Deep Learning for Antarctic Sea Ice Anomaly Detection and Prediction: A Two-Module Framework

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ABSTRACT

The Antarctic sea ice cover plays a crucial role in regulating global climate and sea level rise. The recent retreat of the Antarctic Sea Ice Extent and the accelerated melting of ice sheets (which causes sea level rise) raise concerns about the impact of climate change. Understanding the spatial patterns of anomalous melting events in sea ice is crucial for improving climate models and predicting future sea level rise, as sea ice serves as a protective barrier for ice sheets. This paper proposes a two-module framework based on Deep Learning that utilizes satellite imagery to identify and predict non-anomalous and anomalous melting regions in Antarctic sea ice. The first module focuses on identifying non-anomalous and anomalous melting regions in the current day by analyzing the difference between consecutive satellite images over time. The second module then leverages the current day's information and predicts the next day's non-anomalous and anomalous melting regions. This approach aims to improve our ability to monitor and predict critical changes in the Antarctic sea ice cover.

CCS CONCEPTS

• **Computing methodologies → Machine learning**.

KEYWORDS

Antarctic sea ice, Anomalous melting, Deep learning, Prediction

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1 INTRODUCTION

With rising global sea levels affecting coastal communities worldwide, the rapid retreat of Antarctic sea ice and accelerating ice sheet melt pose significant challenges. In February 2023, the Antarctic Sea Ice Extent (SIE) reached a record low of ~ 1.965 million km^2, representing a concerning $\sim 32\%$ decrease from climatological values [9]. Although sea ice melt itself doesn't directly raise sea levels, it acts as a protective layer for the underlying ice sheets [11]. Notably, Antarctic ice sheet melt has also accelerated, with an estimated 1200 gigatons lost between 2017 and 2022, compared to the previous annual average of ~ 147 gigatons [12].

Our understanding of the factors driving this recent sea ice decline remains limited. Prior to 2015, Antarctic sea ice reached maximum extent during the austral winter. The causes behind this shift since 2015 are not fully understood, highlighting the critical need to investigate the nature of melting patterns, specifically the distinction between stable (non-anomalous) and anomalous melting events [2, 8]. Sea ice acts as a buffer against warm currents, wind, and waves, protecting the ice sheets [11]. A more comprehensive understanding of stable ice conditions (non-anomalous melting or positive class) and anomalous melting events (negative class) is therefore essential for predicting future ice sheet stability and sea level rise. Current limitations in this field include: (a) Poor representation of melting processes in climate models, leading to uncertainties in estimating the timing of sea ice disappearance [2, 8]. (b) Insufficient analysis using multi-year observational datasets [7, 16]. (c) Limited computational resources for handling big data associated with sea ice retreat dynamics.

Previous research has focused on subseasonal prediction of regional Antarctic sea ice [14], and loss of ice sheets [3, 4]. However, these studies haven't explicitly explored the nature of melting patterns in sea ice (like the classification of stable and anomalous melting patterns). Additionally, time series analysis, while a popular tool for studying SIE changes, often struggles to attribute retreat to specific locations [1, 10, 13, 15]. Existing studies examining spatiotemporal variations in sea ice [10] have primarily focused on broader trends in the Arctic and Antarctic, rather than pinpointing specific areas in the Antarctic experiencing anomalous melting [13]. As a result, our physical understanding of Antarctic melting patterns remains rudimentary, hindering accurate predictions [2, 8, 9]. Each grid of satellite data corresponds to a 625 km^2 area, the number of instances of daily anomalous melting surpassing 2500 during this period may result in a substantial loss of sea ice area. Specifically, this could translate to an impact of approximately $\sim 2500 \times 625 = 1562500$ km^2, depicting a significant influence on the Earth's environmental dynamics. Thus, identifying and predicting non-anomalous & anomalous melting is crucial for understanding Earth's environmental dynamics. To the best of our knowledge, no studies have yet been conducted to predict anomalous melting in the Antarctic region using satellite imagery.

This study addresses this gap by proposing a two-module framework that leverages satellite imagery to identify and predict regions experiencing stable sea ice conditions or non-anomalous melting (positive class) and areas undergoing anomalous melting (negative class) within the Antarctic sea ice retreat. This novel approach aims to bridge the knowledge gap in melting pattern analysis and contributes to a more comprehensive understanding of Antarctic sea ice retreat dynamics, ultimately aiding in predicting sea ice retreat.

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2 METHODOLOGY

RGB satellite images are first converted to grayscale to reduce computational complexity, then difference matrices are calculated from consecutive images to capture changes over time. Table 1 shows the datasets used in this study.

Table 1: Data used in this study.

