Arctic Processes Under Ice: Structure in a Changing Climate

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ABSTRACT

The Arctic region is undergoing unprecedented transformations due to Arctic amplification, warming at twice the global average rate [1]. This warming has led to a drastic reduction in sea ice, with predictions of ice-free Arctic summers before 2050 [2]. Such profound changes signal a shift to a new climatic regime, posing significant risks to regional communities, industries, and ecosystems.
This research addresses the urgent need to understand the evolving Arctic environment by harnessing machine learning (ML) to analyse sparse oceanic data. Utilising nearly two decades of Ice Tethered Profilers (ITP) data, complemented by ship-based (U-DASH), and ARGO profiles, this study aims to investigate the structure and dynamics of the Arctic Ocean.
We fit a Gaussian Mixture Model (GMM) to our observations, assigning each data point into a different cluster or class. Despite no spatial information being provided to the model, we find coherent classes emerge. This approach promises to enhance our understanding of Arctic water masses and their evolving role in a changing environment.

INTRODUCTION

This study aims to address the risks posed by rapid changes in the Arctic environment by utilising machine learning techniques to unlock valuable information from limited ocean observations. Now that close to 2 decades of ITP[3] data are available, alongside ship-based (U-DASH [4]) and ARGO [5] profiles, it is possible to start characterising the Arctic and Understanding processes, utilising ML methods to get the most out of the data.
The poster will showcase the use of Gaussian Mixture Model to perform unsupervised clustering on the water masses in the Arctic Ocean, with later focus on understanding the structure and dynamics of the Arctic Ocean to predict how it might evolve in the future under a new climate regime.

