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Investigating the Effects of Sea Ice Melting on Oceanic Warming in the Arctic

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Abstract **-** The drastic effects of anthropogenic forcing have been especially prominent in the Arctic, with atmospheric and oceanic warming, as well as sea ice melting. Recent studies have investigated the predominant drivers of recent changes in the Arctic in the context of anthropogenic forcing. Still, one question left unanswered is the extent to which these changes result from anthropogenic forcing as opposed to internal variability. Our study leverages statistical and machine learning algorithms (MCA/SVD) to investigate the relative contributions of anthropogenic forcing and internal variability by analyzing observational and large ensemble climate model datasets. In addition, we demonstrate that September sea ice melting has played a crucial role in upper Arctic Ocean warming in the fall over the past four decades. In this study, we gain a deeper understanding of the interaction between sea ice concentrations and ocean temperatures through observational and modeling analyses.

Keywords**:** climate models, anthropogenic forcing, internal variability, machine learning

1. Introduction

In 1938, humans first noticed signs of climate change [1], and over the past 40 years, we have noticed significant global warming patterns across the planet [2]. Recent global warming trends in the Arctic as a result of greenhouse gas emissions and anthropogenic forcing have shown their impacts in a multitude of ways, primarily through changes in atmospheric [3] and oceanic temperatures [4], as well as sea ice concentration [5]. While these impacts are evident through observational data and modeling analyses, their drivers are largely unknown, and the extent to which these changes result from anthropogenic forcing versus internal variability remains unresolved. To gain a deeper understanding of the causes of recent climate changes in the Arctic, we analyze and quantify the atmosphere, sea-ice, and ocean interactions in the Arctic and leverage large ensemble climate models to determine the relative impacts of anthropogenic forcing and internal variability on the Arctic climate.

Some previous studies have investigated the impacts of anthropogenic forcing on the Arctic climate [6]. However, little research exists concerning the extent to which anthropogenic forcing and internal variability play a combined role in causing climate change in the Arctic. Much work has addressed the relationship between different factors of the Arctic climate. For example, Olonscheck, Mauritsen, and Notz [7] investigated the linkage between sea ice and atmospheric temperatures, while research by Horvath, Stroeve, Rajagopalan, and Jahn [8] discussed Arctic sea ice melting as a result of variations in atmospheric pressure. Furthermore, research has investigated the impacts of Arctic sea ice concentrations on the atmospheric response using climate models [9]. Nevertheless, little research has directly quantified the relationship between Arctic sea ice concentrations and ocean temperatures due to the sea-ice albedo feedback effect. Therefore, we propose a thorough statistical model to effectively investigate the interactions between sea ice concentrations and ocean temperatures, as well as the impacts of internal and external forces on these factors.

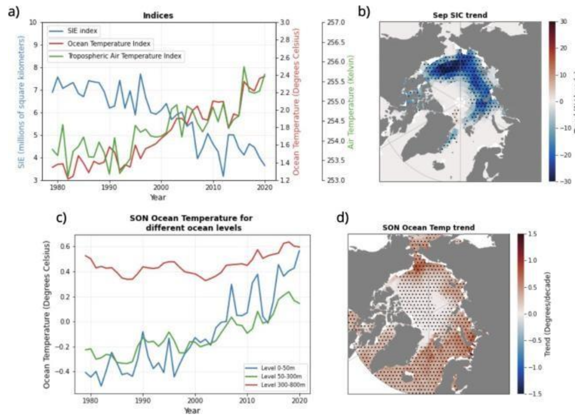

Figure 1: a) Time series of changes in September sea ice extent (millions of square kilometers)), September-October-November (SON) ocean temperature (degrees Celsius), and June-July-August (JJA) tropospheric air temperature (K) in the Arctic from 1979-2020. b) September sea ice concentration trend (%/Decade) from 1979-2020. c) Time series of changes in SON ocean temperatures (degrees Celsius) of various depths from 1979-2020. d) SON ocean temperature trend (degrees Celsius/Decade) from 1979-2020.

2. Methods

Our solution framework exists as a series of techniques in order to obtain crucial information from the data (Fig. 2). We calculate the Arctic domain average of ocean temperature and sea ice concentration on a time series to show their variabilities over the period 1979-2020. We then quantify the correlation between the two variables to demonstrate their interactions and extract their dominant covariation patterns. Finally, we use large ensemble climate model data to isolate anthropogenic forcing and internal variability to examine their relative contributions to Arctic climate changes. These patterns can be further analyzed to determine prominent covariation patterns amongst different climate model members.