Datasets	Satellite data Sources	Resolution/Pixels
Sea Ice Extent Images (satellite images)	SMMR, SSM/I, SSMIS, NIMBUS Passive Microwave .png images	332 × 316 pixels

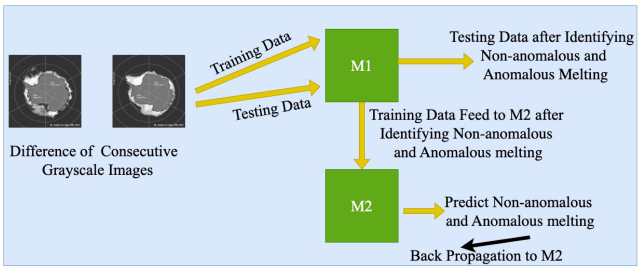

Figure 1: The M1 module in the two-module framework leverages the difference between satellite images to identify and classify regions experiencing anomalous melting events. M2 module, is a CNN, within the two-module framework for Antarctic sea ice anomaly prediction, which takes an anomaly mask generated by the M1 module as input. M2 processes this information to predict the probability of two classes for the following day: non-anomalous melting conditions (positive class) and anomalous melting (negative class).

2.1 M1: Anomalous Melt Identification Module

M1 Module Architecture: The M1 module uses convolutional operations to detect anomalous melting events in Antarctic sea ice by analyzing differences in satellite images, as shown in Figure 1. Initially, a convolutional layer with a specific kernel configuration is applied, emphasizing negative values in the image that often correspond to areas of significant sea ice decrease. The kernel weights are fixed to ensure consistent behavior during anomaly detection, with no backpropagation occurring [17]. Subsequently, two pooling layers, mean pooling and inverse max pooling (shown in Equation 1), are employed consecutively [6]. These layers reduce the image size while capturing crucial spatial information about potential anomalies. **Anomaly Detection:** The model processes the input image and isolates negative values, focusing on potential reductions in sea ice intensity. It uses inverse max pooling and mean pooling to emphasize the magnitude of change and performs pooling operations. Two conditions are established to identify pixels representing potential anomalies. The first condition checks if the processed image value falls below the predefined lower bound threshold, indicating a substantial decrease. The second condition examines the ratio between the average value (using mean pooling) and the magnitude of the change (represented by inverse max pooling). A ratio greater than the lower bound/Q_1 suggests a significant deviation from the typical sea ice patterns [6]. These conditions are combined to create a final anomaly mask, which distinguishes between non-anomalous melting and anomalous melting, highlighting potential anomalous locations in the image. **Anomalous Pixel Identification and Marking:** The module iterates through each image in a batch, identifying pixels that meet the anomaly criteria based on the mask. It marks the corresponding locations of these anomaly pixels in the original grayscale image. **Overall Process:** The code utilizes the M1 module to process batches of grayscale sea ice images. The module strictly utilizes feed-forward computations, excluding backpropagation for parameter updates. It identifies potential anomaly pixels based on the pre-defined thresholds and the M1's internal logic. The final output is a list containing anomaly maps for each image, highlighting areas with potential anomalous sea ice melting events.

$$\mathrm{I[i][j]} = \begin{cases} 0 & \text{if input\_matrix[i][j]} > 0 \\ \text{-input\_matrix[i][j]} & \text{otherwise} \end{cases} \quad (1)$$

$$P[i][j] = -\max_{x,y \in R(i,j)} I[x][y] \quad (2)$$

Here, $input\_matrix[i][j]$ represents the elements of the input matrix. To obtain the inverse max pooling values from the I matrix, we employ the following equation 2 with a negative sign applied to the result of max pooling. In this equation, $R(i, j)$ denotes the set of indices (x, y) within the pooling window corresponding to the position (i, j). For more detailed information about the M1 module, please refer to our previous work [6], from which this method has been adopted.

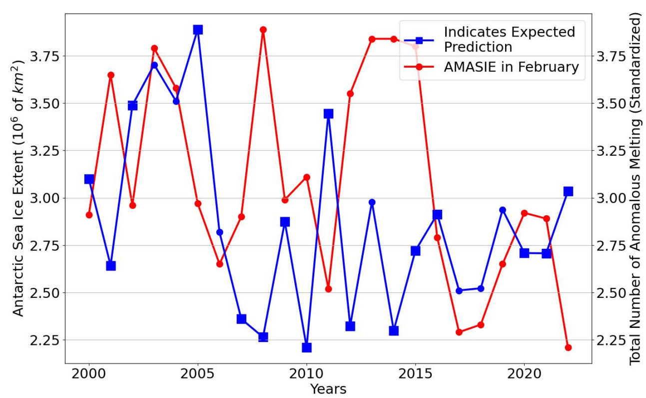

Figure 2: The AMASIE for February, representing the years 2000 to 2022, is illustrated by the red line. The predicted total number of anomalous melts per year obtained through M1 analysis on satellite images is shown in the blue line where the blue box indicates the expected prediction identified by our framework.