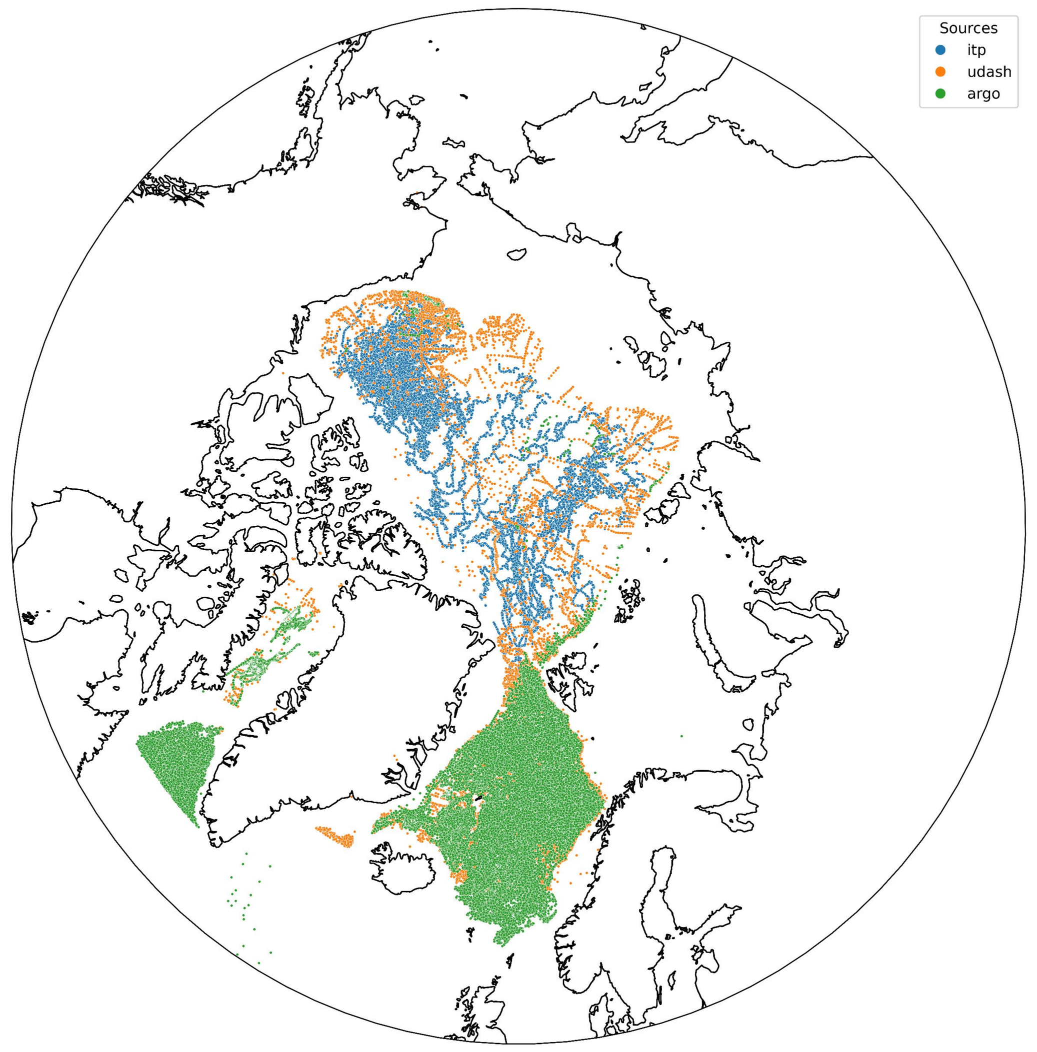

Figure 1 – Map of the location of the profiles, colour coded for the different data sources.

DATA

Measurement of the water characteristics for different depth/pressure levels, 397 797 temperature and salinity profiles from three sources spanning from 1980-01-01 to 2024-01-16:

- Ice Tethered Profiles (ITPs): Sensors attached beneath sea ice moving up and down a tether collecting temperature, salinity, and pressure of the water. [3] (108 590 profiles from 2004-08-20 to 2022-12-23).
- U-DASH: Ship-based data collection of water measurements. [4] (288 532 profile from 1980-01-01 to 2015-10-09).
- ARGO floats: Autonomous floats sinking and surfacing to collect water data in the span of 10 days, then transmit its data via satellites. [5] (675 from 1998-04-08 to 2024-01-16)

The location of the data and its source is shown in Figure 1. However, the data is temporally unbalanced (Figure 2), more data is available post-2005 and more is available during the Summer, and Autumn.

