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Ice Edge Verification

Measuring the skill in our Forecasts and disagreement in our Observations

Thesis

submitted in ful lment of the requirements for the Degree of

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Abstract

Sea ice is one of the most crucial components of the polar system. Alongside its effects on the climate and weather, it also impacts human lives and operations in these regions. Climate scientists, as well as other stakeholders (such as marine industries, mining operations, governmental authorities as well as local/aboriginal population), have a high interest in getting accurate observation and prediction of sea ice presence, and its effective border – the ice edge. In this context, this thesis is focused on the verification of ice presence and ice edge, across different datasets. We do this by describing a new method of generating reference forecasts of the ice edge (as benchmark for predictions at sub-seasonal to seasonal timescales), analysing initial state errors in forecasts and analysis from ECMWF, and comparing the ice presence and ice edge difference between several observational and analysis datasets.

Operational systems generating sea ice forecasts at sub-seasonal timescales are mostly compared against simple references based solely on climatological or initial states, which can lead to a potential overestimation of their prediction skill. In chapter 1, we describe the Spatial Damped Anomaly Persistence (SDAP) method, which combines historical sea ice probability with the initial ice edge anomalies to generate probabilistic reference forecasts of the ice edge. The SDAP forecasts outperform both traditional references, as well as most dynamical forecast models from the Sub-seasonal to Seasonal (S2S) project at long lead times, establishing a more challenging benchmark for operational forecast systems.

Within the S2S database, forecasts from the European Centre for Medium-Range Weather Forecasts (ECMWF) have the highest prediction skill compared to both traditional references and SDAP forecasts, but show significant initial error. In chapter 2, we analyse this initial state issue in the ECMWF forecasts, as well as corresponding analysis from ORAS5, by measuring the errors against observations from OSISAF. We find that the initial state errors are partly due to interpolation issues, and partly systematic underestimation, especially in the summer. We show the spatial distribution of the mean bias and provide evidence that between 10 to

20% of the error can be reduced simply by subtracting the mean bias.

While forecast verification methods assume observations to be 'the truth', observational records also have inconsistencies that have previously only been discussed in concentration or ice extent terms. In chapter 3, we analyse di erences in ice presence between several observational and analysis datasets by measuring the Integrated Ice Edge Error and bias between each pair. We find significant mismatch between observations, particularly in the summer, and identify regions where certain observations disagrees with all other. Our results show that observational records from OSISAF potentially overestimate ice presence, while those from AMSR-E/2 potentially underestimate it.

In the last chapter, we discuss the results from the di erent studies in context of each other and mention how the inconsistencies in observations cast doubt on the forecast errors we initially measured, o ering the possibility of a probabilistic observation and reemphasizing the need for accurate sea ice edge measurements and forecasts.

Contents

Man wants to know, and when he ceases to do so, he is no longer a man.

Fridtjof Nansen

Introduction

I would like to start this thesis by describing, in simple terms, the physical processes that typically take place every year on the surface of the polar oceans. Let us imagine ourselves somewhere north of Greenland at the end of the boreal summer season. With each day, the number of daylight hours are decreasing and it is getting colder over the entire Arctic. As the ambient temperature falls below freezing, water at the top of the oceanic layer slowly starts turning into ice. The ice clumps into floes that might initially be thin and isolated, but as the temperature gets colder, the floes increase in size and thickness, and coalesce with other floes to cover large areas of the ocean. By February, most of the Arctic Ocean is covered by a frozen layer.

This frozen ocean cover is sea ice.

FIGURE 1: Sea ice in the fjords of Svalbard during Spring 2022, showing di erent scales and stages of formation. Picture taken by the author.

0.1 Polar processes

The simplistic description given so far skips a lot of important details regarding the evolution of sea ice. While most of the Arctic does get covered with ice over winter, it is not a constant layer. It is perpetually evolving at the whims of the ocean and the atmosphere, expressed as both dynamic (movement/force related) and thermodynamic (temperature/heat related) processes (Petrich and Eicken, 2016). The floes drift, converge and diverge, leading to cracks, leads and ridges on the ice surface. There is a constant push and pull from both wind and ocean currents, while the topography of the land and ocean bottom also place barriers on how the ice can shift. There are various storms, temperature fluctuations, freshwater influx and precipitation events, each locally a ecting the ice cover. On a bigger scale, the e ects of global radiative forcing and the recent changes associated with it are also reflected by a changing sea ice cover, as we will discuss below.

