMM_{DJF} \sim -0.75 \text{ \% dec}^{-1}$, $MMM_{MAM} \sim -0.59 \text{ \% dec}^{-1}$). Neither central basin experiences wintertime sea ice loss greater than $-1 \text{ \% dec}^{-1}$ in any model, indicating that the losses present in the pan-Arctic mean (panel A) at this time of year are generated primarily in the marginal seas (later confirmed in Figs. 3.6, 3.10.i).

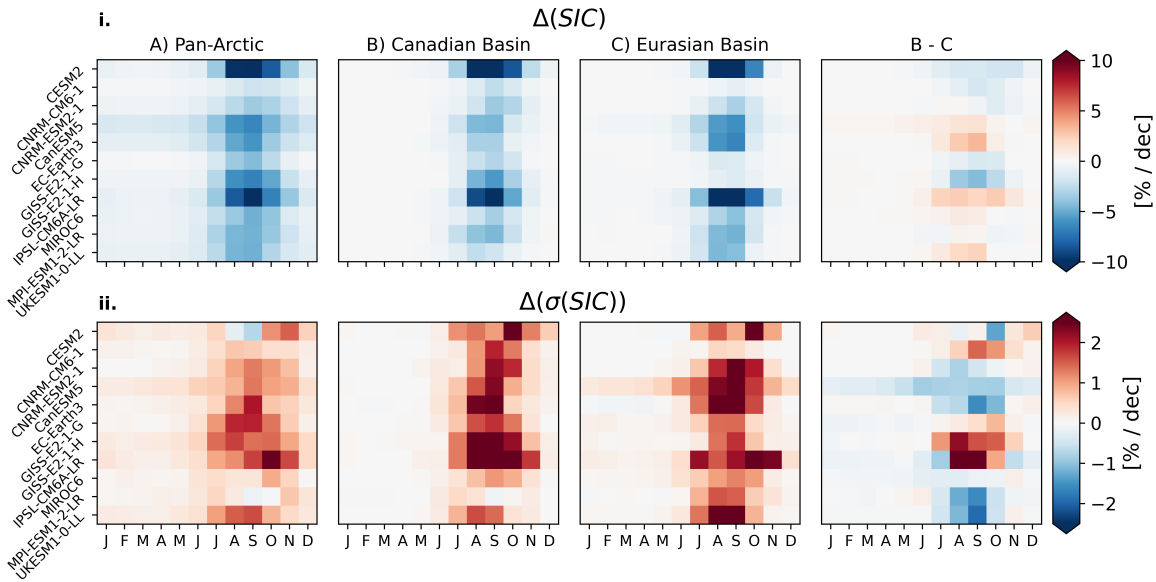


Figure 3.3: CMIP6 sea ice concentration. Monthly decompositions of 1980-2015 trends in sea ice concentration (i) and sea ice concentration internal variability (ii).

The months for which Arctic sea ice decline is most pronounced (June–November) are also the months in which SIC internal variability increases with the largest magnitude (Fig. 3.3.ii). Notably, $\Delta(\sigma(SIC))$ in the central basins outpace the pan-Arctic average (Fig. 3.3.ii.B, C vs. A), implying summer/fall increases to pan-Arctic SIC internal variability are counteracted by decreasing internal variability in the marginal Arctic seas (later confirmed in Fig. 3.9). As with $\Delta(SIC)$, there is substantial disagreement between models on which of the central basins experiences the sharpest summer/fall trend in internal variability (panel B–C). For six of the eleven models, the Eurasian Basin outpaces the Canadian Basin, while the latter outpaces the former in the remaining five. The months during which $\Delta(SIC) < -1 \text{ \% dec}^{-1}$ are also those which experience the weakest trend (or no trend) in SIC internal variability.

Upper Arctic Ocean temperature trends are largest in summer/fall (Fig. 3.4.i), as has been previously documented [Shu et al., 2022]. The central basins, which maintain perennial

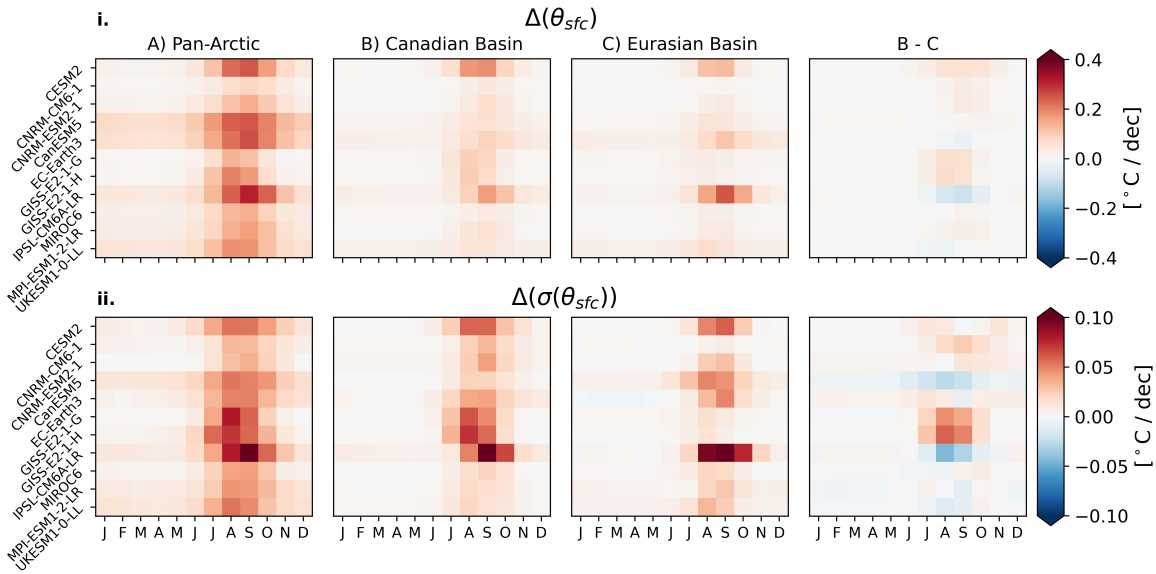


Figure 3.4: CMIP6 upper ocean temperature. Monthly decompositions of 1980-2015 trends in upper ocean temperature (i) and upper ocean temperature internal variability (ii).

sea ice cover by 2015 in all models (Sec. 3.3) [Watts et al., 2021], experience substantially weaker warming than the pan-Arctic average in all seasons. Moreover, the warming of these regions between June and November is essentially uniform (panel B-C), with differences in their respective rates of change less than $|0.1| ^{\circ}\text{C} \text{ dec}^{-1}$ for all models.

These mean state changes are accompanied by enhanced upper ocean temperature internal variability for all models (Fig. 3.4.ii). As with $\Delta(\sigma(\text{SIC}))$, trends in θ_{sfc} internal variability are significantly lower (or non-existent) for months during which the majority of the Arctic is completely ice-covered ($\Delta(\sigma(\theta_{sfc}))_{\text{DJF, JJA}} < 0.01 ^{\circ}\text{C} \text{ dec}^{-1}$). The strongest pan-Arctic increases in σ occur between July and October (JJA ~ 0.033 , SON $\sim 0.034 ^{\circ}\text{C} \text{ dec}^{-1}$), coinciding with months of amplified sea ice melt (Fig. 3.3.i). Qualitatively, the monthly distribution of decadal trends in temperature internal variability bear a striking resemblance to $\Delta(\text{SIC})$ for all models, implying that increased temperature internal variability is linked

to the decline of the Arctic Ocean’s sea ice cover. Moreover, consensus between the models suggest amplified θ_{sfc} internal variability is a robust response to changes in the mean state Arctic climate system. To examine these implications further, the following section expands on the prior results spatially for the months of sea ice minimum (September) and maximum (March) to correlate enhanced temperature internal variability with declining sea ice.

3.2.2 Correlating sea ice decline to enhanced ocean temperature internal variability

Corroborating previous studies, the current generation of climate models exhibits a broad diversity of simulated Arctic sea ice decline (Figs. 3.5, 3.6) which reflect their respective constructions and resultant biases [Watts et al., 2021, DeRepentigny et al., 2022, Pan et al., 2023]. For nine of the eleven models, the majority of September Arctic sea ice decline between 1980 and 2015 is restricted to the marginal seas, with comparatively lower rates of change in the central basins (Fig. 3.5). In general, the transitional boundary from mostly open-ocean to mostly ice-covered grid cells (50% SIC) shifts poleward for all models. CESM2 and IPSL-CM6A-LR (Fig. 3.5.a, h) are notable exceptions to this characterization: both depict pronounced losses in the central Arctic that reflect their respective biases noted by previous studies. At the sea ice maximum (Fig. 3.6), the majority of losses occur either within the Barents Sea or exterior to the basins of study (Fig. 2.1). Interior to these regions, grid cells in the central Arctic and marginal seas exhibit little to no trends and remain above 50% SIC through the end of the historical period in all models.

Amplified September Arctic upper ocean temperature internal variability is strongly anti-correlated to sea ice decline in all models (Fig. 3.7) ($r_{\text{MMM}} = -0.71$). Moreover, the largest in-

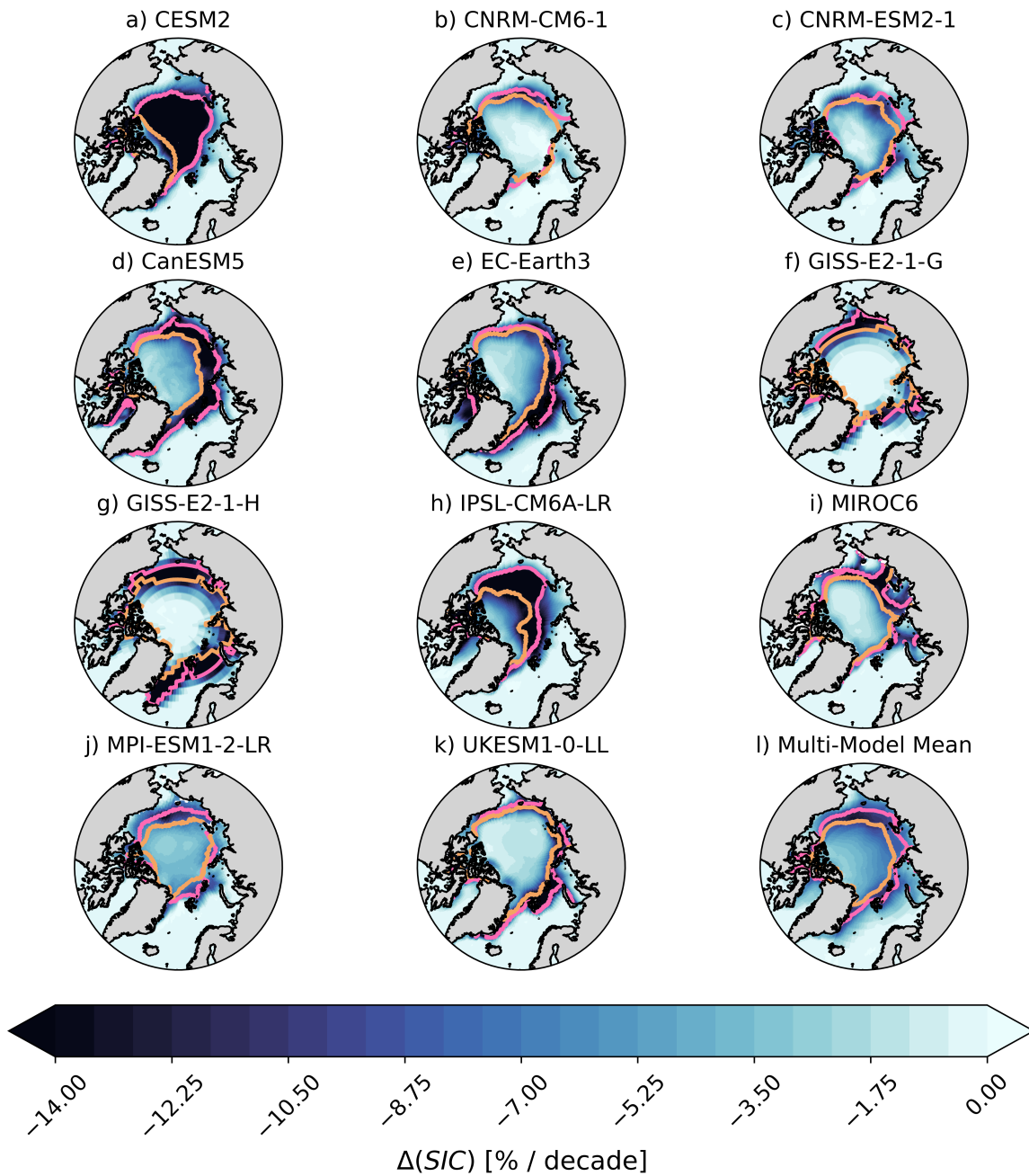


Figure 3.5: CMIP6 1980-2015 trends in September sea ice concentration. *Contours of 50% sea ice concentration in September 1980 (magenta) and 2014 (gold) denote the transition between grid cells that are mostly sea ice-covered and those which are mostly open ocean.*

