Navigating the Depths: Data Science and the Quest to Understand the AMOC's Impact on Our Climate

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Introduction

The Atlantic Meridional Overturning Circulation (AMOC) has a vast impact on the global oceanic system, driving a conveyor belt of warm, salty water from the equator to the North Atlantic. Here, the water cools, sinks, and redistributes heat worldwide, notably contributing to the temperate climate of Europe.

The AMOC operates on the principles of convection, driven by temperature and salinity that affect water density. This natural process propels cold water to great depths, making direct measurements challenging. In the era of global warming, rising temperatures and the influx of freshwater from melting ice caps are altering these delicate gradients, potentially destabilizing the AMOC.

Beyond heat redistribution, in which the AMOC accounts for 90% of northward ocean heat transport (National Centre for Atmospheric Science, n.d), the AMOC plays a crucial role in nutrient distribution and carbon sequestration. As one of the planet's major carbon sinks, it acts as a buffer against atmospheric $CO2$ increases, thereby decreasing global temperature rise. If the AMOC collapsed there would be near to no heat transfer from the equator to the north pole leaving northern regions such as most of Europe without an influx of warm weather which would lead to several problems such as food instability and most likely destroy the economy not just in Europe but globally due to the large influence of the EU.

There is an increasing need to understand the AMOC with its relevance only becoming more important over time as more damage is done to the climate and we become more climate conscious. It’s important to understand not just the current state of the AMOC but how our current actions and policies will influence changes to the AMOC. This is where data science has a pivotal role in being integrated with the research to create solid methodologies to get more accurate and valid results to form well-informed discussions and policies around oceanographic and climate research. To look at the literature it is important to grasp recent observations, the impact of changes in AMOC and how the AMOC can be influenced to then proceed with critical thinking about the data science used in the field and to then lay a solid foundation in a potential future direction of the research.

The incorporation of diverse perspectives, particularly from data science, into AMOC research represents an underutilized avenue for challenging and refining our understanding of this critical climate component.

Current state and recent developments

In recent decades, we have seen growing concern over the stability and strength of the AMOC. Scientific observations and models suggest that the AMOC is experiencing a period of weakening, with potential implications for global climate patterns that could affect weather extremes, sea-level rise, and the health of marine ecosystems. The urgency to understand the AMOC's current state and predict its future trajectories has never been greater, given its significant impact on global climate stability and the well-being of billions of people.

The current state of the AMOC is still up for debate with papers such as Zhang (2008) Showing results showing that the AMOC is strengthening with the evidence being from models although this is not the common consensus as most papers disagree and see the AMOC getting weaker but it has to be said that Zhang (2008) put the current weakening down to multidecadal variation concluding its unclear if its just variation or a long-term trend so as they don’t disagree with seeing the AMOC become weaker it's just the reasoning and concerns that vary. The Intergovernmental Panel on Climate Change is a credible source and their model shows that the AMOC is weakening although this report does use scenarios in which the greenhouse gas concentration is higher than predicted. The IPCC use an RCP 4.5 and 8.5 scenario with 8.5 being on the high end of greenhouse gas concentration. Riahi et al, (2011) point out that using this 8.5 scenario was meant to be used for worst-case scenarios instead it has been widely adopted. Researchers are going to lean towards using extremes in the models as research in what happens if everything goes perfectly doesn’t have as much of a readership. When reading literature, it wasn’t often clear what sort of model scenarios were used and to what extent

The most recent IPCC report (IPCC, 2023) says everything that has been seen to weaken the AMOC is on the rise with the report saying it is either very likely or extremely likely that the Antarctic and Greenland ice sheets have lost mass and the effect of this being observable through increased sea levels is a fact. The report says its human contribution has been the main effect of these although, for Antarctic ice sheet mass loss, it does mention that the evidence for this is limited and there is not as much agreement.

In summary, the AMOC is worse off than it has been historically and is in a downward trend (Caesar et al, 2021), there is a case to be made that we are approaching a turning point (Boers, 2021) which would lead to a sudden decrease in the AMOC but if this does happen research supporting a recovery (Jackson and Wood, 2018) has been seen but is not conclusive with not all the simulations showing a recovering is possible from a critical weakening of the AMOC given different scenarios.

Recent research has highlighted the significant implications of a weakening Atlantic Meridional Overturning Circulation (AMOC) on the climate system, revealing a complex web of effects that span from regional to global scales. The AMOC's slowdown is tied to notable changes in global and regional climates, including ocean cooling south of Greenland, reduced Arctic sea ice loss, and shifts in Northern Hemisphere midlatitude jets, as demonstrated by Liu et al, (2020). Furthermore, Dima et al, (2021) provided evidence that the AMOC's weakening likely commenced in the late 19th century, much earlier than previously suggested, with impacts exacerbated by increasing atmospheric CO2 concentrations that affect North Atlantic heat fluxes and precipitation rates. This weakening has extended into the South Atlantic, leading to a 'salinity pile-up' due to reduced salinity divergence, highlighting the global reach of AMOC changes (Zhu and Liu, 2020). Additionally, the AMOC's slowdown influences marine heatwaves (MHWs), particularly over the North Atlantic warming hole (NAWH), where it reduces the occurrence and duration of MHWs by creating a cooler sea surface temperature mean state, indicating a significant impact on marine ecosystems and weather patterns (Ren and Liu, 2021). Lastly, Thibodeau et al, (2018) linked the last century's warming over the Canadian Atlantic shelves to a weak AMOC, further emphasizing the connection between AMOC strength and regional climate changes. Together, these findings underscore the broad and profound impact of the AMOC's weakening on the Earth's climate system, necessitating continued monitoring and research to better understand these effects and to inform future climate resilience strategies.