2.1. Datasets

In order to achieve our goals, two subsets of reanalysis data are used in this study. First, in order to analyze ocean temperature data, we obtain a subset of data collected by the Ocean Reanalysis System 5 (ORAS5) [10]. This system uses a global eddy-permitting ocean-sea ice ensemble with an eddy-permitting resolution of 0.25^{o} to measure ocean temperature data from 1979-2020. Our primary focus in our analysis is upper (0-50m) ocean temperatures. This dataset enables us to study temporal and spatial patterns of ocean temperature over the past 42 years. We also employed monthly sea ice concentration data for the period 1979-2020, obtained from the Nimbus-7 SSMR and DMSP SSM/I-SSMIS microwave dataset provided by the National Snow and Ice Data Center (NSIDC) [11]. For ocean temperature and sea ice data, we restricted our spatial coverage to 60-90^{o}N, which approximates the Arctic region. We also used monthly air temperature fields from 1979 to 2020 from ERA5 reanalysis data [12].

This study also uses climate models from the Community Earth System Model Large Ensemble (CESM-LEN) dataset, which contains a 40-member ensemble with several varied initial conditions [13]. We utilized these climate models to isolate anthropogenic forcing and internal variability and analyze these factors independently.

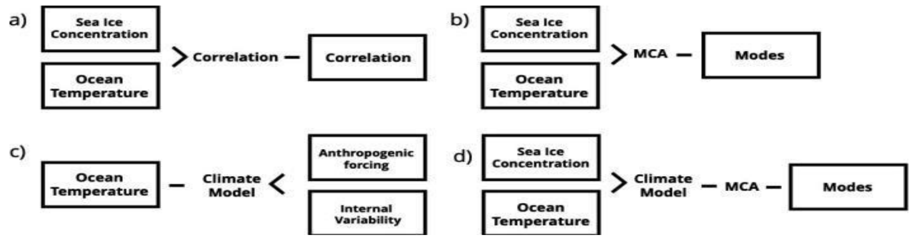

Figure 2: a) Correlation between sea ice concentration and ocean temperature. b) MCA between sea ice concentration and ocean temperature to obtain the most prominent modes. c) Climate model of ocean temperature to find the extent of anthropogenic force contribution.
d) Climate model and MCA of sea ice concentration and ocean temperature to obtain the most prominent modes between climate model members

2.2. Correlation/Covariation Patterns

Firstly, we utilize the basic correlation algorithm to calculate the level of correlation between sea ice concentration and ocean temperature. We place particular emphasis on September sea ice concentration while analyzing the effect of June-July-August (JJA) ocean temperatures on September sea ice, as well as the impact of September sea ice on September-October-November (SON) ocean temperatures. A strong correlation between these variables warrants a deeper investigation into their interactions. This prompts the use of a Maximum Covariance Analysis (MCA) algorithm to determine the most prominent modes affecting these two variables. MCA uses singular value decomposition (SVD) techniques [14] to determine patterns that exhibit high fractions of covariance between the ocean temperature and sea ice spatial patterns. This allows for identifying modes that significantly contribute to correlated trends between sea ice and ocean temperature in the Arctic.

2.3. Climate Modeling

The 40-member ensemble from the CESM-LEN dataset contains members with slightly varying initial conditions, in which the same model runs 40 times with small perturbations in the initial conditions. These initial conditions concern the internal variability of climatic conditions. Therefore, we can utilize these models to isolate anthropogenic forcing and internal variability in the climate system. A fast minus slow composite algorithm [15] is used to separate groups of members showing fast and slow ocean warming for a given time period. Having identified members of fast and slow warming groups, we average the corresponding trends of SON ocean temperatures in each group and calculate the difference between the two ocean temperature composites. By doing so, we can remove the internal variability of the simulated variable from its forced component in the climate world. The sum of 40 members roughly equates to the cancellation of internal variability. By comparing the mean of all the members with the observed ocean temperature trend, we calculated the relative contribution of anthropogenic forcing and internal variability to the Arctic climate. Furthermore, we ran an MCA algorithm for all 40 members of the climate models to compare dominant covariation patterns between sea ice concentration and ocean temperature to gain deeper insight into the interactions between these two variables in the climate model.

2.4. Implementation

Each algorithm can be implemented to investigate various factors concerning the Arctic climate. For example, the correlation calculated from subsection 2 can be used to identify the interrelationship between sea ice and ocean temperatures. The climate models from subsection 3 help gain further insight into these interactions while determining an approximated percentage of anthropogenic forcing and internal variability on Arctic climate change. Fig. 2 summarizes the algorithms used and the information gathered from them.