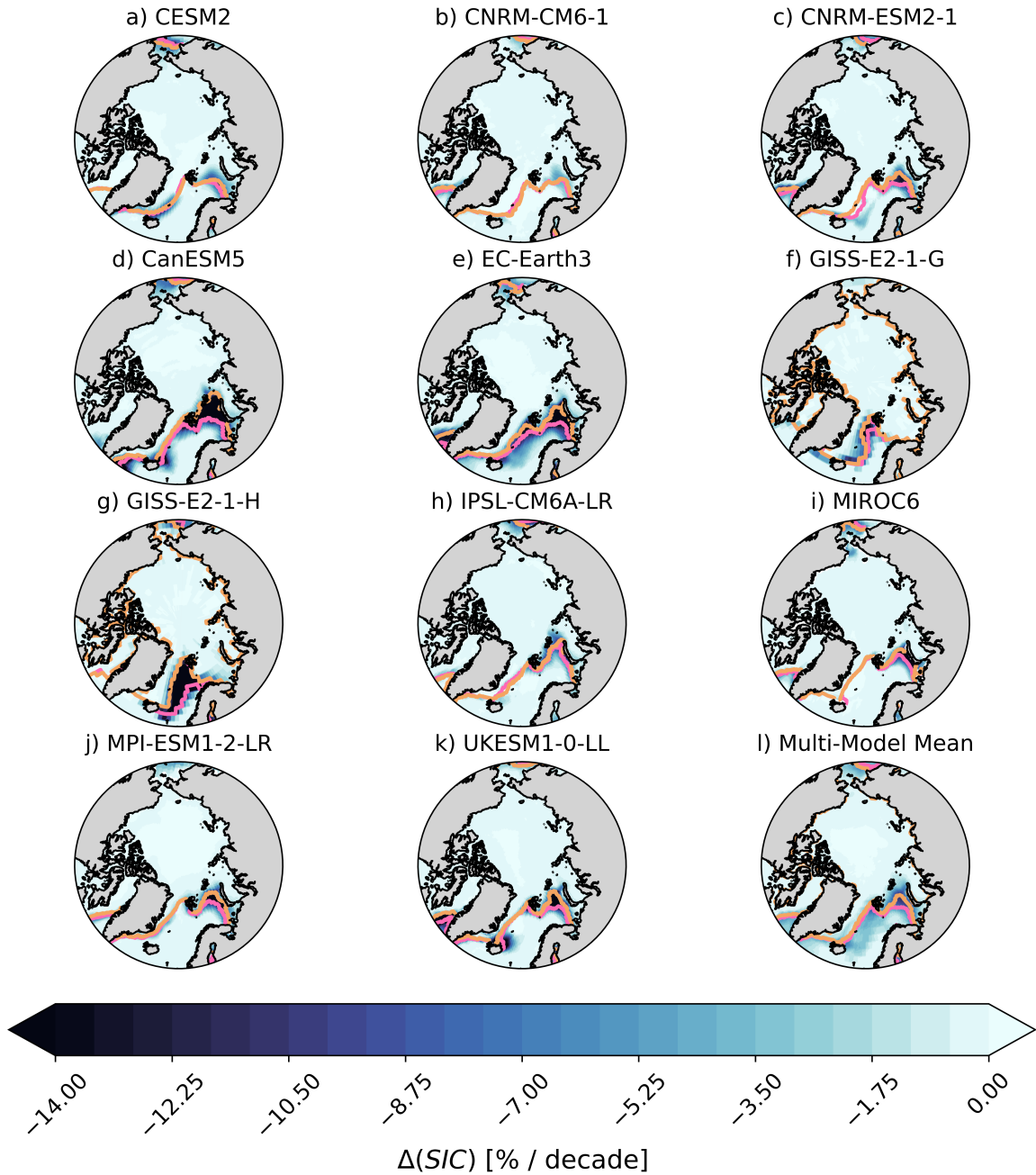


Figure 3.6: CMIP6 1980-2015 trends in March sea ice concentration. *As in Fig. 3.5, but for March.*

creases to $\sigma(\theta_{\text{sfc}})$ are closely co-located with growing open-air regions of the ocean (between the 1980 and 2014 50% SIC contours), indicating that the removal of sea ice cover enables

temperature variance to increase. This relationship holds even for models with known biases in amplified Arctic sea ice melt ($r_{\text{CESM2}} = -0.76$, $r_{\text{IPSL-CM6A-LR}} = -0.79$) and across both coarse and higher-resolution grids (e.g., $r_{\text{GISS-E2-1-G}} = -0.81$, $r_{\text{UKESM1-0-LL}} = -0.80$), further implying this mechanism for change is a robust physical feature. Decreasing upper ocean temperature internal variability in the Barents and Chukchi seas is also a semi-consistent feature across models, indicating that ensemble members are converging upon the September ensemble mean in these ice-free regions by the end of the historical period. Interior to the 50% SIC contour, trends in temperature internal variability are either considerably weaker or non-existent (e.g. Fig. 3.7.d, i), which is consistent with the damping effect of sea ice on temperature variance [Rainville et al., 2011, Athanase et al., 2026].

During the sea ice maximum (Fig. 3.8), the correlation to $\Delta(\text{SIC})$ weakens and remains ($r_{\text{MMM}} = -0.43$). Grid cells interior to the 50% SIC contour (i.e. regions of the ocean sufficiently insulated from air-sea interactions by sea ice) exhibit little to no trends in temperature internal variability. As in September, March trends are closely co-located with regions of increasing open water, which occurs primarily in the Barents Sea and exterior to the basins of study for all models. Exceptions of note to this framework are EC-Earth3 (e), IPSL-CM6A-LR (h), and MPI-ESM1-2-LR (j): EC-Earth3 and IPSL-CM6A-LR depict decreasing wintertime $\sigma(\theta_{\text{sfc}})$ in the Siberian Seas, with increasing $\sigma(\theta_{\text{sfc}})$ in the Canadian Arctic Archipelago. In contrast, MPI-ESM1-2-LR depicts weakly increasing $\sigma(\theta_{\text{sfc}})$ in the Kara, Laptev, and Beaufort Seas. In all, the persistent year-round correlation of $\Delta(\sigma(\theta_{\text{sfc}}))$ to $\Delta(\text{SIC})$ across all models, with the strong co-location of the former to growing open-ocean regions, helps to confirm declining Arctic sea ice as a mechanism for amplified upper ocean temperature internal variability.

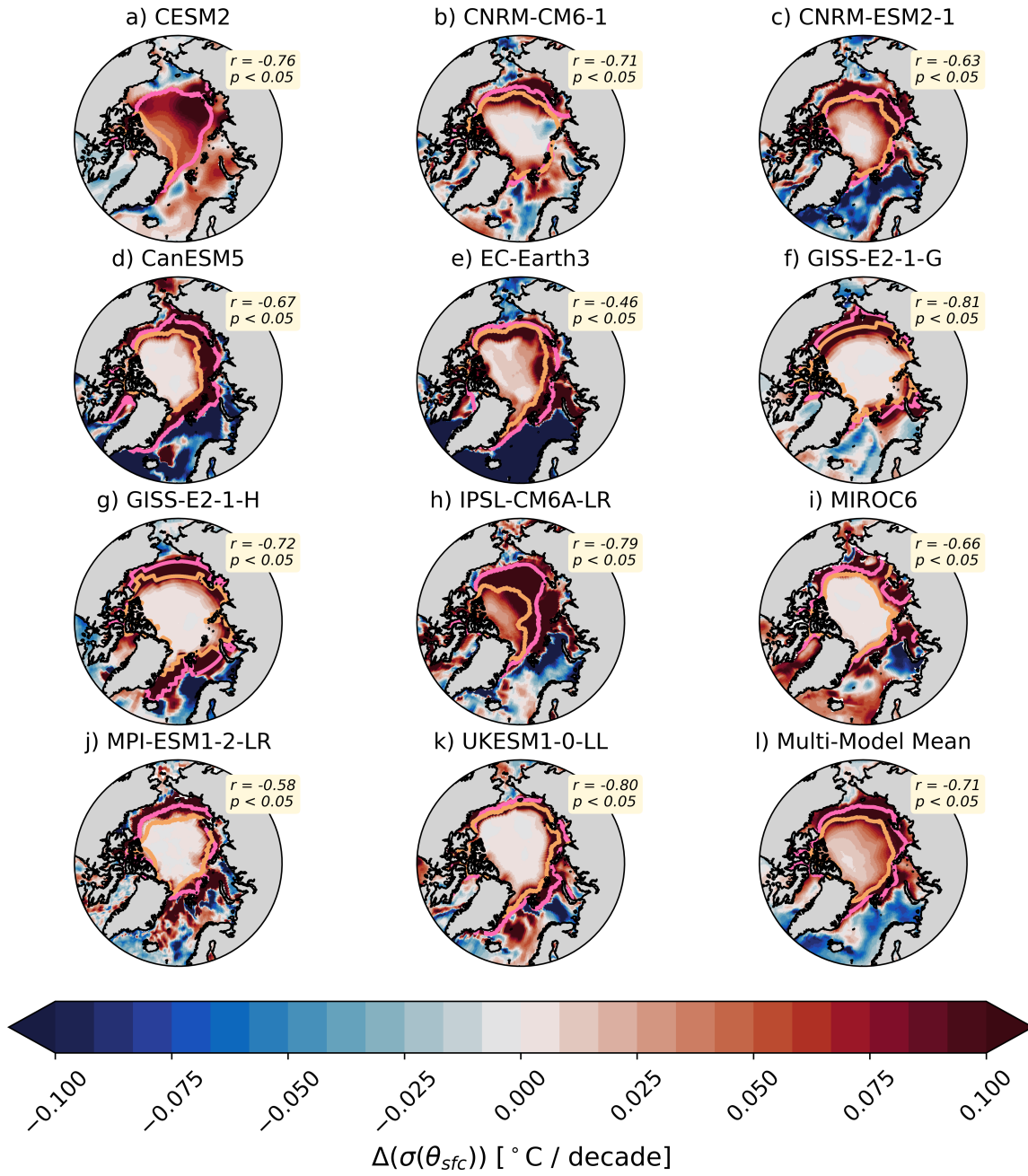


Figure 3.7: CMIP6 1980-2015 trends in September ocean temperature internal variability. As in Fig. 3.4, with September 1980 (magenta) and September 2014 (gold) 50% sea ice concentration contours. Results from the Pearson pattern correlation to $\Delta(\text{SIC})$ (Sec. 2.3) are printed in boxes at the upper right of each plot. Box shading denotes the correlation statistical significance (yellow, $p < 0.05$) or lack thereof (red, $p > 0.05$).

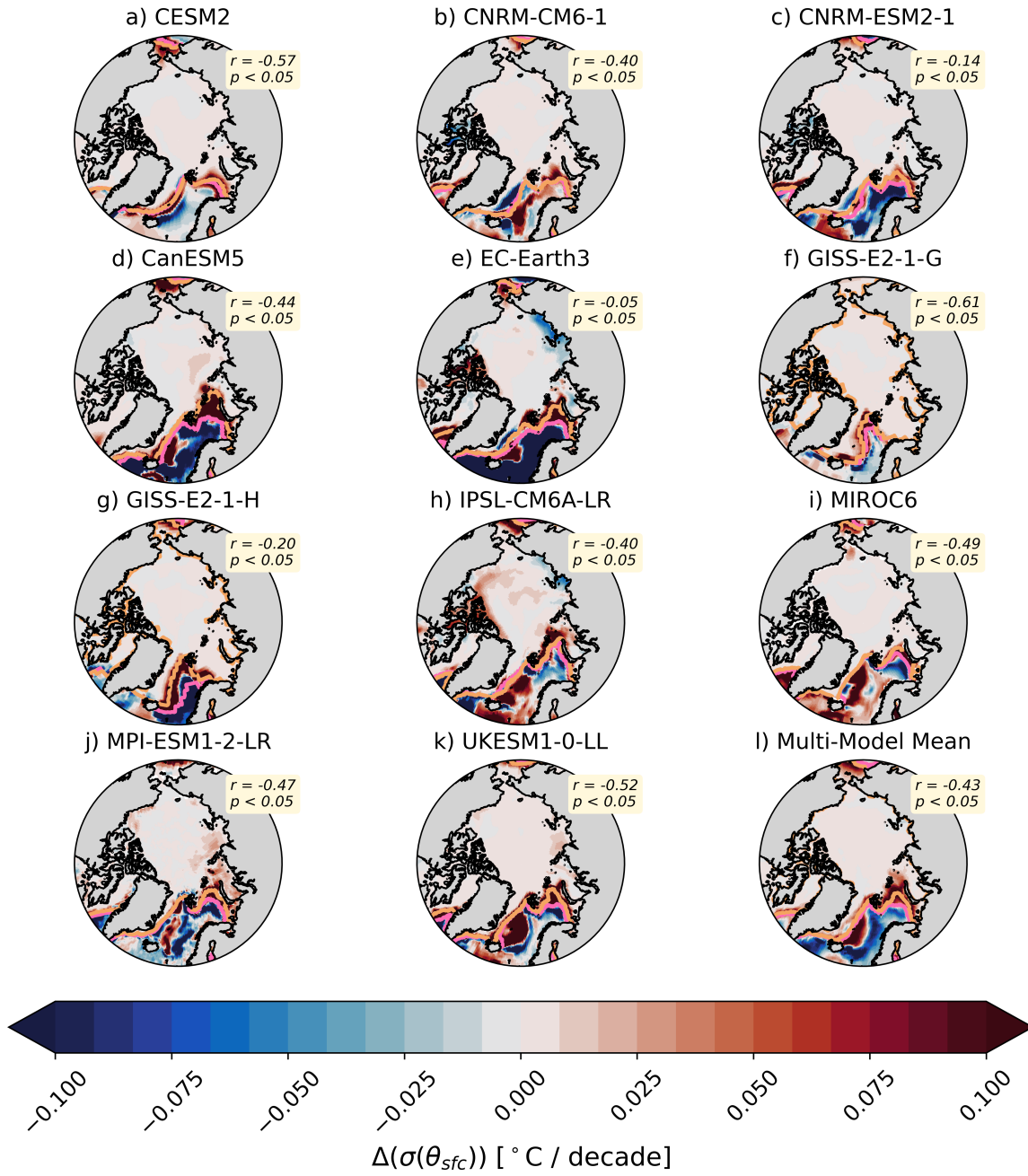


Figure 3.8: CMIP6 1980-2015 trends in March ocean temperature internal variability. As in Fig. 3.6, March 1980 (magenta) and March 2014 (gold) contours of 50% sea ice concentration are over-plotted. Results from the Pearson pattern correlation to $\Delta(\text{SIC})$ (Sec. 2.3) are printed in boxes at the upper right of each plot. Box shading denotes the correlation statistical significance (yellow, $p < 0.05$) or lack thereof (red, $p > 0.05$).