Up to this point, I have only described the processes that take place from late summer to the end of winter, but what happens afterwards is equally important. By the end of April, the Arctic starts to be exposed to more and more sunlight, and the ambient temperature increases likewise. The ice cover starts to melt, the surface slowly covered by the melt-water, and the large floes break into smaller pieces, leading to increasingly larger gaps. The amount of ice keeps decreasing as we go further into the summer until it reaches a minimum right at the turn of the season.

However, not all of the ice melts away. Thicker ice floes, usually those that have already survived previous summers, can last through the summer into the next winter (Haas, 2016). Much of the ocean north of Canada and Greenland has historically been ice-covered throughout the summer, although the actual cover is changing fast due to climate change. How much sea ice lasts over the summer is a matter of immense importance and its connections to the climate are manifold, as we will learn further below.

Although the previous paragraphs mentioned only the Arctic, sea-ice is present at both poles (Meredith and Brandon, 2016). The fundamental physics governing the evolution of sea-ice is the same in Antarctica as it is in the Arctic - freezing over winter, thawing through spring and melting in the summer. However, the coastal topography at the two poles are very di erent, and this a ects the sea ice distribution as well. The Arctic is an ocean surrounded by continents on most sides, with only a few exchange gates with the other oceans. Antarctica, on the other hand, is a continent surrounded by the Southern Ocean. There is more exchange of heat and water from the subtropics and more of the ice can be carried away from the coast. Alongside, the thermal halocline isolating the ice from the warm deep waters in the Arctic, is not present in the southern hemisphere. Consequently, less of the ice survives through the austral summer and the overall ice cover in the southern hemisphere is younger and thinner compared to the northern hemisphere.

0.2 Sea ice in the climate

The presence of sea ice, in both hemispheres, is deeply intertwined with the global climate system. The forward relation is already quite evident – from freezing to melting, sea ice is modulated by the dynamic and thermodynamic shifts in the atmosphere and the ocean, which are affected by the polar and global climate at a large scale. Another world with different climate conditions would have drastically different sea ice (Yang et al., 2019), and a warming world has already brought extensive changes to the sea ice coverage (Landrum and Holland, 2020).

The relation is equally important in the other direction. The freezing of sea ice affects the salinity and vertical mixing of ocean layers (Liang and Losch, 2018), while the cover insulates the ocean surface from the atmosphere (Budikova, 2009). It affects both atmospheric and oceanic circulations in the polar regions (Aagaard and Carmack, 1989). Most importantly, the high albedo of sea ice enables a large portion of the incoming solar radiation to be reflected back to space, and a decrease in the sea ice cover causes an increase in the amount of sunlight trapped within the atmosphere (Perovich and Polashenski, 2012).

As it happens, the global climate is changing and the sea ice cover is indeed decreasing, particularly in the Arctic. This is seen in many of the sea ice related variables (which we will describe below) – Arctic ice extent and ice area is decreasing, mean thickness is lower and sea ice volume loss is quite high (Comiso et al., 2008; Parkinson and Cavalieri, 2008; Stroeve and Notz, 2018). The effects of climate change manifest more acutely in the Arctic than elsewhere on earth, a process termed "Arctic Amplification" (not just due to the albedo change, but also an effect of the local temperature Lapse rate; see Pithan and Mauritsen, 2014). As the Arctic warms, the sea ice melts and the albedo of the Arctic decreases, abosrbing more sunlight, in turn further warming the Arctic (and the planet as a whole), melting the ice more and further continuing this positive feedback cycle. Studies have already established that the current climate conditions have brought about a 'new Arctic'

(Landrum and Holland, 2020) and it is predicted that summer in the Arctic will be completely ice free by 2050 (Årthun et al., 2021; Wang and Overland, 2009).

0.3 Studying sea ice

While we have described sea ice and its role in the climate so far, let us now take a step back and examine how it is analyzed and represented in scientific contexts. There are two main methodologies driving most sea ice related studies: observations and numerical modeling. Observations themself can involve in situ research, or remote sensing. Furthermore, there are also some studies employing lab-based methods to better understand sea ice (e.g. using ice cores; see Abram et al., 2013). In this thesis however, we are only using data from remote sensing and modeling approaches, in order to have complete coverage.

Before going in depth about these methods however, it is important to acknowledge that trying to understand sea ice did not start with modern climate research. Indigenous people that have been living north of the Arctic Circle have been keen observers of the sea ice condition in their surroundings for centuries (Usher, 1971). They keep track of the growth and melt seasons, tidal movements and the thickness of ice floes, to be able to safely travel and hunt on the ice and fish in the polynyas (Huntington et al., 2016). Much of their research, and their methods, are only recently coming to light in wider discourse (Eicken, 2010). Similarly, the Vikings are known to have monitored sea ice conditions as it related to their voyages and settlements in the north Atlantic (Haine, 2008).