3. Results

3.1. Observational Trends

Fig. 1 shows spatial and time series trends of September-October-November (SON) upper (0-50m) ocean temperature and September sea ice concentration for the period 1979-2020. Observational data shows that the lowest recorded ocean temperature was 1.21°C (in 1982), while the highest temperature was 2.38°C (in 2020). Similarly, trends of sea ice extent

(SIE) show the highest SIE of 7.70 million km^2 (in 1996) as opposed to the lowest extent of 3.16 million km^2 (in 2012). Overall, trends indicate regions of the Arctic losing up to 30% of sea ice and oceans warming by up to 1-1.5^{o}C per decade over the last 42 years. The most considerable impacts have been observed on the upper layers of the Arctic Ocean (0-50m). Thus, perceptibly, ocean temperatures and sea ice concentrations in the Arctic have changed dramatically over the last four decades.

3.2. Observational Data Correlation

To illustrate the lag processes that link the September sea ice pattern to SON upper ocean temperature change, we calculate the lead-lag correlations between sea ice and upper ocean temperature among different seasons, which show distinct patterns (Fig. 3). SON upper ocean temperature shows a strong correlation with September sea ice throughout the Arctic region besides the central oceans (Fig. 3a). The high correlation between June-July-August (JJA) ocean temperatures and September sea ice is primarily confined to the Pacific side of the Arctic Ocean and is weaker over the Atlantic side (Fig. 3b). Moreover, the magnitude of the correlation is lower between JJA ocean temperature and Sep. sea ice than between Sep. sea ice and SON ocean temperature.

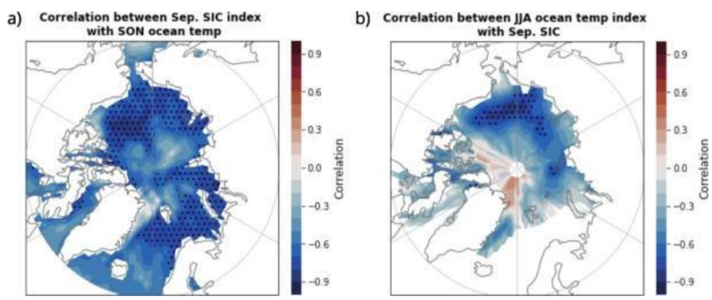

Figure 3: a) Spatial correlation plot between September sea ice extent index and September-October-November (SON) ocean temperatures. b) Spatial correlation plot between June-July-August (JJA) ocean temperature index and September sea ice concentration. Black stippling in all plots indicates statistically significant correlations at the 95% confidence level.

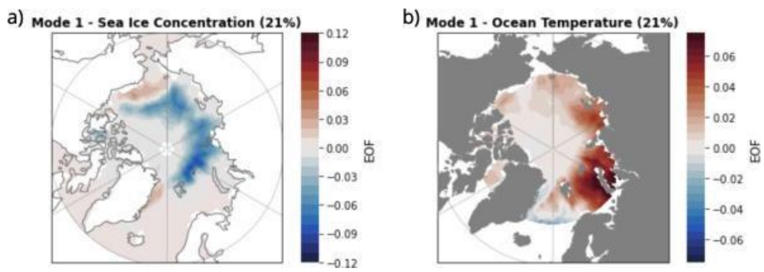

Figure 4: a) Detrended spatial plot of the first mode of sea ice concentration following MCA of September sea ice concentration and SON ocean temperatures. b) Detrended spatial plot of the first mode of ocean temperature following MCA of September sea ice concentration and SON ocean temperatures.

3.3. MCA Using Observational Data

Fig. 4 shows the spatial plots of the first mode of MCA of sea ice concentration and upper ocean temperature in the Arctic (contributing to 21% of covariance). MCA results use detrended variables, which approximately removes anthropogenic forcing. This mode depicts the most substantial covarying patterns between these two variables. Importantly, the MCA analysis is performed on detrended data. The close match between the observed trends and the MCA patterns suggests that the observed trend substantially arises from internal variability rather than linear trends.