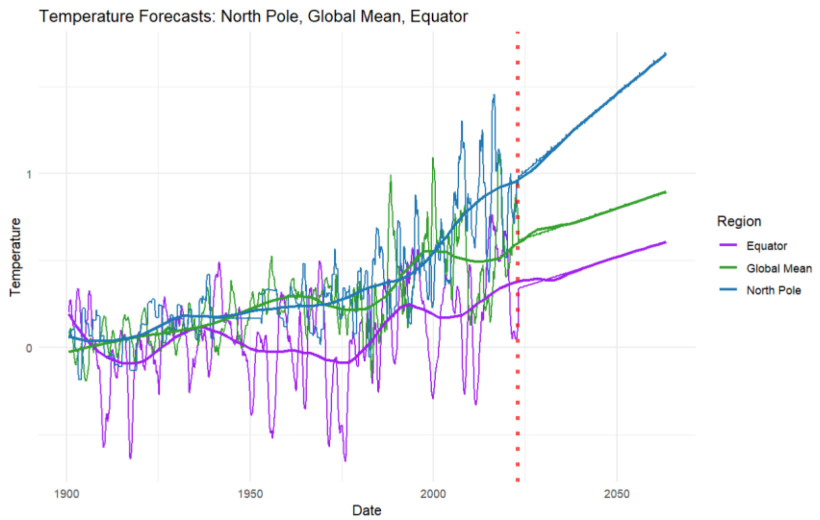

Figure 1. Increases in ocean surface temperature over time with forcasted predictions past 2023 (shown by red line)

It's easy to look at the proxy measures for the AMOC and what state they are in now especially when looking at surface temperatures. Figure 1 shows the current rate of change and a basic forest for the next 40 years. There's a disproportionate rate of increasing temperatures at the North Pole compared to at the equator which is the exact sort of behaviour that'll weaken the AMOC. It is also to be noted that the Paris Accord which is an international treaty on climate change has a goal of keeping temperature increases under 2 degrees from preindustrial times but is measuring temperature based on a mean good enough and should the more specific regional approach be taken when it comes to policy agreements.

Climatic Extremes Linked to AMOC Variability

The AMOCs' influence extends from affecting regional temperatures to impacting rainfall distribution and the frequency and intensity of hurricanes. The AMOC's variability is intrinsically linked to the Atlantic Multidecadal Variability (AMV), a phenomenon that induces temperature fluctuations across the North Atlantic and surrounding continents over decades (Zhang et al, 2019).

The study by Jackson et al (2023) further elaborates on the difficulties encountered in accurately simulating the AMOC within climate models. The paper underscores the need for addressing model biases, particularly those related to salinity, which significantly affect the simulation of the AMOC's strength and variability. These biases complicate the task of accurately predicting how changes in the AMOC could influence climatic extremes, including periods of enhanced hurricane activity or shifts in monsoon patterns.

Moreover, Jackson et al (2023) highlight the importance of improving the resolution and parameterization of climate models to enhance the representation of the AMOC. Enhancing model accuracy is crucial for better predicting the AMOC's impact on the AMV and, consequently, on climatic extremes. The research points towards a pressing need for a multidisciplinary approach, integrating ocean dynamics, atmospheric data, and paleoclimatic insights to refine our models and predictions regarding the AMOC.

The implications of underestimating AMOC variability are far-reaching, affecting not only climate predictions but also policy and planning decisions. Accurate simulations of the AMOC are crucial for preparing for climate-related extremes, such as severe storms and droughts. As such, the insights from Jackson et al (2023) underscore the urgency of addressing the current gaps in climate modelling related to the AMOC. By enhancing our models to accurately capture the AMOC's variability, we can improve our understanding of its impacts on climatic extremes, thereby facilitating better-informed climate adaptation and mitigation strategies.

In conclusion, the AMOC's role in influencing climatic extremes through its variability and the associated challenges in modelling its behaviour underscore the complexity of the Earth's climate system. The continued efforts to refine climate models and understand the AMOC's dynamics are essential for advancing our predictive capabilities and developing robust climate policies that can effectively address the impacts of climatic extremes.

Ocean Plankton and Ecosystem Health

The AMOC, acting as a conveyor belt of ocean water, heat, and nutrients, not only regulates the climate across the Atlantic but also plays a critical role in sustaining marine life, particularly plankton, the foundation of the oceanic food web.

Plankton communities, composed of phytoplankton and zooplankton, are highly sensitive to changes in water temperature and nutrient availability, both of which are directly influenced by the AMOC. Phytoplankton, microscopic plants that photosynthesize, rely on sunlight and nutrients to thrive. The northward flow of warm, nutrient-poor waters on the surface and the southward flow of colder, nutrient-rich waters at depth, characteristic of the AMOC, create environments conducive to plankton blooms in specific regions and times of the year. Variability in the AMOC can lead to shifts in these conditions, altering the timing, location, and intensity of plankton blooms (Frajka-Williams et al, 2019).