3.2.3 Regional trend magnitudes relative to the pan-Arctic sum trend

To more directly investigate the regional co-location of $\Delta(\sigma(\theta_{\text{sf}}))$ and $\Delta(\text{SIC})$ across models, the following section compares the magnitude of the September and March trends normalized to their pan-Arctic total trend, Σ_{Arctic} (Figs. 3.9, 3.10). Note that Σ_{Arctic} , as the sum of separately-calculated and area-weighted basin-average trends (Fig. 2.1), differs from each model's pan-Arctic mean trend (i.e. Figs. 3.3.A and 3.4.A), which is the average over all area-weighted grid cells in the Arctic. The benefit of this perspective is that it facilitates a qualitative, multi-model regional assessment of where changes in the Arctic Ocean are occurring relative to each other, as well as succinctly illustrating which regions experience the fastest change (i.e., a summarization of Figs. 3.5-3.8). Normalization against the pan-Arctic sum is described by equation 3.1.

$$x_{\text{norm}} = \frac{x}{\sum_{i=1}^n x_i} \quad (3.1)$$

3.1: Normalization formula used to scale basin trends relative to the pan-Arctic sum trend. For each model, x is the long-term trend calculated for a single basin. n is the total number of basins into which the domain of study is partitioned (7), and i denotes a particular basin (e.g. 1: Eurasian Basin, 2: Barents Sea, etc.). Hence, iterating through the denominator gives the sum of all separately-calculated basin trends in the Arctic Ocean and is used to normalize x between -1 and 1.

At the sea ice minimum, the Arctic marginal seas experience the fastest rate of sea ice decline between 1980 and 2015 (9/11 models, Fig. 3.9.i). Of these models, the Siberian Seas dominate sea ice loss in six, with the remaining set depicting the fastest change occurring in the Canadian Arctic Archipelago (CNRM-CM6-1), the Chukchi Sea (GISS-E2-1-G), and the Barents Sea (GISS-E2-1-H). Symptomatic of their aforementioned central Arctic biases,

CESM2 and IPSL-CM6A-LR depict the fastest sea ice decline in the Canadian and Eurasian basins, respectively. The marginal Arctic seas also show decreasing SIC internal variability across 7 or more models (e.g. the Chukchi (10/11), Siberian (7/11), Barents (9/11) and Kara (9/11) Seas) (Fig. 3.9.ii). This indicates that, within and between each model, ensemble members consistently tend toward ice-free conditions in these regions by the end of the historical period. Conversely, regions of the Arctic that retain perennial sea ice by the end of the historical period (i.e. the Canadian Basin, Eurasian Basin, and the Canadian Arctic Archipelago) portray the strongest increasing $\sigma(\text{SIC})$, which suggests members from each ensemble diverge in their rates of sea ice decline in these regions.

In agreement with Fig. 3.4.i-A, amplified September warming of the Arctic Ocean occurs in all basins (Fig. 3.7.iii), with the Barents and Kara seas experiencing the sharpest rate of change in seven of eleven models. For the remaining models (CESM2, CNRM-CM6-1, GISS-E2-1-G, and MIROC6), the largest upper ocean warming occurs in the Chukchi Sea. Despite the robust spatial distribution of warming across models, the trends in September $\sigma(\theta_{\text{sfc}})$ more closely resemble $\Delta(\text{SIC})$ than $\Delta(\theta_{\text{sfc}})$ (Fig. 3.9.iv vs. 3.9.i). For example, the sharpest increases of $\sigma(\theta_{\text{sfc}})$ occur in the Siberian Seas (7/11), which also experience the sharpest $\Delta(\text{SIC})$. This suggests that declining sea ice cover is a more important contributor to September trends in upper Arctic Ocean temperature internal variability than warming alone.

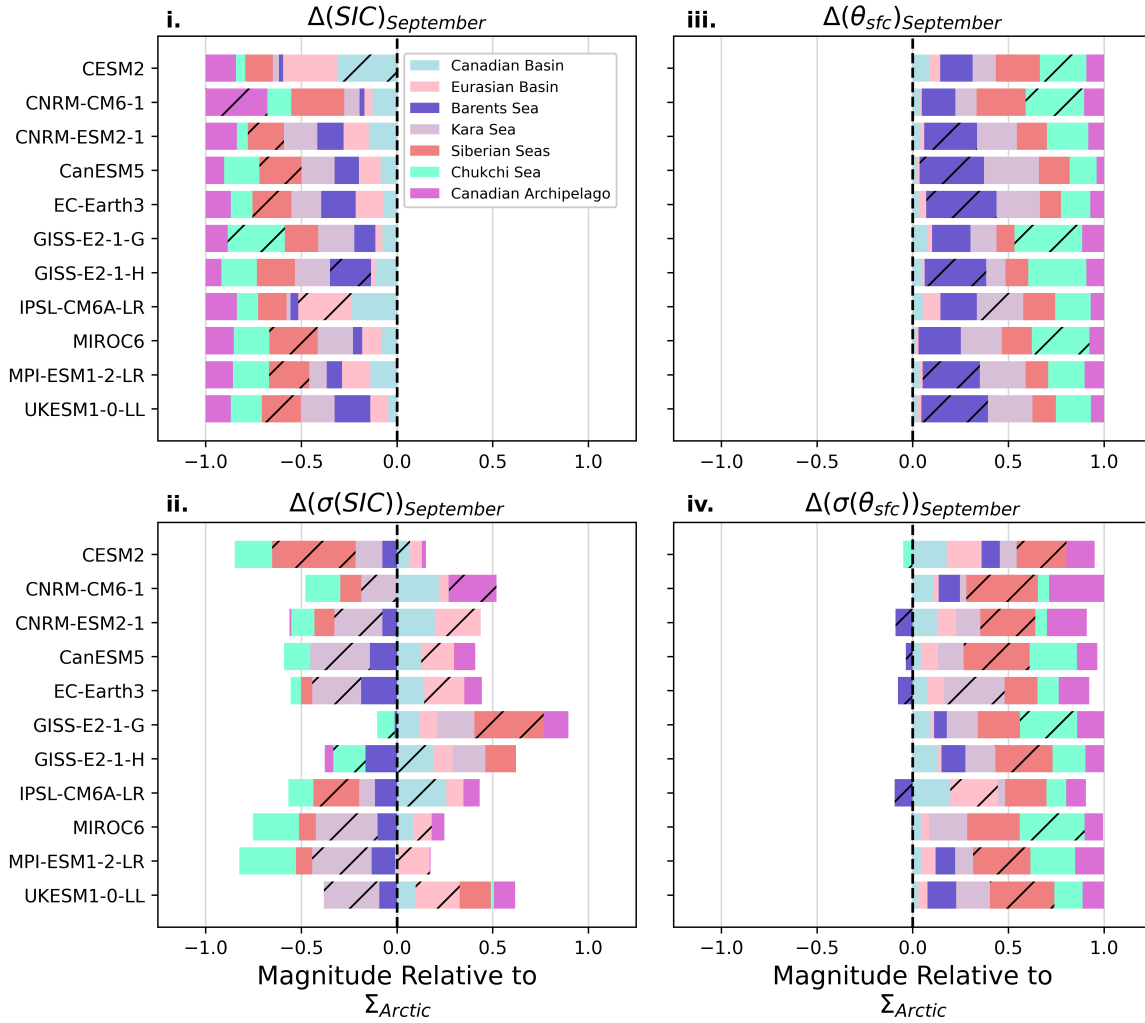


Figure 3.9: CMIP6 1980-2015 sub-basin September magnitudes of $\Delta(SIC)$ (i.), $\Delta(\sigma(SIC))$ (ii.), $\Delta(\theta_{sfc})$ (iii.), and $\Delta(\sigma(\theta_{sfc}))$ (iv.) normalized to their respective sums, Σ_{Arctic} . Hatching on either side of the zero line (vertical black dashed) indicates the basin with the largest positive/negative trend relative to Σ_{Arctic} .

At the sea ice maximum, corroborating previous research, the Barents and Kara seas experience the sharpest decline of March sea ice concentration in all models (Fig. 3.10.i), coinciding with enhanced atmospheric and oceanic warming and the poleward transport of increasingly warm Atlantic water by the end of the historical period [Watts et al., 2021]. These two marginal seas also dominate increased SIC internal variability in 10 of the 11 mod-

els (6/11 Barents, 4/11 Kara), (3.10.ii), with only MIROC6 depicting the largest $\Delta(\sigma(\text{SIC}))$ in the Chukchi Sea. This makes sense given that the rest of the Arctic Ocean is still consistently ice-covered ($\text{SIC} > 50\%$) at this time of year in all models. Hence, SIC ensemble spread is only able to increase in regions where $\text{SIC} < 50\%$, as is the case for these marginal seas (Fig. 3.6).

In March, warming, sea ice decline, and increased upper ocean temperature internal variability are largest in the Barents Sea for the majority of models. This makes sense given the aforementioned clamping effect of sea ice cover on upper ocean temperature and its variance; $\sigma(\theta_{\text{sfc}})$ is only able to change in regions where direct interactions between the ocean and atmosphere are possible (e.g. turbulent ocean-atmosphere heat fluxes, wind-driven mixing, etc.) [Athanas et al., 2026]. At the sea ice maximum, this primarily occurs in the Barents Sea because it is the only basin of study to experience substantial wintertime sea ice loss by the end of the historical period in all models.

Together, these analyses paint a clear picture of the influence of Arctic sea ice decline on amplified upper ocean temperature internal variability. Namely, the reduction of sea ice cover facilitates more efficient communication across the air-sea interface, which enhances temperature variance. Moreover, consensus across the current generation of climate models confirm they capture this relationship despite crucial limitations imposed by their constructions, which are discussed in Section 4. The following section repeats the prior analyses for upper ocean salinity, salinity internal variability, and their connection to Arctic sea ice decline.

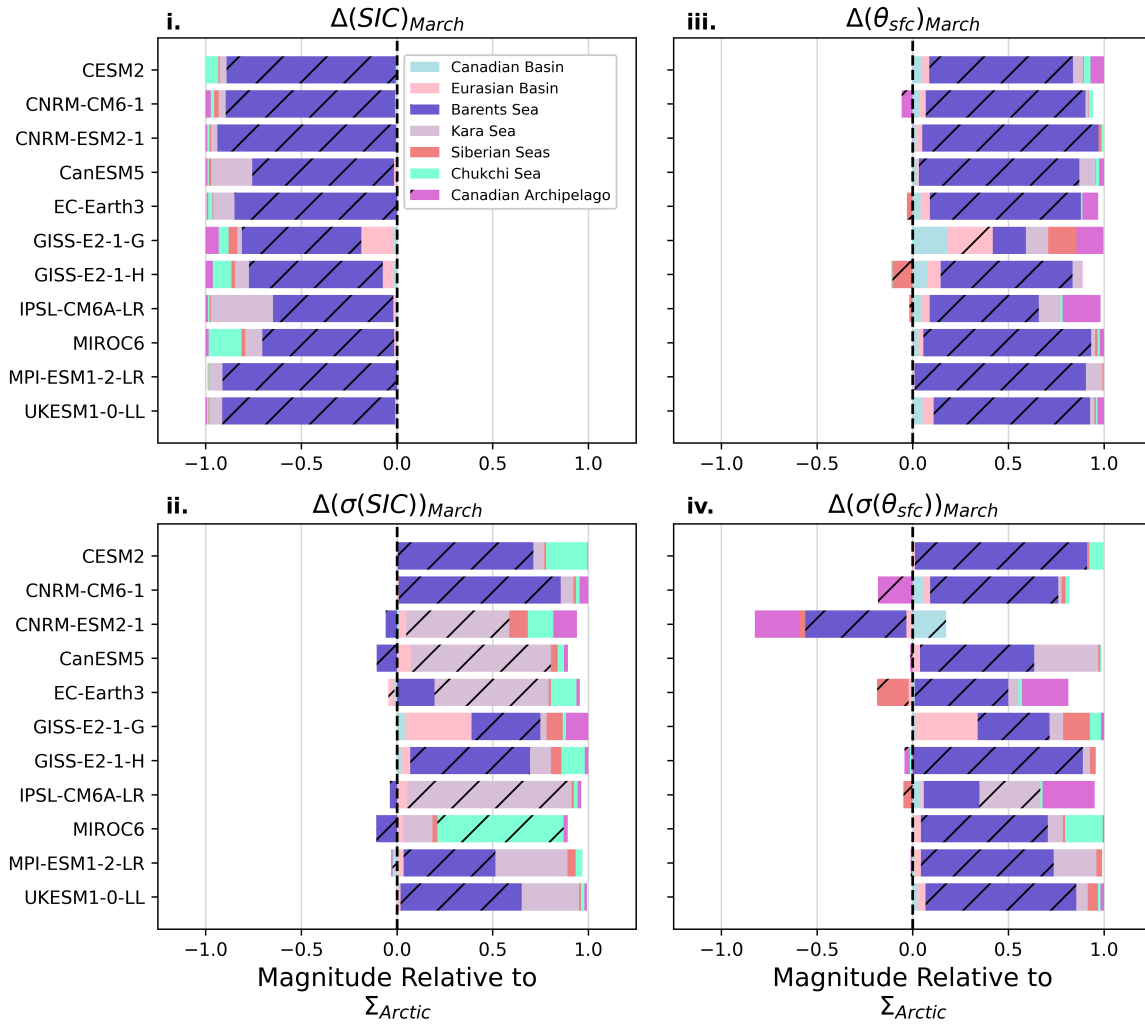


Figure 3.10: CMIP6 1980-2015 sub-basin March magnitudes of $\Delta(SIC)$ (i.), $\Delta(\sigma(SIC))$ (ii.), $\Delta(\theta_{sfc})$ (iii.), and $\Delta(\sigma(\theta_{sfc}))$ (iv.) normalized to their respective sums, Σ_{Arctic} . Hatching on either side of the zero line (vertical black dashed) indicates the basin with the largest positive/negative trend relative to Σ_{Arctic} .