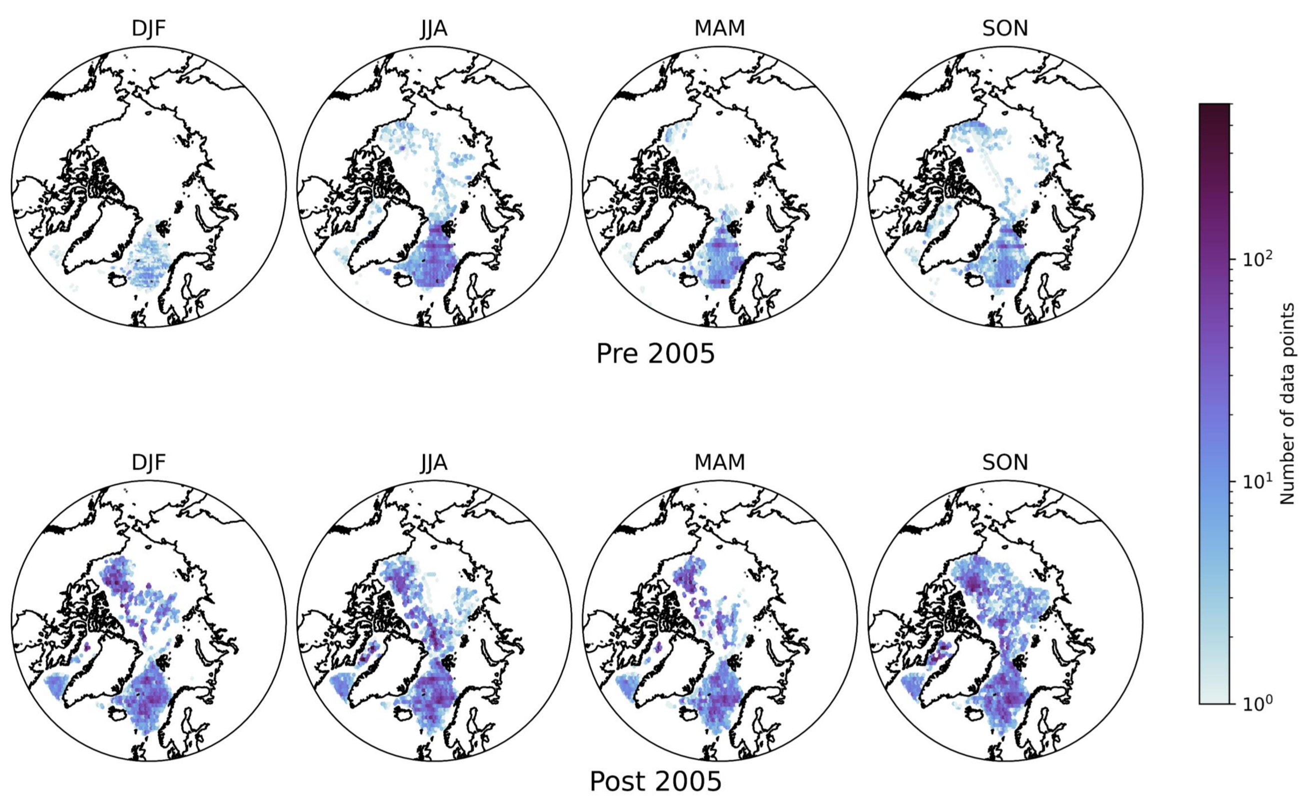

Figure 2 - Spatial density of measurements by season pre- and post-2005, described in "Data"

[1] https://doi.org/10.1038/s43247-022-00498-3
[2] https://doi.org/10.1029/2019GL086749
[3] https://doi.org/10.7289/v5mw2f7x
[4] https://doi.org/10.5194/essd-10-1119-2018, (data: https://doi.pangaea.de/10.1594/PANGAEA.872931)
[5] https://doi.org/10.3389/fmars.2020.00700
[6] https://doi.org/10.1017/eds.2023.40
[7] https://doi.org/10.1029/2018JC014629

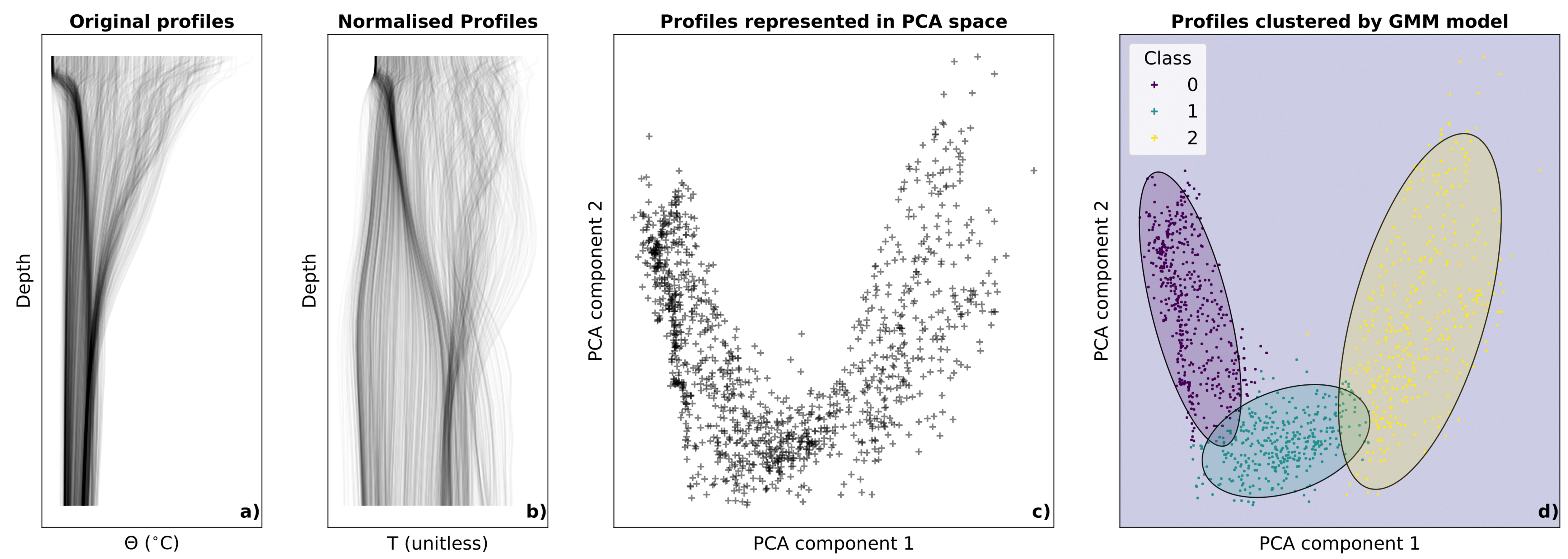

Figure 3 – Illustration of the pipeline used in this study. first original profile (a), then moved to a normalised (b), then Principal Component representation, and Clustering in eigenspace. Figure extracted from [6].
Note: this is an illustration only and the data is not from this study.