There were waves of voyages into the Arctic and Antarctic in the 18th and 19th centuries, bringing with them troves of knowledge about the presence and persistence of sea ice in the polar regions (MacLaren, 1994). Nansen's Fram expedition in the 1890s was a high point of scientific endeavour and discovery (Johnson, 1983). While wars raged around the world, scientists continued learning more about sea ice. Overhead military flights and under ice submarine voyages, especially in the cold war era, kept logs that would later be of great scientific value (Kwok and Rothrock, 2009). Several field campaigns have been instrumental in improving our knowledge of sea ice and in 2019-2020, the MOSAiC expedition spent a year in the Arctic (Shupe et al., 2020), representing what might be the pinnacle of polar research so far.

Remote sensing

In 1858, French artist and photographer Nadar took an aerial photograph of Paris from a balloon (Bann, 2009), e ectively giving birth to the concept of remote sensing. It took several years before this name actually got used, but in the intermediate period the process got widely accepted and applied. Balloons, planes, rockets, and even pigeons took to the sky, capturing an aerial view of the planet (Verhoeven, 2009). Satellite based observations, initially limited to military use, began in the 50s. Then in 1972, Landsat-1 was launched, the first satellite actually made for scientific research. Now, there are several remote sensing instruments on di erent satellite platforms, providing high resolution records of various sea ice variables (Carsey, 1989; Kwok, 2010), some of which are used in this thesis.

Technological development has made satellite-based imagery a familiar concept to us all and it is possible to view remote locations via the "eye in the sky" almost in real-time (a visit to http://observer.farearth.com/observer/ can be recommended for some fascinating examples). Retrieving quantified measurements of sea ice condition is, however, not trivial as the sensors on a satellite platform do not observe the planetary surface the same way a person at the poles would. We refer the interested reader to Carsey (1989) and Spreen and Kern (2016) for detailed descriptions of the steps involved in remote sensing of sea ice and give a very simple overview here.

Various satellites carry passive microwave (PMW) sensors on board, which are capable of observing the thermal radiation emitted from the planetary surface at di erent frequencies. In the polar regions, radiation emitted from the sea ice surface has a very di erent signature (in terms of brightness temperature) compared to that from the ocean. Using openings in the ice ("tie-points") and the polarization of the sensor to calibrate this di erence, di erent algorithms can convert it into a measurement of ice presence. Fortunately, the PMW sensors can see through the clouds very well, although atmospheric conditions do a ect the measurements (Spreen and Kern (2016)), which are addressed by di erent correction schemes. There are different PMW sensors and algorithms in use, and the various combinations result in di erent datasets of sea ice measurement. We will see some of the more widely used datasets in chapter 3.

There are also other (non-PMW) sensors aboard satellites, as well as aircraft or ship based remote sensing platforms. Some of these instruments measure di erent sea ice variables than the fraction of ice cover. In this thesis however, we are focused solely on the edge and presence of sea ice, and are interested in long term pan-hemispheric comparisons. Ship, aircraft or ground based observations, which are generally limited in their coverage, have therefore not been included in our studies. One final point that needs emphasis, is that all of these datasets are measurements of the true condition and just as any measurement, can have o sets from the 'truth' as we will discuss further in the thesis.

Numerical modeling

The second wheel driving forward our knowledge of sea ice is numerical modelling. Models fill in a lot of gaps in our understanding of sea ice, and climate research as a whole, as observations are limited in nature, do not generally allow for experimentation and give us a single state. In models we can add, omit or change various variables and processes, in order to simulate the past or present, or to make forecasts and future projections.

Since the first conception of a mature sea-ice model in 1971 (Maykut and Untersteiner, 1971), experiments could compare observational results with model output to further our understanding of sea-ice physics and processes. This led to further improvements in model development, increasing their use case. During the 80s, they started to be coupled with the ocean model (allowing for exchange of variables) and included within global climate models (Huntington et al., 2016). Over time, there has been a rapid expansion in the variety of their application, from 1D single column modeling to automated prediction systems that have high resolution, oceanic processes and coupling between several components (Lemieux et al., 2015; Johnson et al., 2019; Zuo et al., 2019). It is this last type of model that we are concerned with in this thesis.