3.3 Salinity internal variability

3.3.1 Monthly salinity long-term trends

Despite large seasonal variations in upper Arctic Ocean salinity (i.e. decreasing during sea ice-melting months, increasing during sea ice-growth months) [Peralta-Ferriz & Woodgate,

2015], the magnitude of forced freshening is relatively uniform year-round with only slight amplification during certain months of the year (Fig. 3.11.i). This is in stark contrast to the strong seasonal enhancement of sea ice decline and warming observed across models in Section 3.2. While the models all depict freshening of the upper Arctic Ocean, they do so with varying magnitudes. EC-Earth3, IPSL-CM6A-LR, and UKESM1-0-LL depict the strongest freshening between the pan-Arctic and central basin averages, with essentially equal rates of freshening between the two central basins (Fig. 3.11.i.B-C). In contrast, CNRM-CM6-1 and GISS-E2-1-H show little to no freshening in the pan-Arctic mean in all seasons ($\Delta(S_{\text{sfc}}) < -0.1 \text{ g kg}^{-1} \text{ dec}^{-1}$). There are also slight discrepancies in the timing of seasonal freshening amplification between models. For example, in EC-Earth3, pan-Arctic upper ocean freshening is strongest in the late fall and early winter (November through January), as opposed to late summer and early fall, when freshwater input to the upper ocean via sea ice melt should be largest. Since the seasonal cycle of salinity in the Arctic is not exclusively tied to the production/melt of sea ice, this discrepancy may be explained by how EC-Earth3 resolves other relevant factors such as riverine input and precipitation [Serreze et al., 2006, Haine et al., 2015, Shu et al., 2018].

While all models agree on relatively uniform year-round freshening of the upper Arctic Ocean that is generally evenly-distributed between the two central basins, their trends in salinity internal variability differ substantially (Fig. 3.11.ii). As with the annual mean (Fig. 3.2.iv), EC-Earth3 ($\Delta(\sigma(S_{\text{sfc}}))_{\text{annual}} \sim -0.041 \text{ g kg}^{-1} \text{ dec}^{-1}$) and UKESM1-0-LL ($\sim 0.043 \text{ g kg}^{-1} \text{ dec}^{-1}$) are opposing outlier extrema, with the rest of the models generally depicting weakly positive $\Delta(\sigma(S_{\text{sfc}}))$. Compared to $\Delta(S_{\text{sfc}})$, there are more models with contrasting inter-basin salinity internal variability trends, which remain fairly uniform year-round (Fig. 3.11.ii.B-C).

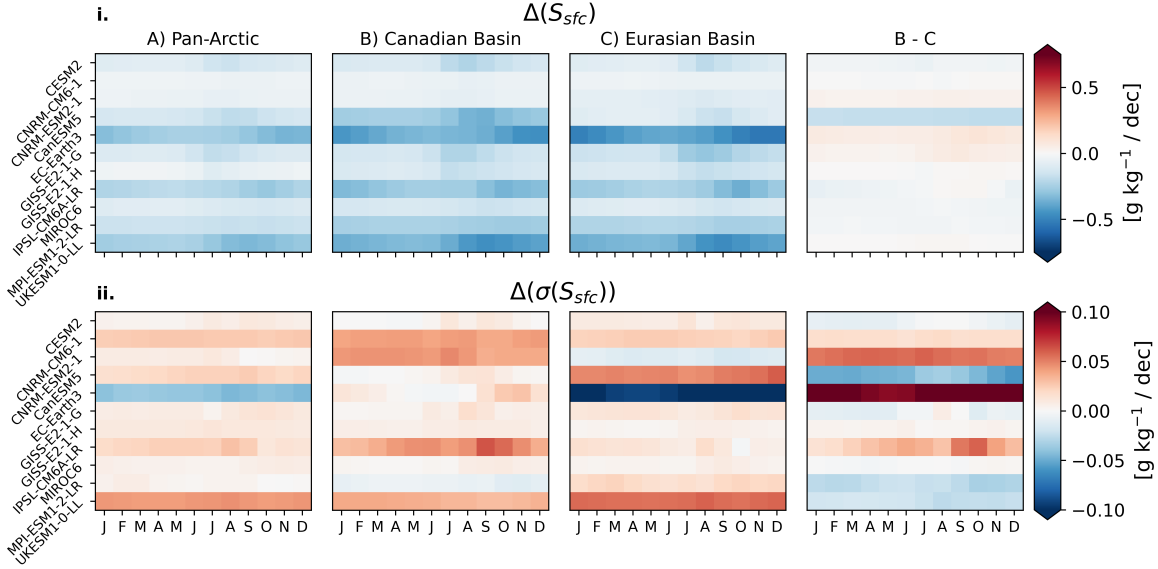


Figure 3.11: CMIP6 upper ocean salinity. Monthly decompositions of 1980-2015 trends in upper ocean salinity (i) and upper ocean salinity internal variability (ii).

3.3.2 Correlating $\Delta(\sigma(S_{sfc}))$ to $\Delta(SIC)$

There is substantial spatial heterogeneity in the magnitude of $\Delta(\sigma(S_{sfc}))$ between models (Fig. 3.12). Unlike the trends in September temperature internal variability (Fig. 3.9), long-term trends in September salinity internal variability exhibit low anti-correlation with $\Delta(SIC)$ ($r_{MMM} = -0.45$). EC-Earth3, which depicts strongly opposing trends in $\sigma(S_{sfc})$ between the Canadian and Eurasian Basins, is not statistically significant in its anti-correlation with $\Delta(SIC)$ at this time of year. In general, $\Delta(\sigma(S_{sfc}))$ is only weakly connected to the reduction of sea ice cover in all models. Furthermore, all models (except MIROC6) depict spatially varying trends interior to 50% SIC, indicating that the insulation from atmospheric interactions by sea ice is not likely to be an important factor in setting trends in salinity internal variability. Rather, in these regions, diapycnal mixing underneath the sea ice (e.g. via ice drift momentum transfer and brine rejection convection), precipitation/runoff variability, and other processes may play a more important role in determining salinity

ensemble spread [Serreze et al., 2006]. Crucially, many of these are processes that the current generation of climate models struggle to depict accurately for reasons including coarse grid resolutions, vertical mixing parameterizations, and precipitation biases [Shu et al., 2018, Khosravi et al., 2022]. These potential drivers of modulated salinity internal variability are discussed in greater detail in Section 4.

In March, $\Delta(\sigma(S_{sfc}))$ and $\Delta(SIC)$ are effectively uncorrelated for all models ($r_{MMM} = 0.06$, $p > 0.05$), with under-ice trends in internal variability similar to those in September. Comparing Figs. 3.12 and 3.13, there is little change in the location of regions with pronounced trends in salinity internal variability, despite the vast differences in the state of sea ice on opposite ends of the year (e.g. IPSL – CM6A – LR_{September} v.s. IPSL – CM6A – LR_{March}). So, despite the large inter-model differences in the patterns and magnitudes of $\Delta(\sigma(S_{sfc}))$, each model’s $\Delta(\sigma(S_{sfc}))$ remains consistent year-round.

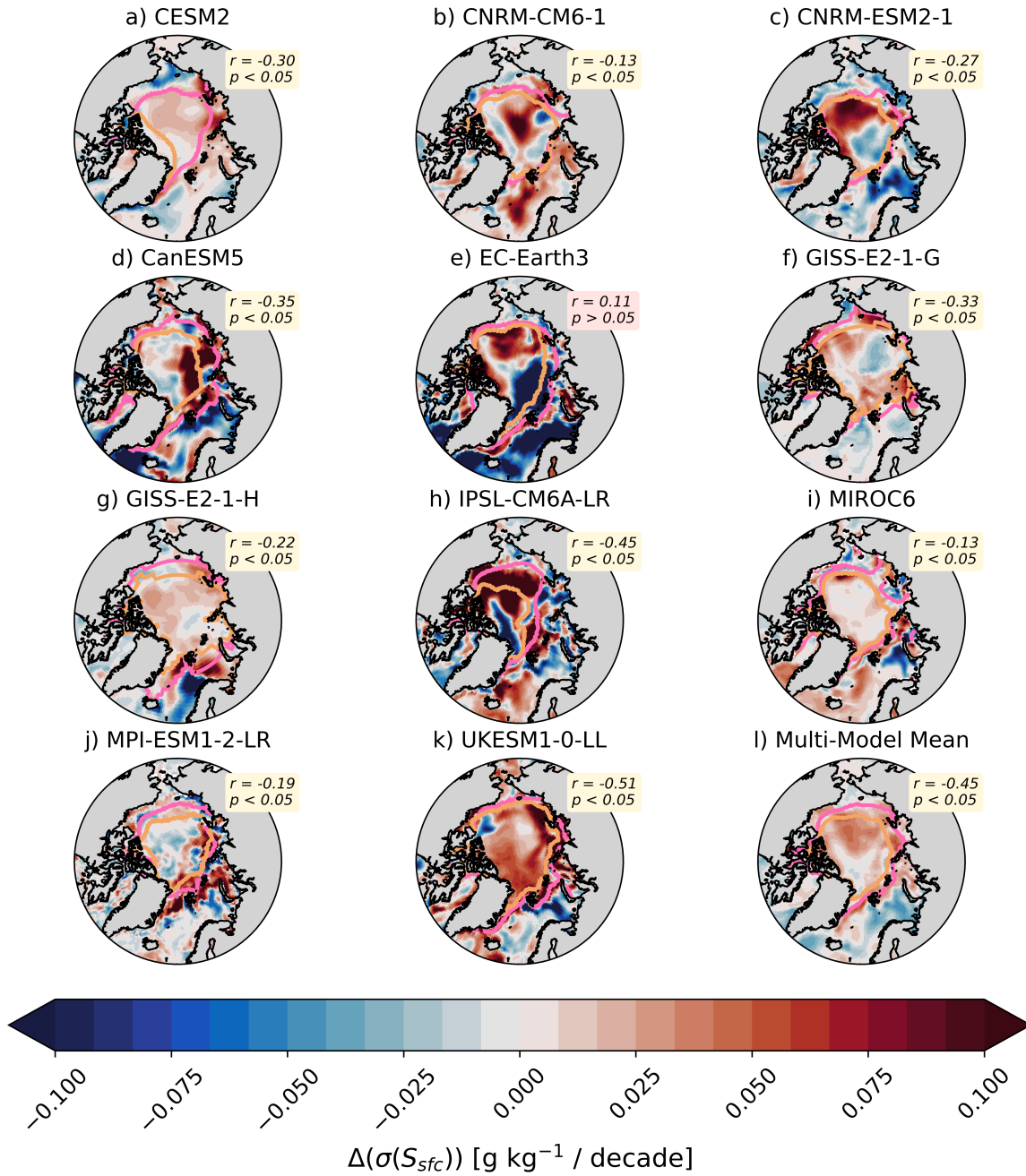


Figure 3.12: CMIP6 1980-2015 trends in September ocean salinity internal variability. As in Fig. 3.4, September 1980 (magenta) and September 2014 (gold) contours of 50% sea ice concentration are over-plotted. Results from the Pearson pattern correlation to $\Delta(\text{SIC})$ (Sec. 2.3) are printed in boxes at the upper right of each plot. Box shading denotes the correlation statistical significance (yellow, $p < 0.05$) or lack thereof (red, $p > 0.05$).