Recent studies have indicated a weakening of the AMOC, which has implications for plankton populations and, by extension, the entire marine ecosystem. A slowdown in the AMOC reduces the northward transport of warm water in the Atlantic, potentially leading to the cooling of the northern latitudes. This cooling can affect the stratification of ocean waters, impacting the upwelling of nutrients from the deep. Nutrient availability is a critical driver of phytoplankton productivity; thus, changes in nutrient upwelling can significantly affect the base of the marine food web. For example, decreased phytoplankton productivity due to reduced nutrient availability can lead to a decline in zooplankton populations, which rely on phytoplankton as their primary food source. This, in turn, impacts fish and marine mammals higher up the food chain, potentially leading to declines in biodiversity and fishery yields, which many coastal communities depend on for food and economic activity (Boers, 2021).

Moreover, the role of phytoplankton in carbon sequestration cannot be overstated. By absorbing carbon dioxide from the atmosphere during photosynthesis, phytoplankton contribute to the biological carbon pump, a critical process in the global carbon cycle. Variations in AMOC strength and the resultant impacts on phytoplankton productivity could influence the ocean's capacity to sequester carbon, with broader implications for global climate regulation (Caesar et al, 2021).

The potential for abrupt and unforeseen changes in the AMOC presents a significant uncertainty in predicting the future of marine ecosystems. Paleoclimate records suggest that past shifts in the AMOC have been associated with rapid climate changes and corresponding shifts in marine ecosystems. Today, as the climate continues to warm, understanding the interplay between the AMOC, plankton populations, and marine ecosystem health becomes increasingly critical.

Marine ecosystems, particularly in the North Atlantic, are also at risk. The AMOC plays a pivotal role in transporting heat and nutrients across the Atlantic, supporting a diverse range of marine life. A disruption could lead to shifts in fish populations, impacting fisheries and the broader marine food web (Frajka-Williams et al, 2019). Additionally, there's a concern over the broader implications for global carbon cycles, given the role of the North Atlantic in carbon sequestration (Boers, 2021).

AMOC and Sea-Level Rise

A notable mechanism through which the AMOC influences sea-level rise is thermal expansion. As the AMOC weakens, less warm water is transported from the equator to the poles, leading to an accumulation of heat in the North Atlantic. This excess heat causes seawater to expand, contributing to sea-level rise (Levermann et al, 2013). Furthermore, the redistribution of heat due to changes in the AMOC can affect atmospheric temperatures and, consequently, the melting rates of ice caps and glaciers, adding to global sea levels through freshwater influx (Church et al, 2013).

The melting of the Greenland ice sheet presents a critical feedback loop in the context of AMOC weakening. Studies have shown that as the AMOC slows down, North Atlantic warming intensifies, accelerating ice melt in Greenland. This meltwater discharge further dilutes the North Atlantic, inhibiting the formation of dense water masses crucial for the continuation of the AMOC, thereby potentially leading to further weakening of the circulation (Bakker et al, 2017). This feedback mechanism highlights the complex interplay between oceanic and cryospheric components of the Earth system.

Regional impacts of AMOC changes on sea-level rise are profound and uneven, with certain areas experiencing more significant effects than others. The U.S. East Coast, for instance, has been identified as a hotspot for accelerated sea-level rise, partially attributable to AMOC slowdown. This region's vulnerability is compounded by local oceanic and atmospheric processes, which are influenced by the broader changes in the AMOC (Ezer et al, 2013). As such, understanding the regional fingerprints of AMOC-induced sea-level rise is essential for local to national-scale planning and adaptation efforts.

Adapting to the challenges posed by AMOC-related sea-level rise necessitates a multifaceted approach, including enhanced monitoring, predictive modelling, and implementation of resilient infrastructure. The RAPID monitoring program across the Atlantic at 26.5°N, for example, provides invaluable data on AMOC strength and variability, offering insights into its potential impacts on sea levels (Smeed et al, 2014). Such observational efforts, coupled with advanced climate models, are critical for refining our understanding of the AMOC's behaviour under future climate scenarios and informing mitigation and adaptation strategies. Continued research and monitoring are imperative to unravel the complexities of the AMOC-sea level nexus, enabling societies to anticipate changes and implement effective adaptation measures. The intricate relationship between the AMOC, ice melt, and thermal expansion underscores the interconnected nature of Earth's climate system, highlighting the need for an integrated approach to climate science and policymaking.

Polar Ice Melt and Freshwater Influx

Recent studies have underscored the significance of polar ice melt, notably from the Greenland Ice Sheet, in contributing to freshwater influx into the North Atlantic, which could potentially weaken the AMOC (Caesar et al,2021). This process is primarily driven by the reduction in water salinity, diminishing the density of surface waters and thereby affecting their ability to sink, a critical mechanism driving the AMOC (Boers, 2021).

The implications of a weakened or disrupted AMOC are profound, affecting not only regional climates but also global weather patterns, sea-level distribution, and marine ecosystems. A notable consequence is an alteration in heat distribution across the Atlantic, which could lead to cooler temperatures in Northern Europe and exacerbated weather extremes (Weijer et al, 2020). Furthermore, recent research highlights the potential for significant sea-level rise along the U.S. East Coast, directly linked to a slowdown in the AMOC (Caesar et al, 2021).

The historical context provides valuable insights into the potential for rapid and dramatic changes in the AMOC. Paleoclimatic evidence suggests that the AMOC has previously experienced significant fluctuations, leading to abrupt climate changes (Thornalley et al, 2018). This historical precedent underscores the critical need for continued monitoring and research to better understand the current dynamics and future trajectory of the AMOC in response to ongoing polar ice melt.