Modern prediction systems

While the use of sea ice models for forecasting purposes is a recent development (Guemas et al., 2014), there are now several operational and research centers around the world producing sea ice prediction at various timescales (Vitart et al., 2017). Fig.2 (derived from Carrieres, 2017) gives a simple depiction of the various components that may be included in a modern prediction system, although the individual setup of the prediction system can di er depending on the institution.

Forecasts are often started from the initial conditions for a short cycle to find the background state. This is then corrected by incorporating observations by the Data Assimilation system (described below). The resulting output (called the analysis) is then used by the forecast system and the underlying processes are then

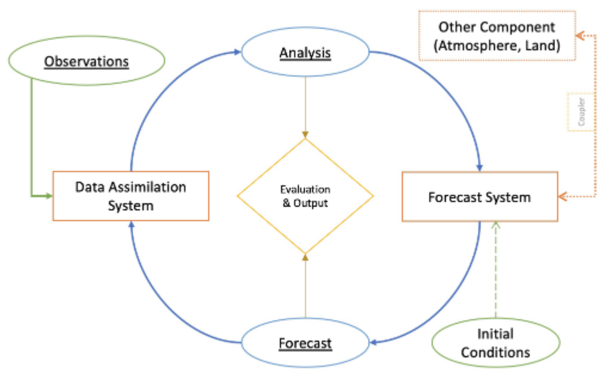

FIGURE 2: Schematic showing various components of a modern prediction system (derived from Carrieres, 2017). In this thesis, we are focusing on verification of Observation, Analysis and Forecast.

run for a given number of time steps (or iterations) to derive the actual forecasts (Carrieres, 2017). The (ice-ocean) forecast system can also be coupled with other components (such as the land or atmospheric models), in order to pass variables at chosen intervals of model run, depending on the system.

Data Assimilation (DA), as the name suggests, is the process of bringing together data from several sources, essentially integrating observations with model runs using minimization operations (Mu et al., 2020). Through DA, we can take incomplete and erroneous observations and fill the spatio-temporal gaps with the help of model physics (rather than simple interpolation). The resulting analysis is then a more complete and accurate picture of the initial state, which can be used by the forecast system to generate forecasts. Several e orts have made to use available observations over long periods, often retrospectively, to build a complete (and corrected) collection of atmospheric and oceanic variables (especially well established for atmospheric variables; see Hersbach et al., 2020). Such reanalysis (as they are called) are typically done with a fixed model version, so that it is more consistent over time and can also be used for climate-related studies. Other analysis are more "operational", designed with a particular target or to be fed into operational forecasts (Zuo et al., 2019).

In operational forecast centers, there is currently a push for improving prediction capabilities at sub-seasonal to seasonal (S2S) timescales (Vitart et al., 2017). This is especially pertinent for marine operations in the polar regions, as decreasing ice cover and increasing economic activities have brough an increase in marine traffic to the polar regions (Palmer, 2013). The role of sea ice in modulating S2S predictability (including for atmospheric variables) has also highlighted the importance of improving the forecast skills in our ice-ocean models (a more detailed description, given by Chevallier et al., 2019, is recommended as an excellent overview). Perfect model studies have shown that sea ice extent is predictable at interannual timescales (Day et al., 2016), although a 'spring barrier' for predictability can lead to lower predictive skills in the summer (Bushuk et al., 2020). In this context, we will analyse forecasts made at S2S timescales in Chapter 1 of this thesis.

Sea ice variables

Data from both sources, observations or numerical models, are produced on a 2D representation of the planetary surface, divided into individual grid cells. The grid cells are the basic area units of the region of interest (most likely the poles in our case), akin to a pixel in graphical displays. The actual arrangement of such cells is determined by the grid and resolution of the observational data or the model and can range from regular lat-lon grid, to hexagonal (Pinori et al., 2008) or even an irregular mesh (Sein et al., 2017).

This short description of grid distribution can help us understand a very important concept in the sea ice community (and this thesis) – that of sea ice concentration (SIC). In simple words, sea ice concentration is the percentage of a grid cell that is covered by ice. This is a very important variable in both modeling and observational applications, allowing us to record or model cells that have both liquid water and ice within it. This formulation ignores the thickness or distribution of sea ice within the grid cell, but results in a standardized form of measuring ice cover.