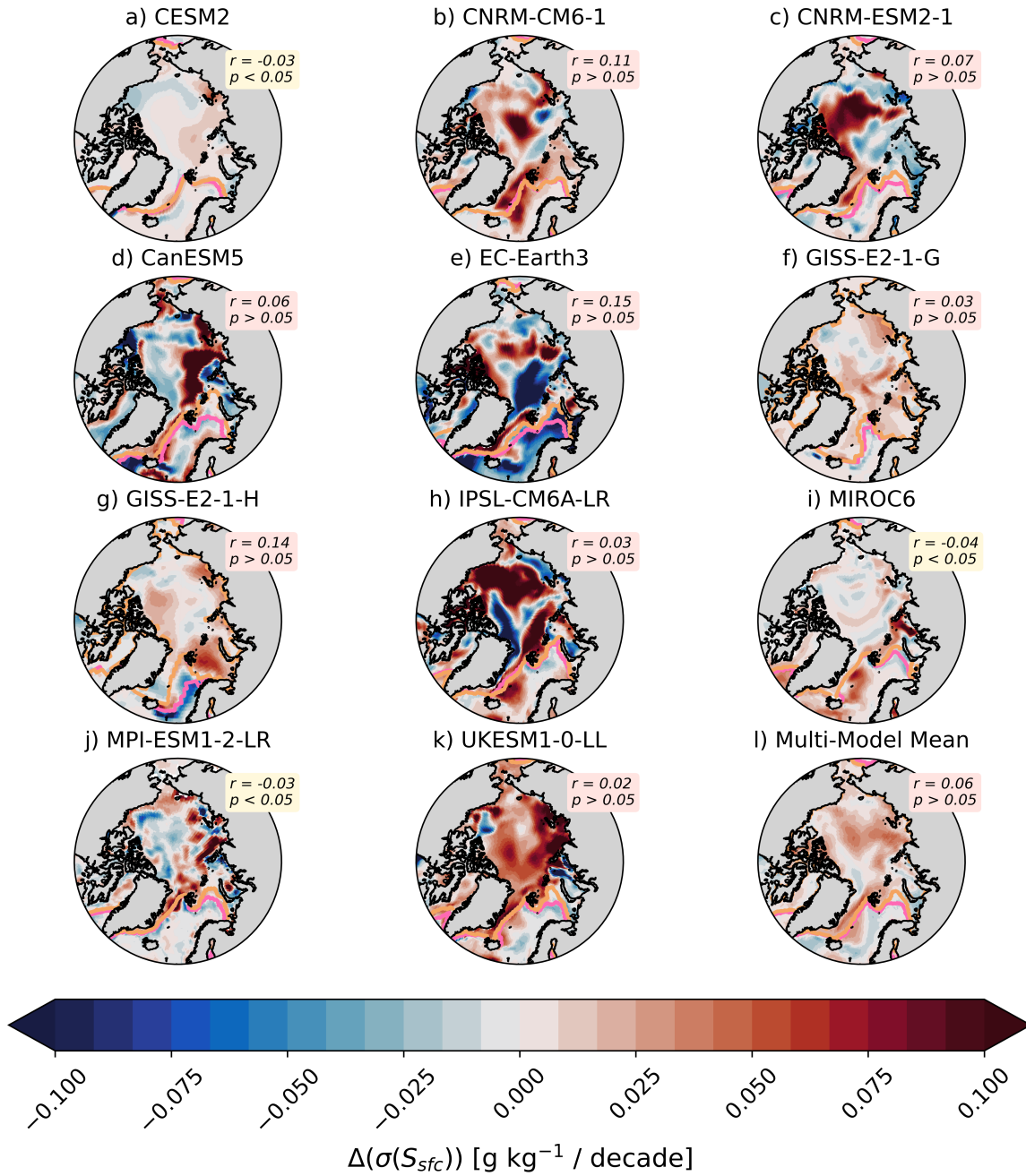


Figure 3.13: CMIP6 1980-2015 trends in March ocean salinity internal variability. As in Fig. 3.4, March 1980 (magenta) and March 2014 (gold) contours of 50% sea ice concentration are over-plotted. Results from the Pearson pattern correlation to $\Delta(\text{SIC})$ (Sec. 2.3) are printed in boxes at the upper right of each plot. Box shading denotes the correlation statistical significance (yellow, $p < 0.05$) or lack thereof (red, $p > 0.05$).

3.3.3 Regional trend magnitudes relative to the pan-Arctic sum trend

At the sea ice minimum, the largest rates of freshening occur in the Canadian Arctic Archipelago (5/11 models), the Canadian Basin (2/11), and the Eurasian Basin (4/11) (Fig. 3.14.iii). The Siberian Seas, while they don't experience the sharpest change in any model, are also a consistent region of freshening (9/11). Despite freshening of the upper ocean being a robust feature of the pan-Arctic mean for all models, the Barents (7/11), Kara (5/11), and Chukchi (6/11) Seas are semi-consistent regions of salinification. This is likely a combined signature of enhanced evaporation under ice-free conditions and increased Atlantic water inflow and subsequent entrainment into the polar mixed layer by the end of the historical period [Boisvert et al., 2015, Polyakov et al., 2017]. Few to none of the basins that dominate freshening or salinification are reflected in their respective $\sigma(S_{sfc})$ trends (3.14.iv), which indicates there is little correspondence between a basin's salinity trend and salinity internal variability trend. Moreover, there is little to no consensus on which regions experience increasing versus decreasing salinity internal variability, with the basins of maximum/minimum change in either direction differing between models. This resounding lack of overlap between the basins of maximum/minimum $\Delta(\sigma(S_{sfc}))_{\text{September}}$ and those of $\Delta(\text{SIC})_{\text{September}}$ (3.14.i) strongly suggest that these two signatures of change are unrelated across models.

Similar to the results during the sea ice minimum, models show little correspondence between the patterns of sea ice melt, freshening, and salinity internal variability trends during the sea ice maximum (Fig. 3.15). Although the majority of Arctic sea ice loss and increased SIC internal variability occur in the Barents and Kara Seas across the models, neither region

shows consistent trends in salinity internal variability across models. Furthermore, the basins that dominate wintertime freshening (i.e. the Canadian Arctic Archipelago (4/11), Canadian Basin (2/11), and Eurasian Basin (5/11)) are not the same basins that dominate $\Delta(\sigma(S_{\text{sfc}}))_{\text{March}}$.

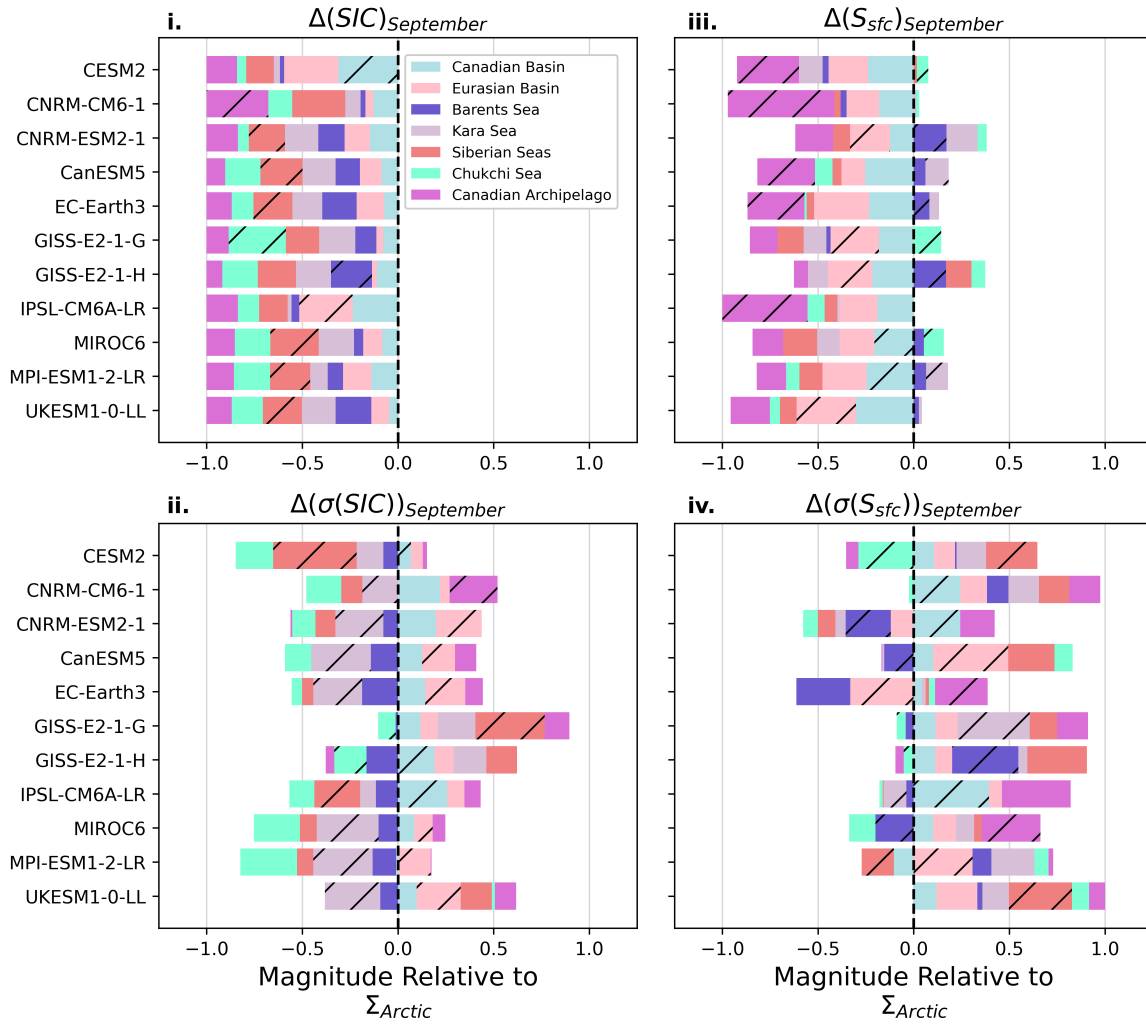


Figure 3.14: CMIP6 1980-2015 sub-basin September magnitudes of $\Delta(SIC)$ (i.), $\Delta(\sigma(SIC))$ (ii.), $\Delta(S_{\text{sfc}})$ (iii.), and $\Delta(\sigma(S_{\text{sfc}}))$ (iv.) normalized to their respective sums, Σ_{Arctic} . Hatching on either side of the zero line (vertical black dashed) indicates the basin with the largest positive/negative trend relative to Σ_{Arctic} .

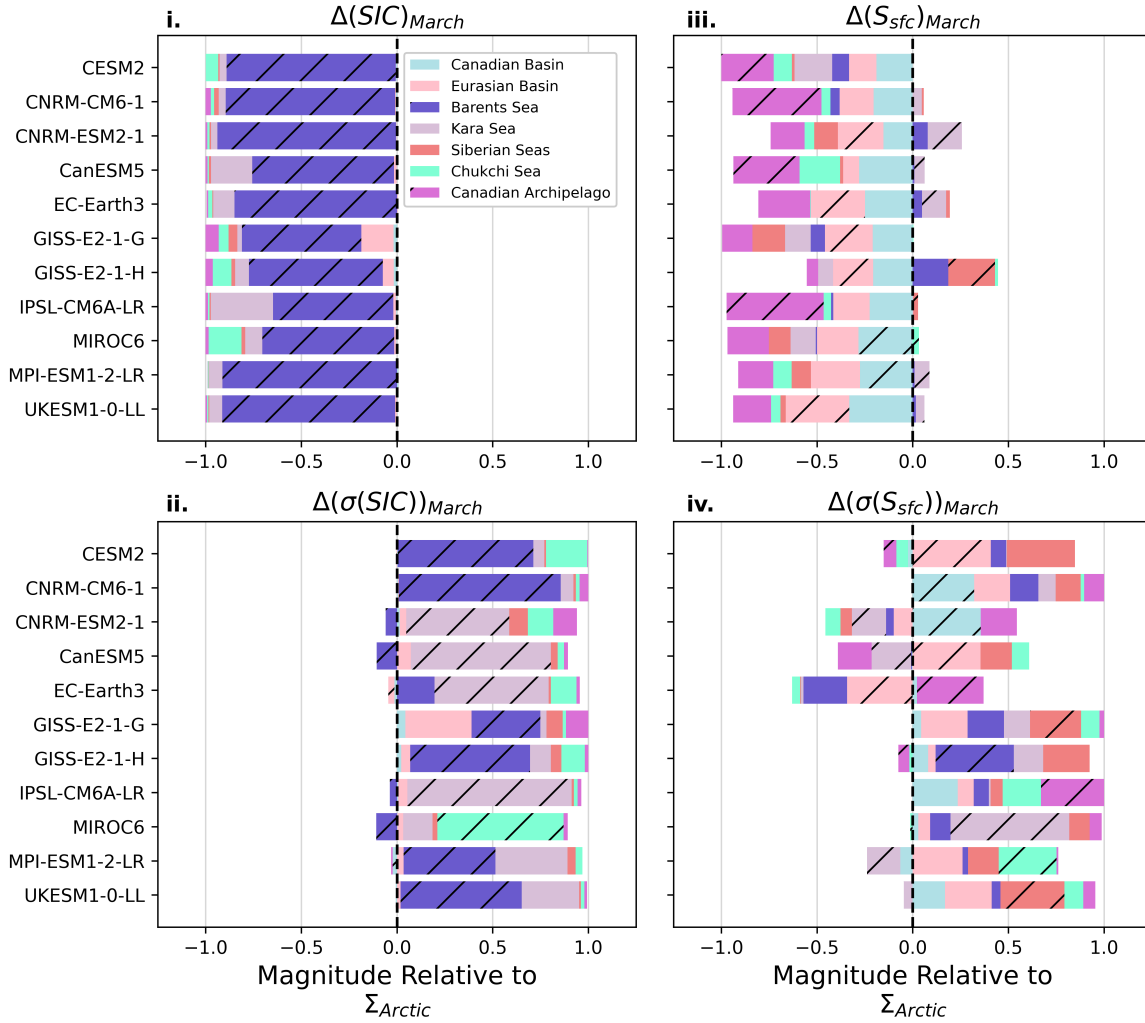


Figure 3.15: CMIP6 1980-2015 sub-basin March magnitudes of $\Delta(SIC)$ (i.), $\Delta(\sigma(SIC))$ (ii.), $\Delta(S_{sfc})$ (iii.), and $\Delta(\sigma(S_{sfc}))$ (iv.) normalized to their respective sums, Σ_{Arctic} . Hatching on either side of the zero line (vertical black dashed) indicates the basin with the largest positive/negative trend relative to Σ_{Arctic} .

In all, these analyses indicate that the current generation of climate models disagree on the recent historical trends in upper Arctic Ocean salinity internal variability. Each of the examined models depict trends in $\sigma(S_{sfc})$ that differ in sign, magnitude, and location across the Arctic, despite simulating consistent patterns of warming, freshening, and sea ice melt. While the relationship between declining sea ice and increased temperature

internal variability is likely robust, the same cannot be said of the relationship between the former and $\Delta(\sigma(S_{sfC}))$. Potential reasons for this discrepancy are discussed in the following section.

Chapter 4

Discussion

4.1 Statistical differentiation of trends from historical internal variability

The primary objective of this thesis is to compare recent historical trends in upper Arctic Ocean temperature and salinity internal variability and their relationships to declining sea ice across the current generation of climate models. To this end, robust anti-correlations between increased temperature internal variability and sea ice decline were quantified, which the models consistently depict. In contrast, trends in salinity internal variability exhibit far more heterogeneity in their sign, magnitude, and spatial distribution across models, and display comparatively lower or no correlation to $\Delta(\text{SIC})$ depending on the time of year.