Efforts to monitor the AMOC, such as the RAPID array at 26°N and the Overturning in the Subpolar North Atlantic Program (OSNAP), have provided crucial data on its current state. These observational networks, alongside advanced climate models, are essential tools for predicting future changes and informing policy and adaptation strategies (Lozier et al, 2019).

In conclusion, the freshwater influx from polar ice melt poses a significant risk to the stability and function of the AMOC, with far-reaching implications for climate, sea-level rise, and marine ecosystems. The intricate relationship between ice melt, freshwater influx, and ocean circulation underscores the urgency of addressing climate change and enhancing our understanding of these complex systems. Continued research, monitoring, and integration of observational data with modelling efforts are imperative for anticipating future changes and mitigating their impacts on global climate and ocean health.

Data Science approach

The AMOC's complexity, compounded by factors such as wind patterns, temperature gradients, and salinity variations, poses substantial challenges to accurately measuring its components and understanding its behaviour (Lozier et al, 2019). Unlike more accessible surface currents like the Gulf Stream, the AMOC's primary mechanisms operate in the deep ocean, rendering direct measurements particularly challenging.

The AMOC exhibits pronounced spatial and temporal variability, complicating the task of obtaining comprehensive observations across its entire expanse. Traditional observational methods, including Argo floats, offer limited utility in capturing the AMOC's full depth, as they primarily sample the upper ocean. Moreover, the critical regions of AMOC activity, notably the polar areas, present harsh conditions that hinder measurement efforts, elevating logistical challenges and the costs associated with comprehensive data collection (Boers, 2021).

Historically, the direct measurement record of the AMOC is relatively brief, which restricts our understanding of its long-term trends and dynamics. Consequently, researchers often rely on proxy data, such as sediment cores and sea-level changes, to infer historical AMOC behaviour. While invaluable, these methods introduce uncertainties and may not fully encapsulate the AMOC's intricacies (Thornalley et al, 2018).

To predict the AMOC's future behaviour under varying climate scenarios, scientists employ numerical models. However, accurately modelling such a complex system is fraught with uncertainties. These models may not entirely represent the myriad interactions within the ocean-atmosphere system, leading to potential discrepancies between model forecasts and actual observations. Additionally, the AMOC's dynamic nature, influenced by external factors including climate change, amplifies the complexity of modelling efforts and magnifies uncertainties regarding its future state (Weijer et al, 2020).

Given these challenges, the study of the AMOC necessitates interdisciplinary collaboration, employing advanced observational technologies and data science methodologies. Enhanced satellite observations, coupled with autonomous underwater vehicles like Argo floats, have provided new insights into the ocean's thermal and saline structures, essential for understanding the AMOC (Boers, 2021). Moreover, advancements in computational capabilities have enabled the development of high-resolution ocean models, significantly improving our capacity to simulate the AMOC and predict its future behaviour (Weijer et al, 2020).

Incorporating big data analytics and machine learning algorithms into AMOC research has emerged as a promising avenue for analyzing complex datasets, identifying patterns, and optimizing observational strategies. These data-driven approaches not only augment our understanding of the AMOC but also refine the reliability of future projections (Lozier et al, 2019; Boers, 2021).

In conclusion, the comprehensive study of the AMOC, characterized by its intricate dynamics and substantial influence on the climate system, presents a formidable challenge. Addressing these challenges necessitates a multifaceted approach, leveraging innovative measurement techniques, advanced modelling capabilities, and cutting-edge data science strategies. Through concerted interdisciplinary efforts, we can enhance our understanding of the AMOC's role within the Earth's climate system and refine our predictions of its response to ongoing and future climatic changes.

Addressing uncertainty

Addressing the uncertainties surrounding the Atlantic Meridional Overturning Circulation (AMOC) is crucial for enhancing our understanding and predictive capabilities regarding its impacts on global climate systems. A significant challenge lies in the gaps within observational networks, which lack comprehensive spatial and temporal coverage, thus limiting the accuracy of AMOC assessments (Frajka-Williams et al, 2019). Additionally, climate models vary in their representation of key physical processes influencing the AMOC, such as deep water formation and freshwater inputs, leading to divergent predictions about its future state (Weijer et al, 2020). Efforts to mitigate these uncertainties include expanding observational efforts, like the Overturning in the Subpolar North Atlantic Program (OSNAP), to improve understanding of the AMOC's variability and trends (Lozier et al, 2019). Moreover, enhancing climate models to more accurately simulate the AMOC's dynamics and its interactions with the atmosphere and cryosphere is essential (Weijer et al, 2019). Embracing multidisciplinary approaches and fostering international collaboration are key strategies for pooling resources, sharing data, and advancing the collective knowledge of the AMOC and its climatic implications (Caesar et al, 2021). Models are getting better with time which is to be expected as computers get more powerful and algorithms improve which should lead to more common consensus in the field and allow for more informed policy decisions.

Conclusion

The synthesis of recent research underscores a concerning trend of weakening in the AMOC, attributed largely to anthropogenic climate change. This weakening portends significant shifts in weather patterns, with the potential for increased climatic extremes and disruptions to marine biodiversity and productivity. The impacts on human societies, particularly through changes in fisheries, agriculture, and increased vulnerability to sea-level rise, call for urgent attention and action.

Addressing the inherent uncertainties in understanding the AMOC's dynamics highlights the indispensable role of data science. Enhanced monitoring efforts, advanced modelling techniques, and the integration of big data analytics and machine learning have emerged as pivotal tools in refining our comprehension and predictive capabilities concerning the AMOC. These technological advancements offer a new way to navigate the uncertainty of future climate scenarios.