METHODOLOGY AND RESULTS

First creating a training dataset by subsampling the full dataset, in order to reduce spatial bias and eliminate seasonal bias. This results in 66 745 profiles spanning from 1980-01-08 to 2024-01-16.

Figure 3 shows the steps employed in training a Gaussian Mixture Model (GMM)[7]; this figure does not use data from this study, and only shows the temperature.
Using profiles for both temperature and salinity between the depth of 0 and 750 (Figure 3a), they are first normalised (Figure 3b) by removing the mean and scaling to unit variance. After which, a Principal Component Analysis (PCA) is performed (Figure 3c).
From that, using unsupervised clustering: a GMM, on the PCAs of the temperature and salinity (Figure 3d shows an example fitting on only 3 classes to two temperature PCAs)

Figure 5 shows the results of the fitting of a GMM using 4 classes on the first two PCAs of the temperature and first two PCAs of salinity. Figure 6 shows the mean temperature and salinity profiles for each class.

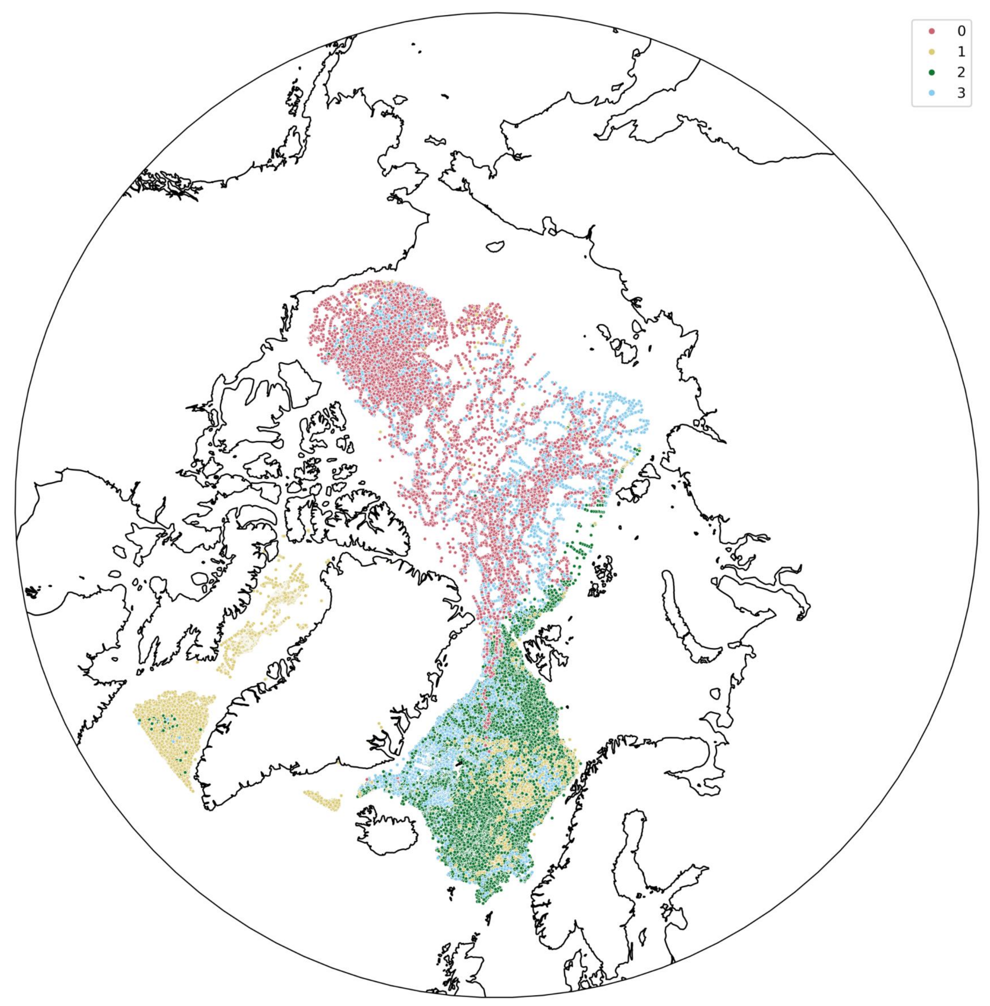

Figure 5 – Map of the location of the profiles, colour coded with class assigned by the GMM.