How likely were these trends in internal variability to occur in the historical period? By definition, internal variability is an irreducible, unpredictable, and (via the results of

this thesis) non-stationary component of climate uncertainty. Therefore, it's reasonable to suggest the trends in upper ocean temperature and salinity internal variability shown here could've occurred in the absence of forcing (i.e., the null hypothesis). To confirm whether or not this is the case, following [Swart et al., 2015], the 1980-2015 pan-Arctic September and March trends in $\sigma(\theta_{sfc})$ and $\sigma(S_{sfc})$ from each model were compared to all other 35-year trends between 1850 and 1980. Statistical significance (and therefore differentiation from unforced historical internal variability) was assessed at the 95% confidence level, assuming underlying normal distributions of $\Delta(\sigma(\theta_{sfc}))$ and $\Delta(\sigma(S_{sfc}))$. Despite the low sample size ($n=96$ per model), since the forced response of upper Arctic Ocean temperature and salinity began onward of 1980, we expect the central limit theorem to hold for ensemble standard deviation trends prior to this year (i.e. 35-year σ trends are randomly centered about zero). Hence, a normal distribution is likely a reasonable assumption to make and a useful metric for assessing the likelihood of 1980-2015 internal variability trends.

1980-2015 trends in September $\sigma(\theta_{sfc})$ are statistically different from the historical record across all models and the multi-model mean (Fig. 6.1), indicating that there was less than a 5% chance for the 35-year temperature internal variability increase to occur in the absence of forcing. This statistical significance holds for the majority of models (8/11) and the MMM in March (Fig. 6.2), despite upper ocean warming and sea ice losses being far less pronounced in the winter than the summer [Serreze & Stroeve, 2015, Stroeve & Notz, 2018]. This differentiation from the unforced historical internal variability across models and on opposite ends of the year supports the conclusion that increased upper ocean temperature internal variability is a robust year-round response to forced changes in the Arctic Ocean. The same cannot be said for either September or March 1980-2015 trends in salinity internal variability (Figs. 6.3 & 6.4). The majority of models do not exhibit trends which are statistically different from

any that occurred earlier in the historical period. Rather, only GISS-E2-1-G, GISS-E2-1-H, and UKESM1-0-LL retain statistically different increases to $\sigma(S_{sfc})$ on opposite ends of the year, which via the previous analyses, are poorly correlated to the loss of sea ice. As such, the found 1980-2015 trends in pan-Arctic salinity internal variability do not exist beyond the threshold of natural variability, and therefore could've occurred in the absence of forcing.

The following section explores potential air-ice-sea mechanisms behind the increased temperature internal variability that could explain the results in Sections 3.1 and 3.2. Possible sources of the disagreement in the modeled salinity internal variability trends found in Section 3.3 are then discussed, before summarizing the thesis's key findings and presenting directions for future research in the following chapter.

4.2 Forced response air-ice-sea mechanisms for enhanced Arctic Ocean temperature internal variability

Simplified schematics of the mechanisms for enhanced upper Arctic Ocean temperature internal variability in response to sea ice loss are given by Figs. 4.1 & 4.2. For all of recorded history, the Arctic Ocean has existed with perennial sea ice cover, which acts to mediate or prohibit communication between the upper ocean and atmosphere depending on its concentration, reflectivity, and thickness (Fig. 4.1) [Rainville & Woodgate, 2009, Landrum & Holland, 2022, Siddiqui & Horvat, 2026]. As the Arctic climate continues to tend towards seasonally sea ice-free conditions within the next several decades [Heuzé & Jahn, 2024, Jahn et al., 2024], thermodynamic interactions between the upper ocean and atmosphere are

projected to continue to intensify [Polyakov et al., 2020, Muilwijk et al., 2024, Zanowski et al., 2026]. In the central Arctic basins and marginal seas, the thinning, increasingly mobile ice pack is less able to convert and dissipate wind energy as internal stress. As a result, the excess energy (now in the form of both wind and frictional sea ice stress) increases upper ocean surface stress (i.e. the sea surface absorbs more mechanical energy from both the atmosphere and mobile sea ice). This increase accelerates horizontal currents and vertical mixing of the upper Arctic Ocean via Ekman processes and the generation of internal waves [Muilwijk et al., 2024]. On smaller scales, increasing surface stress coincides with enhanced upper ocean mesoscale eddy activity in all basins [Li et al., 2024], which was demonstrated by [Le Gloannec et al., 2025] to drive increases in both oceanic temperature and salinity internal variability in the Arctic-North Atlantic sector. The models examined in this thesis are too coarse in resolution (~ 100 km) to resolve these finer mesoscale features, but the results of [Muilwijk et al., 2024] confirm they indeed capture the broader increase of ocean surface stress in regions of reducing sea ice packs. Therefore, the thesis's results are consistent with the connection between sea ice decline, wind-driven mixing intensification, and the amplified upper ocean temperature internal variability found by [Le Gloannec et al., 2025].

In observations and CMIP6-generation models, reduced Arctic sea ice cover also modulates turbulent ocean-atmosphere heat fluxes by amplifying their seasonal magnitudes through the end of the century (i.e. growing open-ocean area permits more heat loss to the atmosphere in the fall and winter and increased ocean heat uptake in spring and summer) [Screen & Simmonds, 2010, Shu et al., 2022, Zanowski et al., 2026]. In higher resolution models (e.g. eddy-resolving), these turbulent heat fluxes are further enhanced by projections of amplified upper-ocean eddy activity [Manucharyan & Thompson, 2022].

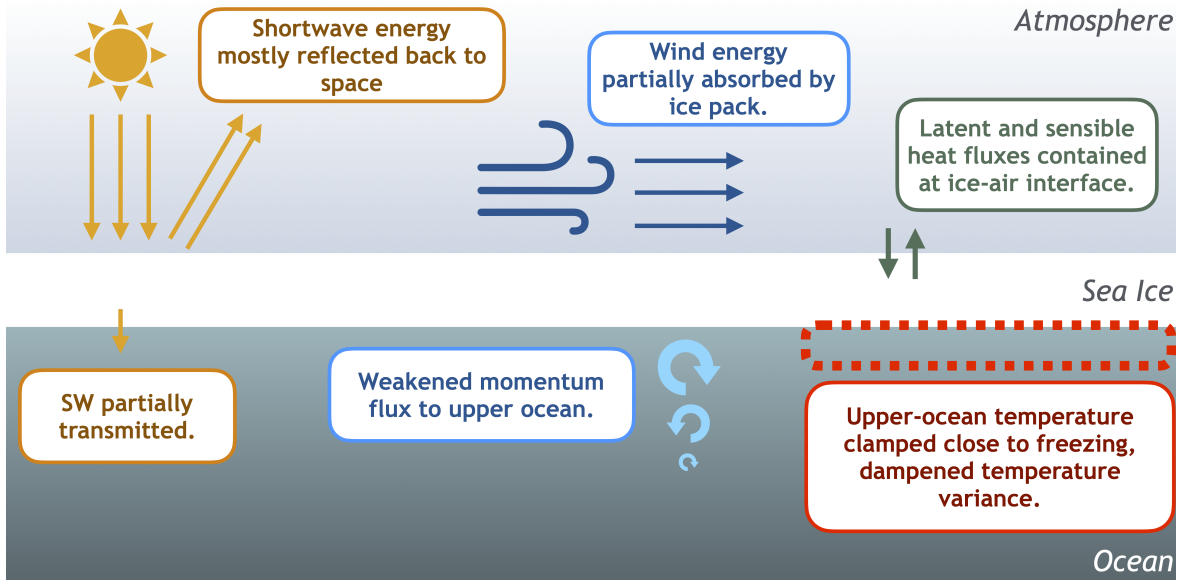


Figure 4.1: Simplified diagram describing key present-day thermodynamic influences of sea ice cover on upper Arctic Ocean temperature variance. Adapted from [Muilwijk et al., 2024].

Enhanced ocean-atmosphere heat fluxes facilitate increasing temperature internal variability (i.e. widening ensemble spread) by allowing for a broader range of possible upper Arctic Ocean temperatures, which otherwise would not be achieved with sufficient sea ice cover [Rainville et al., 2011] (Fig. 4.2). The results of this thesis, when paired with those from [Shu et al., 2022], thusly support this cause-and-effect relationship.

As stated in the prior paragraphs, while the current generation of CMIP models capture the broader forced trends in Arctic Ocean surface stress and heat flux variability, their horizontal resolutions are too low to permit or resolve mesoscale upper-ocean eddies. This is an important omission, given their kinetic energy impact on oceanic heat dissipation via mechanical and turbulent fluxes is highest on length scales of 1 – 10 km [Liu et al., 2024]. The magnitudes of internal variability trends presented in Section 3 are likely underestimates of true internal variability as a result.

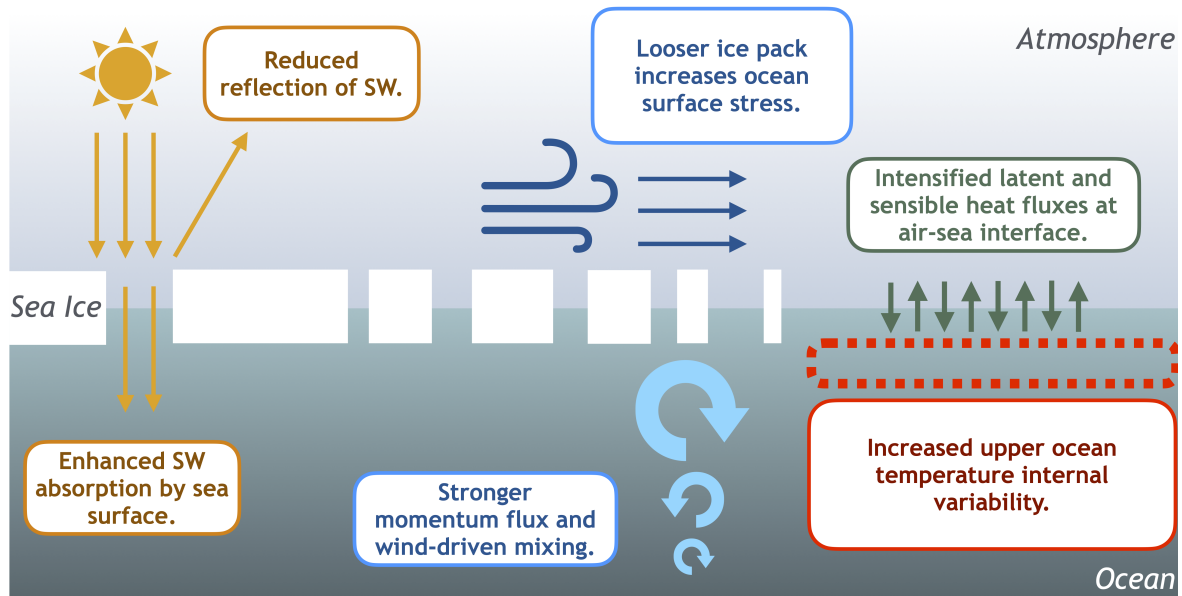


Figure 4.2: Simplified diagram describing key future thermodynamic influences of reduced sea ice cover on upper Arctic Ocean temperature variance. Adapted from [Muilwijk et al., 2024].

4.3 Potential causes for model disagreement in salinity internal variability

4.3.1 Liquid and solid freshwater processes

Upper Arctic Ocean salinity internal variability in any climate model is intrinsically linked with its simulation of the Arctic climate’s liquid freshwater processes. While the discussion of freshwater-induced salinity variability in this study was largely focused on its input to the upper ocean via sea ice melt, the primary sources of liquid freshwater to the Arctic Ocean are river discharge, net precipitation, and the import of low-salinity Pacific water through the Bering Strait [Shu et al., 2018]. These sources of freshwater are largely parameterized and resolved to differing degrees across the current CMIP generation, and are therefore subject to differing model biases [Zanowski et al., 2021, Wang et al., 2022]. Examining these

biases may help to explain the inter-model differences in salinity internal variability trends presented in Section 3.

Riverine input is the dominant source of liquid freshwater to the Arctic Ocean, and it is projected to increase by 30% by the end of the century [Nummelin et al., 2016, Shu et al., 2018, Zanowski et al., 2021, Wang et al., 2022]. Despite overestimating the total liquid freshwater storage, the CMIP6 multi-model mean riverine input to the Arctic Ocean is smaller than that derived from observations [Wang et al., 2022]. These biases partly originate from discrepancies between simulated and observed climatologies of sea surface salinity; the multi-model mean is too salty in the Canadian Basin, Siberian Seas, and the Kara Sea, while being too fresh in the Eurasian Basin and Barents Sea. Constraining representations of riverine input closer to observations across models may therefore increase agreement in trends in $\sigma(S_{sfc})$ by providing more consistent mean state upper ocean salinities from which their ensemble members may vary.

Net precipitation in the Arctic is expected to overtake the Bering Strait Pacific inflow as the second-most dominant source of freshwater by the middle of the 21st century [Zhang et al., 2013, Wang et al., 2022], and is generally well-represented by the CMIP6 multi-model mean in comparison with observations. Despite this, inter-model spread in precipitation minus evaporation (P-E) is the largest of any term in the simulated Arctic LFWC. For the same reason improving river discharge may lead to better agreement in simulated salinity internal variability, inconsistencies in the simulated pan-Arctic atmospheric inputs of freshwater may partly explain the spatial heterogeneity of trends in $\sigma(S_{sfc})$ between models (Figs. 3.12, 3.13).