2.2 M2: Next-Day Non-Anomalous and Anomalous Melt Prediction Module

Building upon the M1 module's capability to detect anomalous sea ice melting events, the M2 module aims to predict the likelihood of such anomalies occurring on the following day which is shown in Figure 1. This section outlines the design and functionality of M2 within the context of anomaly detection and prediction for

Antarctic sea ice data. **M2 Module Architecture:** M2 adopts a CNN architecture specifically tailored for time-series prediction of sea ice anomalies. The description of the M2 is shown in Table 2. It takes the output from the M1 module as input, representing the anomaly mask for the current day. This mask highlights areas identified as potentially undergoing anomalous melting. The M2 consists of several convolutional layers followed by activation functions. These layers learn to extract spatiotemporal features from the anomaly mask, capturing information about the spatial distribution and patterns of anomalous melting events. The specific number and configuration of these layers are subject to hyperparameter tuning for optimal performance. **Prediction Process:** The M2 module receives the anomaly mask generated by M1 for the current day as input. This anomaly mask is then fed into the M2 CNN, where each convolutional layer extracts higher-level features from the previous layer's output, effectively capturing the evolving patterns of sea ice anomalies across space and time. In the prediction phase, the final layer of the M2 module produces a one-channel output representing the predicted probabilities of normal and anomalous sea ice conditions for the next day. A value of 1 corresponds to the probability of normal sea ice conditions (non-anomalous) on the next day, while a value of 0 represents the probability of anomalous sea ice melting occurring on the next day.

Table 2: M2 Model Architecture Summary

Component	Description
Input	Anomaly mask from M1 for the current day (332× 316).
Layers	First convolutional layer followed by ReLU activation (number optimized through hyperparameter tuning). The second convolutional layer is followed by Sigmoid activation. Final convolutional layer with one output channel.
Output Layer Activation	Sigmoid activation to produce probability values between non-anomalous and anomalous melting.
Loss Function	Binary Cross-Entropy (BCE) loss for measuring prediction error.
Training Technique	Early stopping to prevent overfitting and ensure convergence.
Batch Size	32 for efficient training.

Table 3: Training, Testing, and Validation Periods for Sea Ice Anomaly Detection

Training Period	Testing Period	Validation Period
2000 - 2004, 2011 - 2022	2005 - 2009	2010
2006 - 2022	2000 - 2004	2005
2000 - 2010, 2017 - 2022	2011 - 2015	2016
2000 - 2016	2017 - 2021	2022

Leveraging Anomaly Information: M2's strength lies in its ability to leverage the anomaly mask from M1. This information provides valuable context for predicting future anomalies. By analyzing the spatial distribution and characteristics of anomalies detected in the current day, M2 can learn how these patterns might evolve and influence sea ice retreat conditions on the following day. Unlike traditional climate models and statistical methods, which seldom simulate sea ice anomalies and heavily rely on statistical properties of numerical data [7, 14], our approach is uniquely applied to images, allowing for the direct analysis of spatial features and visual patterns in the sea ice data. This image-based methodology enables the model to capture and interpret complex spatial relationships and temporal changes that may be overlooked by conventional techniques, offering a more nuanced and accurate prediction of anomalous sea ice retreat.

2.3 Performance Evaluation of M1 Module

To generate validation of our framework represented in Figure 2, we have employed a comprehensive training, testing, and validation strategy selecting different time periods as shown in Table 3. This comprehensive approach has enabled us to assess the framework's performance across different time periods, ensuring a robust evaluation of our anomaly prediction framework. To assess the reliability of our framework, we have compared its predictions with established data on the Annual Minimum Antarctic Sea Ice Extent (AMASIE) [5]. Figure 2 presents the results. The blue plot with square markers represents the expected anomalous melting events predicted by our framework. The red plot with circular markers depicts the AMASIE for each corresponding year. For improved visualization, the number of predicted anomalies from the framework has been normalized to the range of minimum sea ice extent values. As evident in Figure 2, a clear inverse relationship emerges. Years with a higher number of predicted anomalies by our framework coincide with years exhibiting lower minimum sea ice extent, and vice versa. This suggests that increased anomalous melting events, as predicted by our framework, correlate with a greater decline in sea ice coverage. For instance, in 2010, when the minimum sea ice extent was higher than in 2011, our framework accurately predicted a lower number of anomalies. Conversely, in 2011, with a lower minimum sea ice extent compared to 2010, our framework correctly identified a higher number of anomalies, as expected. This trend holds true for 16 out of the 23 years analyzed. This negative correlation is particularly noteworthy considering that many recent years (including 2020-2022) exhibit a similar association between lower minimum sea ice extent and higher numbers of predicted anomalies [5], and vice versa. It is important to acknowledge that this study focuses on anomalous melting events and excludes steady-state melting, which might have influenced some of the remaining years (7 out of 23). Nevertheless, the findings strongly suggest a connection between lower minimum Antarctic sea ice extent and a higher prevalence of anomalous melting events, particularly in recent years. This observed relationship serves as valuable verification of the framework's capability to detect anomalies effectively. This observed relationship reinforces the reliability of our framework, highlighting its potential in monitoring and predicting significant changes in Antarctic sea ice coverage.