Yet, as we conclude, it is evident that a singular approach is insufficient to address the scale of challenges posed by changes in the AMOC. A concerted effort embracing interdisciplinary collaboration, international cooperation, and a commitment to innovative research is paramount. This collective endeavour must aim not only to advance our scientific understanding but also to inform policy, guide adaptive strategies, and foster resilience against the impending changes heralded by the AMOC's fluctuation.

In facing one of the 21st century's defining challenges—climate change—the study of the AMOC stands as a critical frontier. It is a reminder of the interconnectedness of our global climate system and the need for a unified approach to safeguard our collective future. As we move forward, let this report serve as both a foundation and a call to action, urging us to harness the power of data science and international collaboration in pursuit of a deeper understanding and effective stewardship of our planet's climatic equilibrium.

Bibliography

Bakker, A. M. R., Wong, T. E., Ruckert, K. L., and Keller, K. (2017) Sea-level projections representing the deeply uncertain contribution of the West Antarctic ice sheet. 7(1): 3880.

Boers, N. (2021) Observation-based early-warning signals for a collapse of the Atlantic Meridional Overturning Circulation. 11(8): 680–688.

Caesar, L., McCarthy, G. D., Thornalley, D., Cahill, N., and Rahmstorf, S. (2021) Current Atlantic meridional overturning circulation weakest in last millennium. 14(3): 118–120.

Church, C., Clark, C., Cazenave, C., Gregory, G., Jevrejeva, J., Levermann, L., Merrifield, M., Milne, M., Nerem, N., Nunn, N., Payne, P., Pfeffer, P., Stammer, S., and Unnikrishnan, U. (2013) Sea-Level Rise by 2100. 342(6165): 1445.

Dima, M., Nichita, D. R., Lohmann, G., Ionita, M., and Voiculescu, M. (2021) Early-onset of Atlantic Meridional Overturning Circulation weakening in response to atmospheric CO2 concentration. 4(1): 27.

Ezer, T., Atkinson, L., Corlett, W. B., and Blanco, J. (2013) Gulf Stream's induced sea level rise and variability along the U.S. mid-Atlantic coast. 118: 685–697.

Frajka-Williams, E., Ansorge, I. J., Baehr, J., Bryden, H. L., Chidichimo, M. P., Cunningham, S. A., et al. (2019) Atlantic Meridional Overturning Circulation: Observed Transport and Variability. 6.

Jackson, L. C., and Wood, R. A. (2018) Hysteresis and Resilience of the AMOC in an Eddy-Permitting GCM. 45(16): 8547–8556.

Jackson, Laura C., Hewitt, H. T., Bruciaferri, D., Calvert, D., Graham, T., Guiavarc'h, C., Menary, M. B., New, A. L., Roberts, M., and Storkey, D. (2023) Challenges simulating the AMOC in climate models. 381(2262): 20220187.

Levermann, A., Clark, P. U., Marzeion, B., Milne, G. A., Pollard, D., Radic, V., and Robinson, A. (2013) The multimillennial sea-level commitment of global warming. 110(34): 13745–13750.

Liu, W., Fedorov, A. V., Xie, S.-P., and Hu, S. (2020) Climate impacts of a weakened Atlantic Meridional Overturning Circulation in a warming climate. 6(26): eaaz4876.

Lozier, L., Li, L., Bacon, B., Bahr, B., Bower, B., Cunningham, C., et al. (2019) A sea change in our view of overturning in the subpolar North Atlantic. 363(6426): 516–521.

Mahajan, S., Zhang, R., and Delworth, T. L. (2011) Impact of the Atlantic meridional overturning circulation (AMOC) on Arctic surface air temperature and sea ice variability. 24(24): 6573–6581.

Ren, X., and Liu, W. (2021) The role of a weakened Atlantic meridional overturning circulation in modulating marine heatwaves in a warming climate. 48(23): e2021GL095941.

Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., Kindermann, G., Nakicenovic, N., and Rafaj, P. (2011) RCP 8.5—A scenario of comparatively high greenhouse gas emissions. 109: 33–57.

Smeed, D. A., McCarthy, G. D., Cunningham, S. A., Frajka-Williams, E., Rayner, D., Johns, W. E., Meinen, C. S., Baringer, M. O., Moat, B. I., Duchez, A., and Bryden, H. L. (2014) Observed decline of the Atlantic meridional overturning circulation 2004â€“2012. 10(1): 29–38.

Thibodeau, B., Not, C., Zhu, J., Schmittner, A., Noone, D., Tabor, C., Zhang, J., and Liu, Z. (2018) Last Century Warming Over the Canadian Atlantic Shelves Linked to Weak Atlantic Meridional Overturning Circulation. 45(22): 12,376-12,385.

Thornalley, D. J. R., Oppo, D. W., Ortega, P., Robson, J. I., Brierley, C. M., Davis, R., Hall, I. R., Moffa-Sanchez, P., Rose, N. L., Spooner, P. T., Yashayaev, I., and Keigwin, L. D. (2018) Anomalously weak Labrador Sea convection and Atlantic overturning during the past 150 years. 556(7700): 227–230.