CMIP6 models also exhibit substantial differences in their depictions of historical liquid

and solid freshwater fluxes through the Bering Strait and other Arctic gateways [Zanowski et al., 2021]. For the subset examined in [Zanowski et al., 2021], the discrepancies in the trends between simulated and observational fluxes were attributed mostly to model bias over internal variability, citing both inter-model differences in the sign of trends and higher inter-model than intra-model spread. At present, the Arctic Ocean receives around 30% of its liquid freshwater from Pacific inflow through the Bering Strait [Serreze et al., 2006], with the majority of its liquid and solid export flowing to the North Atlantic Ocean via the Fram Strait, Barents Sea Opening, and straits in the Canadian Arctic Archipelago [Lique et al., 2016]. Discrepancies in these simulated fluxes may partly explain the models' disagreement over the sign and magnitude of September and March salinity internal variability trends between the central basins and marginal seas (Figs. 3.14.iv, 3.15.iv).

Each of the aforementioned Arctic freshwater biases are further subject to uncertainties associated with model resolution [Fuentes-Franco & Koenigk, 2019] and parameterizations of dynamical oceanic processes not-yet included in CMIP6 (i.e. tidal mixing, sea ice-wave interactions, mesoscale eddy activity, etc.) [Wang et al., 2022]. These limitations are especially true for the narrow straits of the Arctic (i.e. the Bering Strait and straits in the Canadian Arctic Archipelago), which are less than 100 km in diameter and whose topographies are therefore only loosely approximated by current-generation coupled models [Lique et al., 2016]. In theory, however, improvements to grid resolutions in future generations of CMIP and their representations of finer-scale solid and liquid freshwater processes and transports may help to resolve disagreements in $\Delta(\sigma(S_{sfc}))$ by ensuring ensemble members have spatially consistent mean states from which to vary.

4.3.2 Ice sheet parameterizations and sub-surface salinity biases

At the time of their initial construction and publication for analysis, the standard historical CMIP6-DECK experiments (the data from which this study’s analyses were performed) did not feature interactive Greenland ice sheet (GrIS) dynamics for any model [Eyring et al., 2016]. Instead, all of its surface mass balance processes (i.e. precipitation accumulation vs. runoff, marine termination, iceberg calving and export, subsurface freshwater plumes) are parameterized [Hofer et al., 2020, Nowicki et al., 2016]. Although the GrIS is the single largest freshwater reservoir in the northern hemisphere [Solomon et al., 2021], it contributes less freshwater to the Arctic than continental river runoff. Still, improved model representation of GrIS processes may improve the representation of salinity internal variability, particularly near Greenland.

As pointed out by [Khosravi et al., 2022], there also exist substantial biases in diapycnal mixing throughout the Arctic Ocean in CMIP6. These inconsistencies with observations are frequently attributed to inaccurate depictions of the sub-halocline Atlantic water layer, which is too thick and deep in the CMIP6 multi-model mean. The current generation of models also tend to disagree on the strength and trends of upper ocean stratification in the Arctic [Mulwijk et al., 2023], and therefore depict diapycnal mixing differently. Given that the entrainment of warm, salty Atlantic water into the cool, fresh polar mixed layer is an essential component of upper Arctic Ocean temperature, salinity, and sea ice variability [Zhang & Steele, 2007], the disagreements in the simulated internal variability shown here may also be partly attributed to these sub-surface biases.

These myriad Arctic Ocean biases are substantial hurdles to accurately simulating pan-

Arctic and regional upper ocean salinity. The results of this thesis are consistent with the aforementioned studies by highlighting the influence of these biases on trends in salinity internal variability. Constraining salinity biases in models to more closely fit observations should theoretically yield more consistent depictions of internal variability by ensuring ensemble members are varying from similar mean states, which at present, they do not.

Chapter 5

Conclusion

5.1 Summary of results

This thesis, to my knowledge, provides the first multi-model CMIP6 assessment of historical temperature and salinity internal variability in the upper Arctic Ocean. Across the considered models, robust anti-correlations between sea ice decline (negative $\Delta(\text{SIC})$) and amplified temperature internal variability (positive $\Delta(\sigma(\theta_{\text{sfc}}))$), even in the presence of substantial model bias, were quantified. By synthesizing this result with existing literature, a relationship between Arctic sea ice decline and upper ocean temperature internal variability is proposed; as sea ice cover declines, more of the upper ocean is exposed to open sea-air interactions. In response, temperature internal variability increases via enhanced atmospheric fluxes of mechanical and thermal energy (Figs. 4.1, 4.2).

In contrast with $\Delta(\sigma(\theta_{\text{sfc}}))$, simulated trends in upper ocean salinity internal variability present a more complicated narrative. Despite all models capturing consistent patterns of freshening and sea ice melt, large inter-model differences were identified in the sign,

magnitude, and spatial distribution of $\Delta(\sigma(S_{sfc}))$. There is a year-round lack of correlation between sea ice decline and trends in salinity internal variability. This result suggests that the modeled changes in salinity internal variability are likely driven by different environmental factors than $\Delta(\sigma(\theta_{sfc}))$, and via comparison to previous studies, likely more susceptible to freshwater model biases.

5.2 Directions for future research & concluding remarks

For the sake of improving predictions of the future Arctic climate, the need to continue constraining model internal variability via the robust assimilation of higher and higher-quality observational data into initial conditions has been well-established [Hawkins & Sutton, 2009]. Concurrent to this aim, this thesis’s findings underscore the need for a more thorough understanding of the drivers of changing Arctic Ocean temperature and salinity internal variability. [Zanowski et al., 2026] connected future increases in upper Arctic Ocean temperature internal variability to amplified seasonal ocean-atmosphere heat fluxes in a single CMIP6-generation model. To place this mechanism into the historical multi-model perspective, these simulated fluxes should also be examined and correlated to $\Delta(\sigma(\theta_{sfc}))$ across CMIP6. Other non-oceanic drivers of temperature and salinity internal variability (e.g. ocean wind stress, riverine and precipitation freshwater fluxes, etc.) would also likely be worth incorporating into the analyses performed here. Additionally, this study did not directly examine potential drivers of $\Delta(\sigma(\theta_{sfc}))$, $\Delta(\sigma(S_{sfc}))$ from beneath the 15-meter depth. Given the importance of upper ocean stratification in determining Arctic Ocean temperature, salinity, and sea ice variability [Carmack, 2007, Timmermans & Marshall, 2020], connecting internal variability trends to vertical mixing and entrainment between water masses across the pycnocline may unlock additional insights. Lastly, while

the models presented in this study represent a broad diversity from institutions around the world, it's possible they may not be entirely representative of true consensus across CMIP6. Developments on this research could therefore aim to incorporate more models and ensemble members into the analyses.

Simulating the internal variability response to the Arctic Ocean's mean state transition to seasonally ice-free conditions necessitates careful consideration of the relevant mechanical and thermodynamic processes that dictate temperature and salinity variance. CMIP6 models, while capturing a robust relationship between sea ice decline and enhanced temperature internal variability, are still somewhat hindered by omissions and parameterizations of these processes, which lead to substantial model biases in their simulated change. For this study, the impact of these biases is most-felt in the substantial disagreement for historical trends in salinity internal variability. Increasing model agreement in internal variability trends in the next generation of climate models, which ultimately serves to improve our predictions of the Arctic Ocean's future state, will thusly rely on the incorporation and fine-tuned parameterization of these processes for all components of the climate system. The results presented in this thesis can be used as a baseline for measuring this improvement.

Chapter 6

Supplementary Information & Tables

Table 1: Summary and specifications of the historical (1980-2015) CMIP6 simulation data used in the study.

Model	Institution	Ocean Component	Sea Ice Component	Variables
CESM2	NCAR	POP2 (320x384)	CICE5.1	thetao, so, siconc [10]
CNRM-CM6-1	CNRM-CERFACS	NEMO 3.6 (362x294)	GELATO 6.1	thetao, so, siconc [10]
CNRM-ESM2-1	CNRM-CERFACS	NEMO 3.6 (362x294)	GELATO 6.1	thetao, so [10], siconc [6]
CanESM5	CCCma	NEMO 3.4.1 (361x290)	LIM2	thetao, so, siconc [10]
EC-Earth3	EC-Earth Consortium	NEMO 3.6 (362x292)	LIM3	thetao, so, siconc [10]
GISS-E2-1-G	NASA-GISS	GISS Ocean (288x180)	GISS SI (144x90)	thetao, so, siconc [10]
GISS-E2-1-H	NASA-GISS	HYCOM Ocean (360x180)	GISS SI (144x90)	thetao, so, siconc [10]
IPSL-CM6A-LR	IPSL	NEMO-OPA (363x332)	LIM3	thetao, so, siconc [10]
MIROC6	MIROC	COCO 4.9 (360x256)	COCO 4.9	thetao, so, siconc [10]
MPI-ESM1-2-LR	MPI-M	MPIOM 1.63 (256x220)	Unnamed Hibler 79	thetao, so, siconc [10]
UKESM1-0-LL	MOHC	NEMO-HadGEM3-GO6.0 (360x330)	CICE-HadGEM3-GSI8	thetao, so, siconc [10]

Table 2: Citations for the historical CMIP6 simulation data used in the study.

Model	Citation	ESGF DOI
CESM2	[Danabasoglu, 2019]	10.22033/ESGF/CMIP6.7627
CNRM-CM6-1	[Voldoire, 2018]	10.22033/ESGF/CMIP6.1375
CNRM-ESM2-1	[Seferian, 2018]	10.22033/ESGF/CMIP6.1391
CanESM5	[Swart et al., 2019]	10.22033/ESGF/CMIP6.1303
EC-Earth3	[Consortium (EC-Earth), 2019]	10.22033/ESGF/CMIP6.4700
GISS-E2-1-G	[Studies (NASA/GISS), 2018a]	10.22033/ESGF/CMIP6.1400
GISS-E2-1-H	[Studies (NASA/GISS), 2018b]	10.22033/ESGF/CMIP6.1421
IPSL-CM6A-LR	[Boucher et al., 2018]	10.22033/ESGF/CMIP6.1534
MIROC6	[Tatebe & Watanabe, 2018]	10.22033/ESGF/CMIP6.881
MPI-ESM1-2-LR	[Wieners et al., 2019]	10.22033/ESGF/CMIP6.6595
UKESM1-0-LL	[Good et al., 2019]	10.22033/ESGF/CMIP6.1567

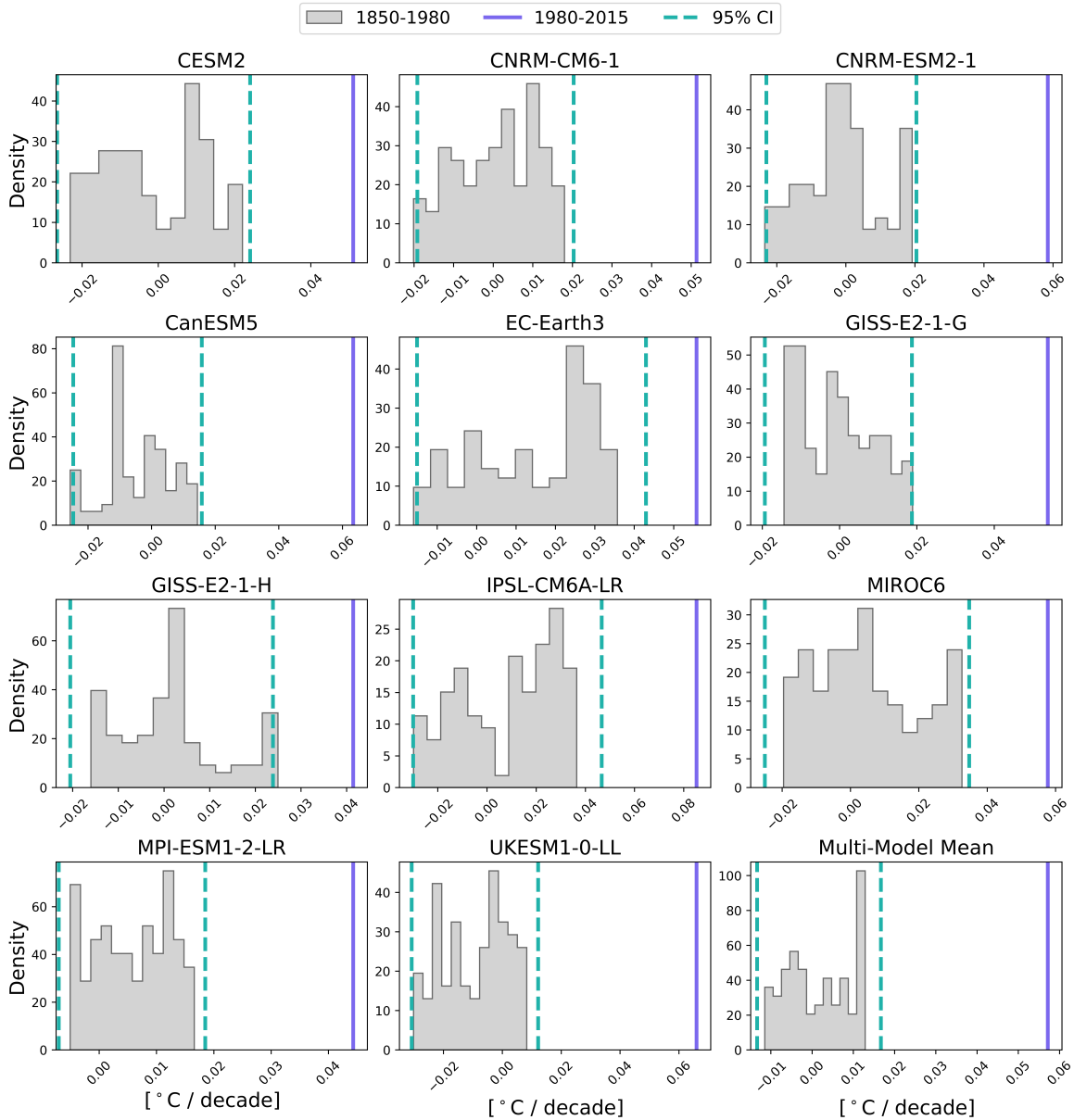


Figure 6.1: Comparison of September 1980-2015 pan-Arctic upper ocean temperature internal variability trends (violet) versus all 35-year trends between 1850-1980 (gray). *Thresholds for statistical significance (turquoise) are given by the upper and lower bounds of the 95% confidence interval (i.e. $p \leq |0.05|$) estimated from a normal distribution centered about each model's mean pre-1980 35-year trend. Models whose 1980-2015 trends are not statistically significant compared to historical internal variability are shaded red.*