3.4. Climate Model – Anthropogenic Forcing Contribution

As shown in Fig. 5, some members in CESM-LEN show a more rapid warming trend of upper ocean temperature in the Arctic, while others show a slower warming trend. Slightly different initial conditions among 40 members in CESM-LEN indicate various internal variables amongst them, with some members containing positive internal variabilities and other members containing negative internal variabilities. The mean of all 40 members of the climate models averages out internal variability and produces the changes in climate as a result of anthropogenic forcing. Since the observational data consists of climate changes due to anthropogenic and internal factors, dividing these values produces the fraction of anthropogenic contribution.

$$\frac{0.01496\ (climate\ model\ average)}{0.02591\ (observational\ data\ index)} \cdot 100 = 56.7\%$$

The total anthropogenic contribution to SON upper ocean temperatures from 1979-2020 was roughly 56.7%, while internal variability contribution accounts for around 43.4% of upper ocean temperature changes in the Arctic.

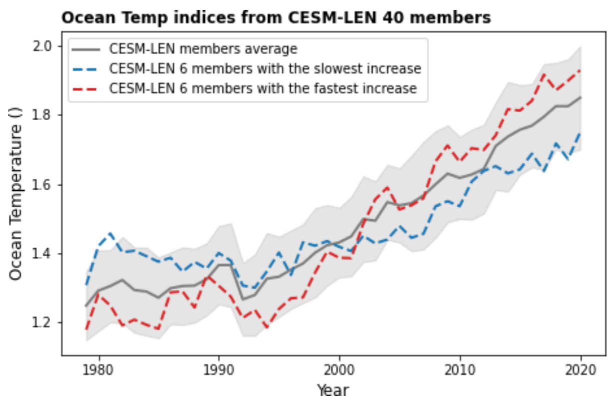

Figure 5: Time series of SON upper ocean temperature indices for CESM- LEN 40 members average (gray line), for six members with the fastest growth (red line), and six members with the slowest growth (blue line) from 1979 to 2020.

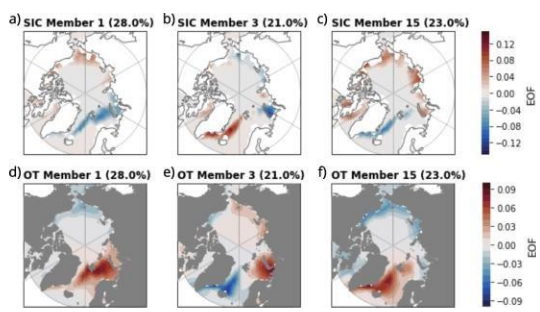

Figure 6: Spatial plots of the first mode of MCA between SON upper ocean temperature and September sea ice in the Arctic choosing three member cases, with member 1 in a. and d., member 3 in b. and e., and member 15 in c. and f.

3.5. MCA In Climate Model

The first mode for three members of the climate model for ocean temperature and sea ice concentration can be seen in Fig 6. The modes are observable in the same regions for the same members of ocean temperature and sea ice concentration, indicating that the variables are strongly correlated and have shared factors affecting their correlation. This also implies that the strong correlation between sea ice concentration and ocean temperature is independent of initial internal variability conditions.

4. Discussion

Our research sets a precedent for the interactions between sea ice and ocean temperature by demonstrating the high lag correlation between September sea ice and SON ocean temperature. This suggests that the ocean needs several months to respond to changes in sea ice. On the other hand, the comparatively lower correlation between JJA ocean temperature and September sea ice may suggest a shorter response time or simultaneous changes of sea ice to ocean warming. Overall, however, these two variables seem to be strongly correlated. The MCA analysis shows that the dominant covarying mode affects ocean temperature and sea ice melting in slightly different regions, with a 21% contribution to the covariance, suggesting that other factors might also result in the observed correlation.

Using the climate model, our study demonstrates that a majority (56.7%) of ocean temperature changes are due to anthropogenic forces. One limitation of this finding is that this value is an approximation rather than a definite value; thus the remaining 43.3% cannot entirely be attributed to internal variability. The final takeaway from this study is from the climate model MCA results, which suggest that all members of the climate model contain dominant patterns which result in strong correlations between sea ice and ocean temperature in the Arctic.

5. Conclusion

Our study is therefore successful in demonstrating the strong coupling relationship between upper ocean warming and sea ice melting in the Arctic. Furthermore, using climate models, we were also able to display the anthropogenic and internal variability contributions to the upper ocean warming in the Arctic. Further research could delve into the interactions between more intricate characteristics of the Arctic ocean and sea ice, such as ocean salinity and ocean advection patterns. A variety of other large ensemble climate models could also be leveraged to compare the extent of anthropogenic forcing and to graph dominant covarying patterns for various other climate model members. We may also attempt to gauge which models effectively capture internal variability. Finally, these climate models might be improved by using machine learning to correct biases present in current climate models.

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