Weijer, W., Cheng, W., Drijfhout, S. S., Fedorov, A. V., Hu, A., Jackson, L. C., Liu, W., McDonagh, E. L., Mecking, J. V., and Zhang, J. (2019) Stability of the Atlantic Meridional Overturning Circulation: A Review and Synthesis. 124(8): 5336–5375.

Weijer, Wilbert, Cheng, W., Garuba, O. A., Hu, A., and Nadiga, B. T. (2020) CMIP6 models predict significant 21st century decline of the Atlantic meridional overturning circulation. 47(12): e2019GL086075.

Zhang, R. (2008) Coherent surface-subsurface fingerprint of the Atlantic meridional overturning circulation. 35(20).

Zhang, R., Sutton, R., Danabasoglu, G., Kwon, Y.-O., Marsh, R., Yeager, S. G., Amrhein, D. E., and Little, C. M. (2019) A Review of the Role of the Atlantic Meridional Overturning Circulation in Atlantic Multidecadal Variability and Associated Climate Impacts. 57(2): 316–375.

Zhu, C., and Liu, Z. (2020) Weakening Atlantic overturning circulation causes South Atlantic salinity pile-up. 10(11): 998–1003.

IPCC, 2023: *Climate Change 2023: Synthesis Report.* Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland, pp. 35-115, doi: 10.59327/IPCC/AR6-9789291691647.

National Centre for Atmospheric Science (NCAS) (n.d.) What is the Atlantic Meridional Overturning Circulation and its role for our planet. Available at: https://ncas.ac.uk/what-is-the-atlantic-meridional-overturning-circulation-and-its-role-for-our-planet (Accessed: 25/03/2024)