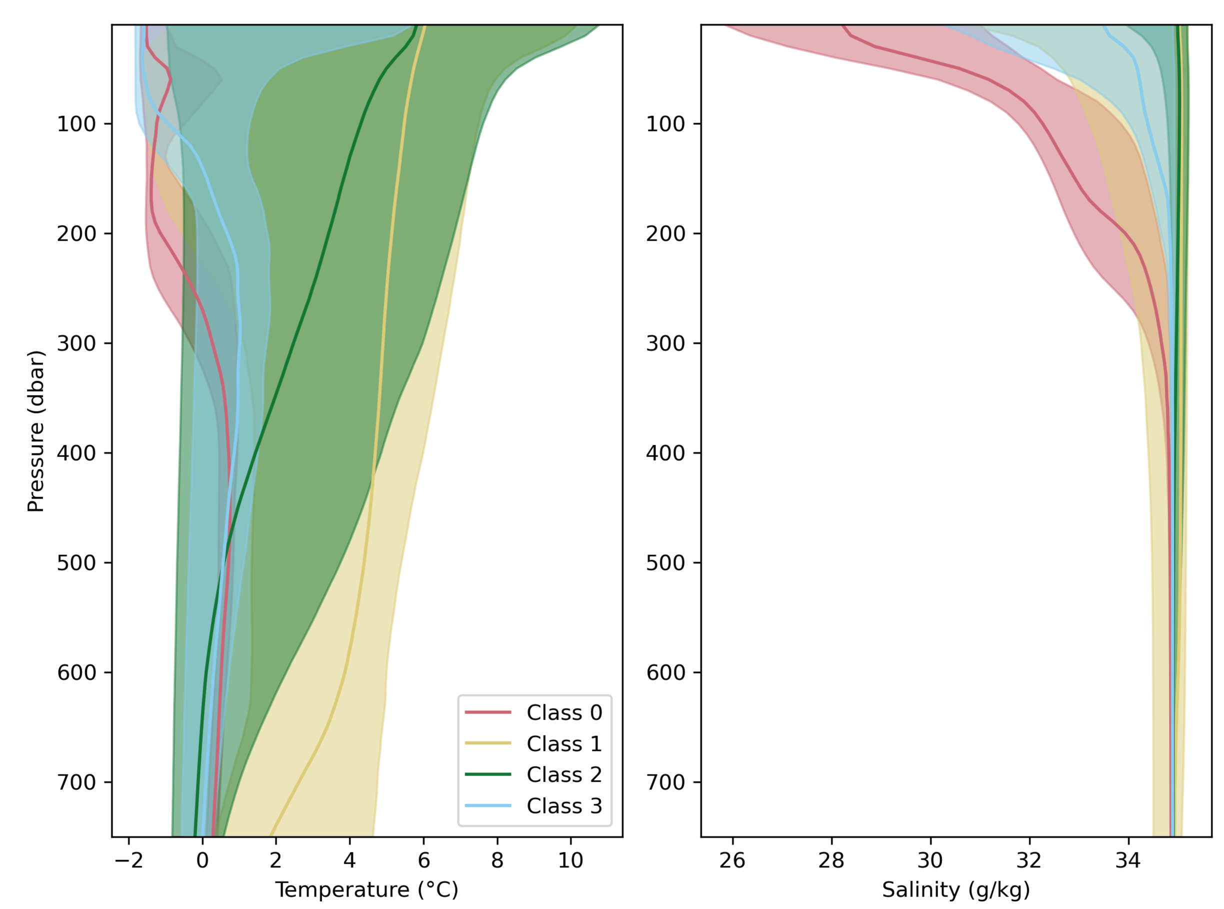

Figure 6 – Mean profile for the temperature and salinity, colour coded with class assigned by GMM

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