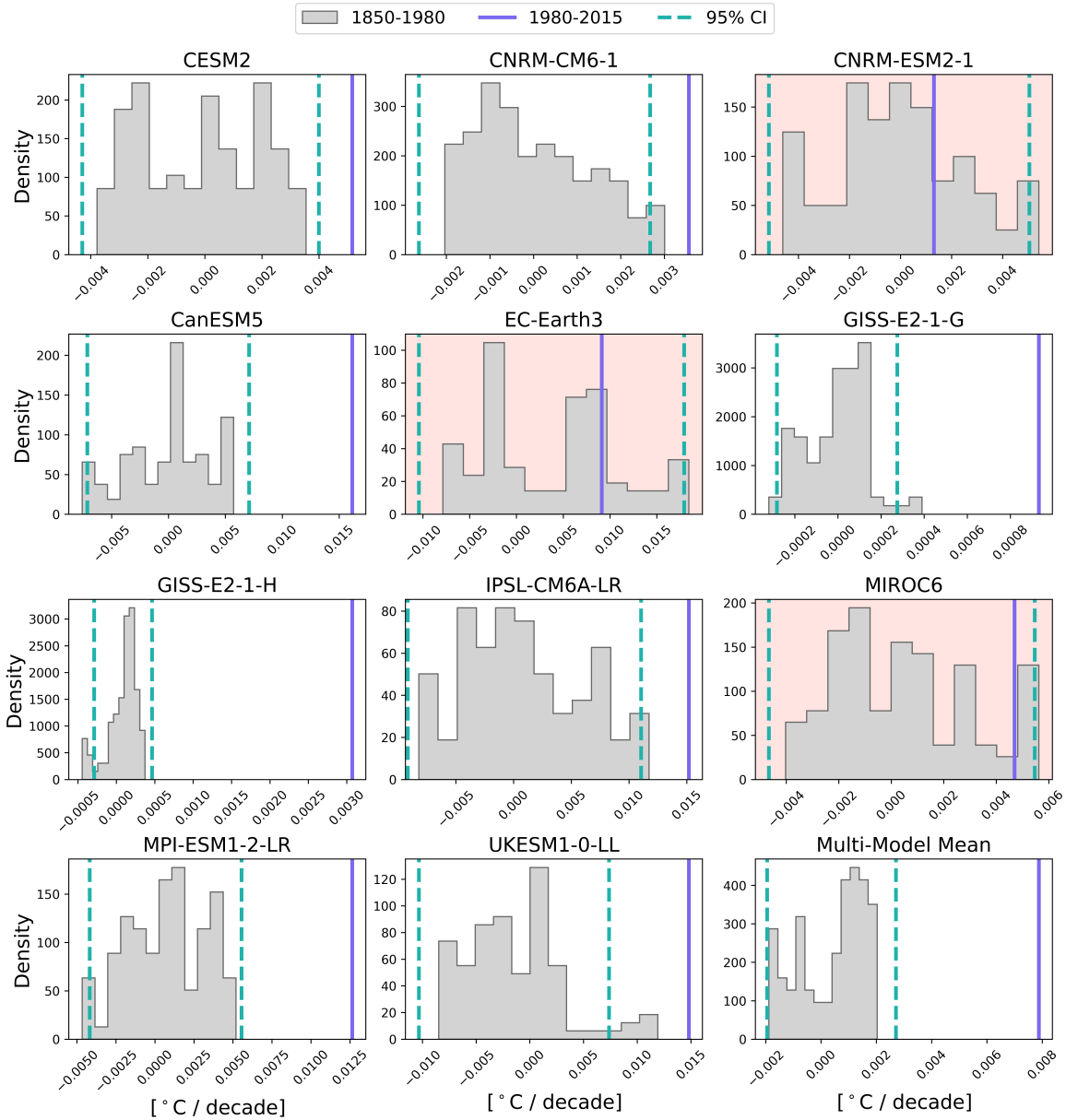


Figure 6.2: Comparison of March 1980-2015 pan-Arctic upper ocean temperature internal variability trends (violet) versus all 35-year trends between 1850-1980 (gray). *Thresholds for statistical significance (turquoise) are given by the upper and lower bounds of the 95% confidence interval (i.e. $p \leq |0.05|$) estimated from a normal distribution centered about each model's mean pre-1980 35-year trend. Models whose 1980-2015 trends are not statistically significant compared to historical internal variability are shaded red.*

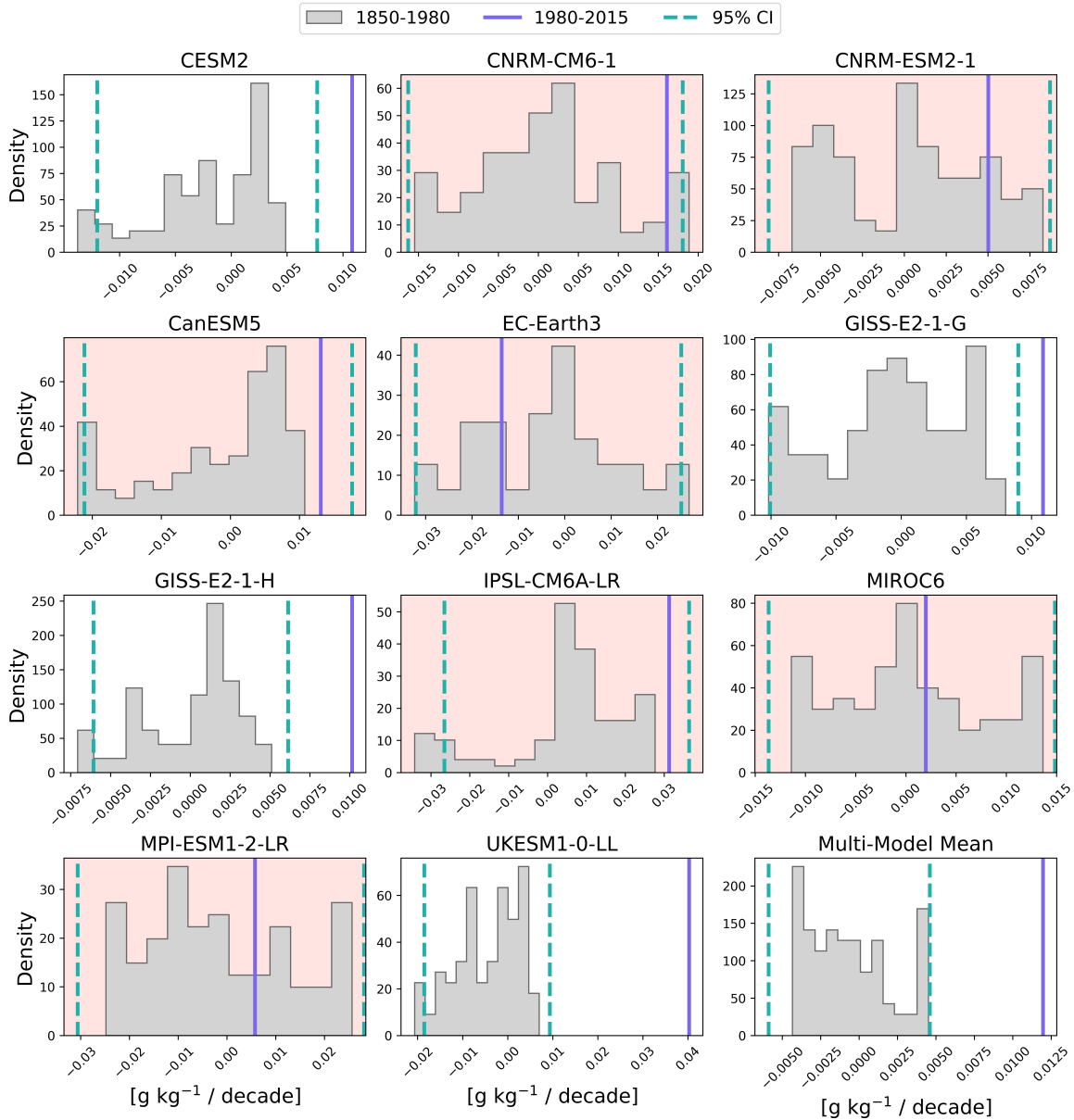


Figure 6.3: Comparison of September 1980-2015 pan-Arctic upper ocean salinity internal variability trends (violet) versus all 35-year trends between 1850-1980 (gray). Thresholds for statistical significance (turquoise) are given by the upper and lower bounds of the 95% confidence interval (i.e. $p \leq |0.05|$) estimated from a normal distribution centered about each model's mean pre-1980 35-year trend. Models whose 1980-2015 trends are not statistically significant compared to historical internal variability are shaded red.

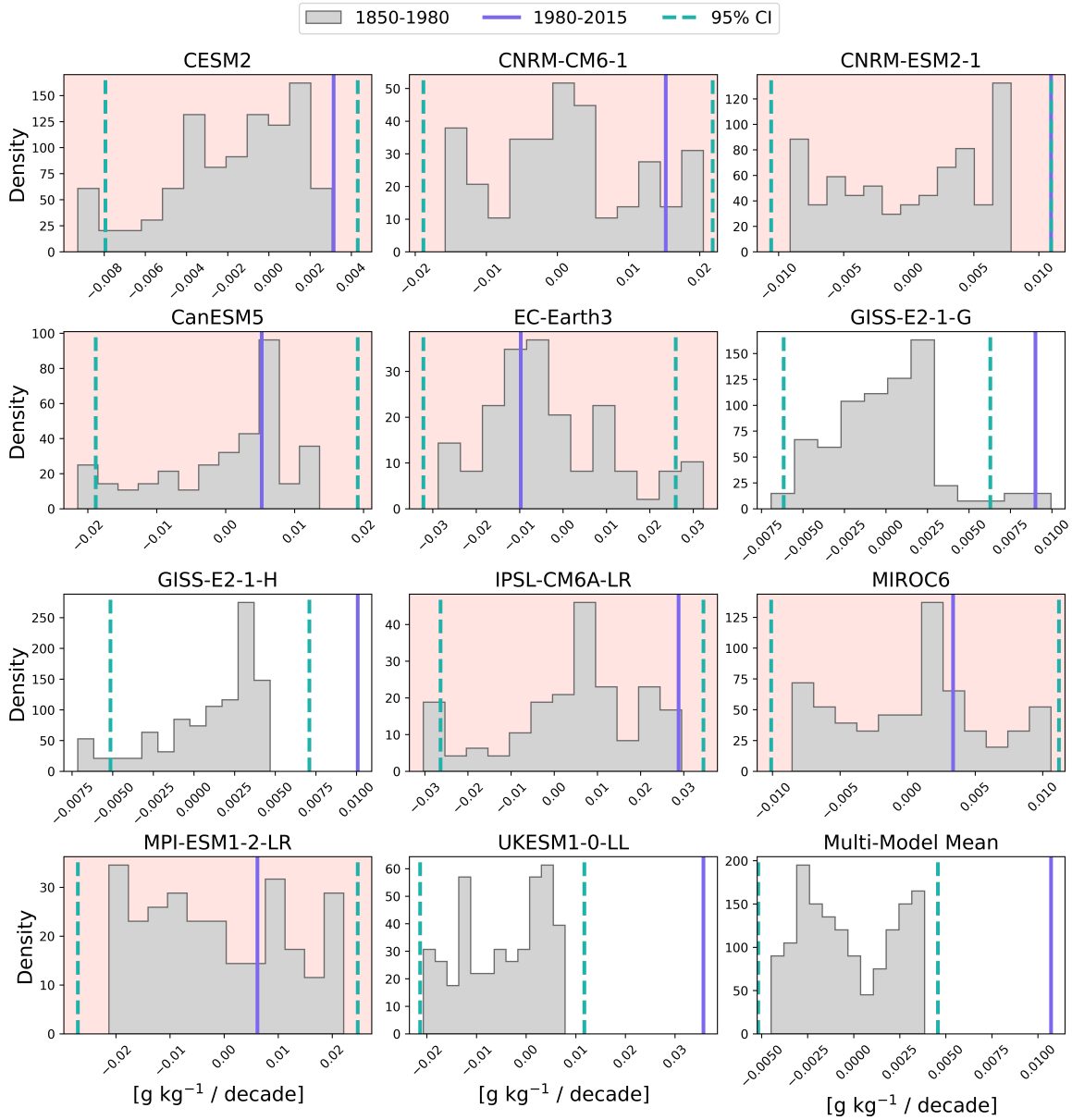


Figure 6.4: Comparison of March 1980-2015 pan-Arctic upper ocean salinity internal variability trends (violet) versus all 35-year trends between 1850-1980 (gray). Thresholds for statistical significance (turquoise) are given by the upper and lower bounds of the 95% confidence interval (i.e. $p \leq |0.05|$) estimated from a normal distribution centered about each model's mean pre-1980 35-year trend. Models whose 1980-2015 trends are not statistically significant compared to historical internal variability are shaded red.

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