R Code for figure 1:

```
library(tidyverse)
library(forecast) # For stl() function
library(lubridate) # For month() function
library(RColorBrewer) # For color scales
library(prophet)

# Load your dataset (adjust path as needed)
saltNP <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/np/saltNP.csv")
currentNP <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/np/currentNP.csv")
seatempNP <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/np/seatempNP.csv")
seawindNP <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/np/seawindNP.csv")
mixNP <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/np/mixNP.csv")

saltM <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/mean/saltM.csv")
currentM <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/mean/currentM.csv")
seatempM <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/mean/tempM.csv")
seawindM <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/mean/seawindM.csv")
mixM <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/mean/mixM.csv")
```

```
saltE <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/equator/saltE.csv")
currentE <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/equator/currentE.csv")
seatempE <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/equator/tempE.csv")
seawindE <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/equator/seawindE.csv")
mixE <- read_csv("C:/Users/archi/Desktop/ADSAS/comms/equator/mixE.csv")

# Define a function to combine data frames for different variables and regions
combine_data <- function(variable, np_data, mean_data, equator_data) {
 combined_data <- bind_rows(
  list(
   np = np_data,
   mean = mean_data,
   equator = equator_data
  ),
  .id = "region"
 )
 # Add a variable column to identify the data type
 combined_data <- mutate(combined_data, variable = variable)
 return(combined_data)
}

# Combine the data for salt
combined_salt <- combine_data("salt", saltNP, saltM, saltE)

# Combine the data for current
combined_current <- combine_data("current", currentNP, currentM, currentE)

# Combine the data for sea temperature
combined_temp <- combine_data("sea_temperature", seatempNP, seatempM, seatempE)

# Combine the data for sea wind
combined_wind <- combine_data("sea_wind", seawindNP, seawindM, seawindE)
```

```
# Combine the data for mix

combined_mix <- combine_data("mix", mixNP, mixM, mixE)


# View the combined data

head(combined_salt)

combined_salt <- combined_salt[, -which(names(combined_salt) == "...3")]

head(combined_current)

combined_current <- combined_current[, -which(names(combined_current) == "...3")]

head(combined_temp)

combined_temp <- combined_temp[, -which(names(combined_temp) == "...3")]

head(combined_wind)

combined_wind <- combined_wind[, -which(names(combined_wind) == "...3")]

head(combined_mix)

combined_mix <- combined_mix[, -which(names(combined_mix) == "...3")]


ggplot(data = combined_salt, aes(x = `DATE-YMD`, y = `PSAL= Hadley-EN4 Salinity () at 5 m`, color
      = region)) +

 geom_line() +

 geom_smooth(method = "loess", se = FALSE) +  # Add a loess smoother

 labs(x = "Date", y = "Salinity", color = "Region", title = "Salinity Over Time with Smoother") +

 theme_minimal()


ggplot(data = combined_current, aes(x = `DATE-YMD`, y = `OTHR= OSCAR surface currents v-NS-
      component (m/s)`, color = region)) +

 geom_line() +

 geom_smooth(method = "loess", se = FALSE) +  # Add a loess smoother

 labs(x = "Date", y = "Surface Current (m/s)", color = "Region", title = "Surface Current Over Time with
      Smoother") +

 theme_minimal()


ggplot(data = combined_temp, aes(x = `DATE-YMD`, y = `HSST= HadISST Temperature (C)`, color =
      region)) +

 geom_line() +
```

```
 geom_smooth(method = "loess", se = FALSE) +  # Add a loess smoother
 labs(x = "Date", y = "Temperature (C)", color = "Region", title = "Temperature Over Time with
      Smoother") +
 theme_minimal()


ggplot(data = combined_wind, aes(x = ` DATE-YMD` , y = ` OTHR= SeaWinds Windspeed v-NS-
      component (m/s)` , color = region)) +
 geom_line() +
 geom_smooth(method = "loess", se = FALSE) +  # Add a loess smoother
 labs(x = "Date", y = "Windspeed (m/s)", color = "Region", title = "Windspeed Over Time with
      Smoother") +
 theme_minimal()


ggplot(data = combined_mix, aes(x = ` DATE-YMD` , y = ` OTHR= CMEMS Mixed Layer Depth (m)` ,
      color = region)) +
 geom_line() +
 geom_smooth(method = "loess", se = FALSE) +  # Add a loess smoother
 labs(x = "Date", y = "Mixed Layer Depth (m)", color = "Region", title = "Mixed Layer Depth Over Time
      with Smoother") +
 theme_minimal()



# Convert the date column to a Date object
combined_temp$Date <- as.Date(combined_temp$` DATE-YMD` )


# Split the dataset by region
region1_data <- subset(combined_temp, region == "np")
region2_data <- subset(combined_temp, region == "mean")
region3_data <- subset(combined_temp, region == "equator")


# Function to decompose and extract trend for each region
decompose_and_extract_trend <- function(region_data) {
 ts_data <- ts(region_data$` HSST= HadISST Temperature (C)` , frequency = 12)  # Assuming monthly
      data
 decomp <- decompose(ts_data)
```

```
  return(decomp$trend)
}

# Apply the function to each region's data
region1_trend <- decompose_and_extract_trend(region1_data)
region2_trend <- decompose_and_extract_trend(region2_data)
region3_trend <- decompose_and_extract_trend(region3_data)

# Add the trend components as new columns in the respective region datasets
region1_data$Trend <- region1_trend
region2_data$Trend <- region2_trend
region3_data$Trend <- region3_trend

# Remove rows with NA values
region1_data <- na.omit(region1_data)
region2_data <- na.omit(region2_data)
region3_data <- na.omit(region3_data)

# Extract the number from the first row of the Trend column
ftv1 <- region1_data$Trend[22]
region1_data$Trend <- region1_data$Trend - ftv1
ftv2 <- region2_data$Trend[17]
region2_data$Trend <- region2_data$Trend - ftv2
ftv3 <- region3_data$Trend[50]
region3_data$Trend <- region3_data$Trend - ftv3




# Combine the datasets back together
final_data <- rbind(region1_data, region2_data, region3_data)

# Remove rows with NA values
```

```r
final_data <- final_data[complete.cases(final_data), ]

# Convert DATE-YMD to Date format if not already done
final_data$DATE_YMD <- as.Date(final_data$`DATE-YMD`)

# Define custom color palette
custom_colors <- c("#1f78b4", "#33a02c", "#e31a1c")

# Plot the data with smoothed lines and custom colors
ggplot(final_data, aes(x = DATE_YMD, y = Trend, color = region)) +
  geom_line() +
  geom_smooth(method = "loess", se = FALSE) +  # Add smoothed line
  scale_color_manual(values = custom_colors) +  # Use custom colors