2.4 Performance Evaluation of M2 Module

This section evaluates the performance of the proposed framework for prediction of anomalies through M2 using a threshold-based approach. A threshold value of 0.9 has been selected to classify pixels exceeding the threshold as not anomalous melting (positive class) and those below as anomalous melting (negative class). The M1 module's output has been used as an input to the M2 module, which has been trained and tested using an 80/20 train-test split. Daily sea ice data has been employed, where data for the current day served as the training input, and data for the subsequent day functioned as the ground truth label. We have used the 2000-2022 satellite images for the framework mentioned above shown in Figure 1. The training and testing procedure has been applied iteratively across multiple years, leaving one year out each time for validation. For instance, 2000-2016 data was used for training, with 2022 acting as the validation year. The evaluation results of 2022 (validation year) demonstrate our framework's effectiveness in classifying daily sea ice melting patterns, achieving high average precision (0.98) and recall (0.93), which indicates accurate identification of both non-anomalous and anomalous melting events. This is supported by a strong average F1 score (0.96) and overall accuracy (0.92). Notably, the average ROC AUC score of 0.70 highlights satisfactory discrimination capability between anomalous and non-anomalous melting patterns [6]. We have validated the performance on randomly selected years, all showing similar kinds of results.

In the context of identifying critical melting events or regions, we can specifically consider instances where the predicted anomaly score surpasses a certain threshold. For example, when we set the threshold for anomalous melting detection at 0.9, the model effectively predicts these high-risk scenarios with a high probability. Above 52% percentage anomalous melting area is identified by our framework. This allows us to prioritize areas experiencing significant melting and potentially implement targeted mitigation strategies. This approach highlights our framework's ability to not only differentiate between non-anomalous and anomalous melting but also pinpoint areas with particularly concerning levels of melt activity. This information is crucial for researchers and policymakers working to understand and manage the complex dynamics of Antarctic sea ice melt.

3 DISCUSSION AND CONCLUSION

This study investigated the development and evaluation of a two-module framework for Antarctic sea ice anomaly detection and prediction. The M1 module demonstrated effectiveness in identifying or predicting anomalous melting events using a CNN architecture. The M2 module, leveraging anomaly information from M1, aimed to predict the likelihood of anomalies occurring on the following day. **Improved Prediction Accuracy:** The integration of M1's anomaly detection capabilities offers a potential advantage for M2. By incorporating information about the current day's anomalies, M2 can potentially achieve more accurate next-day anomaly predictions compared to models that solely rely on historical sea ice data. This enhanced accuracy could be attributed to M2's ability to learn the spatiotemporal patterns of anomalous melting events, allowing it to anticipate their evolution over time. **Early Warning System:** M2's ability to predict next-day anomalies can be particularly valuable as an early warning system for major sea ice melt events. Identifying areas with a high probability of anomalous melting can provide researchers and policymakers with crucial early warning to take necessary actions. This could include deploying resources for further investigation, implementing mitigation strategies, or raising awareness about potential environmental impacts. Overall, our anomaly prediction framework effectively forecasts anomalous events for the next day based on the anomalous events of the current day. The combined M1-M2 framework offers a comprehensive approach to sea ice anomaly analysis. M1's role in anomaly detection provides critical context for M2's predictive capabilities. Further research could explore expanding the early warning to multiple-day prediction. **Hyperparameter Tuning:** Optimizing hyperparameters or identifying more important features for both M1 and M2 can potentially enhance their individual performance and their combined effectiveness. **Data Fusion:** Integrating additional data sources, such as atmospheric data or ocean temperature measurements, could potentially improve the prediction accuracy of M2. **Evaluation Metrics:** Developing tailored evaluation metrics for sea ice anomaly prediction will provide a more comprehensive assessment of the framework's performance. Further research on hyperparameter tuning, data fusion, and dedicated evaluation metrics can refine this framework and enhance its contributions to understanding and managing the complexities of the Antarctic sea ice retreat. The implementation details and data sources used in this study are available on **GitHub**.

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