  labs(x = "Date", y = "Trend", color = "Region") +
  ggtitle("Trend Over Time for Different Regions") +
  theme_minimal()
head(data1)

# Read and preprocess the first dataset
data1 <- region1_data %>%
  select(`DATE-YMD`,Trend) %>%
  rename(ds = `DATE-YMD`, y = Trend) %>%
  mutate(ds = as.Date(ds, format = "%Y-%m-%d"))

# Explicitly convert `ds` to Date to ensure it's the correct type
data1 <- data1 %>%
  mutate(ds = as.Date(ds, format = "%Y-%m-%d"))
# Check if the conversion was successful
if(!all(sapply(data1$ds, inherits, "Date"))) {
  stop("Not all 'ds' values could be converted to Date type.")
}
# Continue with model fitting and forecasting as before...
```

```
model1 <- prophet(data1, interval.width = 0.95)
future1 <- make_future_dataframe(model1, periods = 40 * 12, freq = 'month')
forecast1 <- predict(model1, future1)
# Ensure 'ds' in 'forecast2' is also a Date
forecast1$ds <- as.Date(forecast1$ds)

# Plot the forecast, including uncertainty intervals for the first dataset
plot(model1, forecast1)
prophet_plot_components(model1, forecast1)

# Filtering and plotting adjustment for the first dataset
data_up_to_20231 <- data1 %>%
  filter(ds <= as.Date("2023-01-15"))
forecast_after_20231 <- forecast1 %>%
  filter(ds > as.Date("2023-01-15"))
combined_data1 <- bind_rows(
  data_up_to_20231 %>% select(ds, yhat = y),
  forecast_after_20231 %>% select(ds, yhat, yhat_lower, yhat_upper)
)

# Plotting for the first dataset
p1 <- ggplot() +
  geom_line(data = data_up_to_20231, aes(x = ds, y = y), color = 'black') +
  geom_ribbon(data = forecast_after_20231, aes(x = ds, ymin = yhat_lower, ymax = yhat_upper), fill =
      'grey', alpha = 0.5) +
  geom_line(data = forecast_after_20231, aes(x = ds, y = yhat), color = 'blue') +
  geom_smooth(data = combined_data1, aes(x = ds, y = yhat), method = 'loess', se = FALSE, color =
      'red', span = 0.3) +
  labs(x = 'Date', y = 'Temperature', title = 'North Pole Temperature Forecast') +
  theme_minimal()
print(p1)
```

```
# Read and preprocess the second dataset
data2 <- region2_data %>%
  select(`DATE-YMD`, Trend) %>%
  rename(ds = `DATE-YMD`, y = Trend) %>%
  mutate(ds = as.Date(ds, format = "%Y-%m-%d"))
# Explicitly convert `ds` to Date to ensure it's the correct type
data2 <- data2 %>%
  mutate(ds = as.Date(ds, format = "%Y-%m-%d"))
# Check if the conversion was successful
if(!all(sapply(data2$ds, inherits, "Date"))) {
  stop("Not all 'ds' values could be converted to Date type.")
}
# Continue with model fitting and forecasting as before...
model2 <- prophet(data2, interval.width = 0.95)
future2 <- make_future_dataframe(model2, periods = 40 * 12, freq = 'month')
forecast2 <- predict(model2, future2)
# Ensure 'ds' in 'forecast2' is also a Date
forecast2$ds <- as.Date(forecast2$ds)
# Plot the forecast, including uncertainty intervals for the second dataset
plot(model2, forecast2)
prophet_plot_components(model2, forecast2)
# Filtering and plotting adjustment for the second dataset
# This should reference `data2` not `data`
data_up_to_20232 <- data2 %>%
  filter(ds <= as.Date("2023-01-15"))
forecast_after_20232 <- forecast2 %>%
  filter(ds > as.Date("2023-01-15"))
combined_data2 <- bind_rows(
  data_up_to_20232 %>% select(ds, yhat = y),
  forecast_after_20232 %>% select(ds, yhat, yhat_lower, yhat_upper)
)
# Plotting for the second dataset
```

```
p2 <- ggplot() +
  geom_line(data = data_up_to_20232, aes(x = ds, y = y), color = 'black') +
  geom_ribbon(data = forecast_after_20232, aes(x = ds, ymin = yhat_lower, ymax = yhat_upper), fill =
      'grey', alpha = 0.5) +
  geom_line(data = forecast_after_20232, aes(x = ds, y = yhat), color = 'blue') +
  geom_smooth(data = combined_data2, aes(x = ds, y = yhat), method = 'loess', se = FALSE, color =
      'red', span = 0.3) +
  labs(x = 'Date', y = 'Temperature', title = 'Global Mean Temperature Forecast') +
  theme_minimal()
print(p2)


# Read and preprocess the third dataset
data3 <- region3_data %>%
  select(`DATE-YMD`, Trend) %>%
  rename(ds = `DATE-YMD`, y = Trend) %>%
  mutate(ds = as.Date(ds, format = "%Y-%m-%d"))
# Fit the Prophet model with a specified confidence interval for the third dataset
model3 <- prophet(data3, interval.width = 0.95)
future3 <- make_future_dataframe(model3, periods = 40 * 12, freq = 'month')
forecast3 <- predict(model3, future3)
# Ensure 'ds' in 'forecast3' is also a Date
forecast3$ds <- as.Date(forecast3$ds)
# Plot the forecast, including uncertainty intervals for the third dataset
plot(model3, forecast3)
prophet_plot_components(model3, forecast3)
# Filtering and plotting adjustment for the third dataset
data_up_to_20233 <- data3 %>%
  filter(ds <= as.Date("2023-01-15"))
forecast_after_20233 <- forecast3 %>%
  filter(ds > as.Date("2023-01-15"))
combined_data3 <- bind_rows(
  data_up_to_20233 %>% select(ds, yhat = y),
  forecast_after_20233 %>% select(ds, yhat, yhat_lower, yhat_upper)
```

```
)
# Plotting for the third dataset
p3 <- ggplot() +
  geom_line(data = data_up_to_20233, aes(x = ds, y = y), color = 'black') +
  geom_ribbon(data = forecast_after_20233, aes(x = ds, ymin = yhat_lower, ymax = yhat_upper), fill =
      'grey', alpha = 0.5) +
  geom_line(data = forecast_after_20233, aes(x = ds, y = yhat), color = 'blue') +
  geom_smooth(data = combined_data3, aes(x = ds, y = yhat), method = 'loess', se = FALSE, color =
      'red', span = 0.3) +
  labs(x = 'Date', y = 'Temperature', title = 'Equatorial Temperature Forecast') +
  theme_minimal()
print(p3)

# Add a 'source' column to each combined data frame
combined_data1$source <- 'North Pole'
combined_data2$source <- 'Global Mean'
combined_data3$source <- 'Equator'

# Combine the data frames into one
combined_all <- bind_rows(combined_data1, combined_data2, combined_data3)

# Custom color definitions
custom_colors <- c('North Pole' = "#1f78b4", 'Global Mean' = "#33a02c", 'Equator' = "purple")

date_to_mark <- as.Date("2023-01-15")

# Plot using ggplot2 without CI bars and with custom colors
p_all <- ggplot(combined_all, aes(x = ds, y = yhat, color = source)) +
  geom_line() +
  geom_smooth(se = FALSE, method = 'loess', span = 0.3, aes(color = source)) + # Smooth line over
      both actual and forecast
  geom_vline(xintercept = as.numeric(date_to_mark), linetype = 'dotted', color = 'red', size = 1.5, alpha
      = 0.7) + # Add red dotted line at 2023-01-15
```

```
labs(x = 'Date', y = 'Temperature', title = 'Temperature Forecasts: North Pole, Global Mean, Equator',
    caption = "Figure 1. Increases in ocean surface temperature over time with forcasted
    predictions past 2023 (shown by red line)") +

theme_minimal() +

scale_color_manual(values = custom_colors) +

guides(color = guide_legend(title = "Region"))


print(p_all)
```