Whether or not a grid cell is 'ice-covered' is generally determined by setting a threshold percentage and assigning every cell with concentration equal to or higher than that threshold to be "ice-covered". This transforms the measured or modeled concentration value into a binary field – ice or no ice. Any end user needing to decide whether or not a certain region has ice can then look at this binary field and clearly distinguish which grid cells are frozen. The threshold in use can also di er based on the user's needs – a hunting party traveling on top of the ice may prefer a low threshold, while an ice-breaker ship might accept a higher threshold. It is common practice in the polar science community to use 15% concentration as the standard threshold for ice presence, but this can di er, as we will see further in the thesis.

Following this, we can now learn about ice extent and ice area. Ice extent is

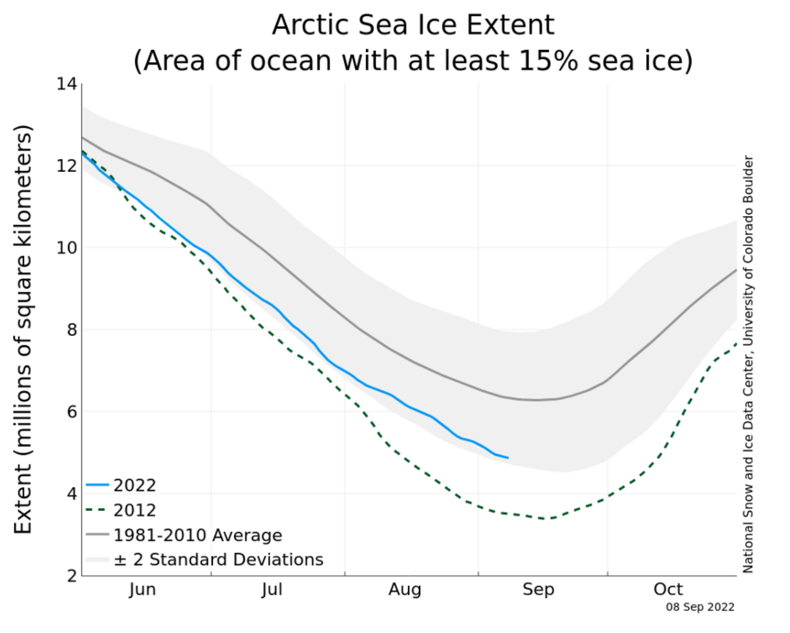

FIGURE 3: Arctic Sea Ice Extent measurements from NSIDC (2022), showing daily time-series for 2022 (as of 8 Sep 2022), alongside the record low year of 2012 and the 1981 to 2010 average.

the sum of area of all the grid cells that are considered to be ice covered (based on the threshold). This results in an area measurement, usually pan-hemispheric, which can be compared over time, or across di erent model systems. Sea ice extent is di erent from another commonly discussed value, sea ice area, which is measured by multiplying the concentration of each grid cell by its area and taking the overall sum. Both area and extent are very useful measurements for understanding the seasonal cycle over each year (as the poles freeze and thaw), as well as year to year changes and long-term trends in sea ice (as seen in Fig.3 from NSIDC, 2022).

Similarly, the contour of the threshold concentration gives us the ice edge, which is the e ective border of ice presence. This is a very important variable, and in fact the focus of this entire thesis. The ice edge is of immense interest, not just to scientists, but also other stakeholders, as it allows for a clear demarcation of the ice-covered seas. The ice edge is used by several governmental bodies in legal and policy making contexts (Bay-Larsen et al., 2020; Veland and Lynch, 2016). Therefore, verifying that the ice edge is accurate (in both observation and forecast) is very important.

0.4 Ice Edge Verification

When we talk about forecasts, the first question that comes to mind is "How good are they?". To find the answer, we take the forecasts and the corresponding observations, and measure the accuracy with a verification metric. For ice-edge, two very useful metrics in use are the Integrated Ice Edge Error (IIEE; Goessling et al., 2016), and its probabilistic counterpart - the Spatial Probability Score (SPS; Goessling and Jung, 2018).We will describe both metrics fully in further chapters, but we can briefly mention here that the IIEE is the total area of mismatch between the forecast and observation of ice presence. This applies for deterministic (or binary) forecasts and observations. For probabilistic data, IIEE is replaced by SPS, which also considers the probability of ice presence (and can be considered the spatial integral of the Brier score). In practice, the observational ice edge is mostly a deterministic state, derived from the concentration threshold approach, which means the probability of ice presence can be assumed to always be either 0 (no ice) or 100% (ice). For an ensemble output, each ensemble member gives a similar deterministic state and simply averaging over them gives the probability (although other means of determining a probability of ice presence exist, as we will see in chapter 1). Similar to observations, a deterministic forecast can also be considered to be a probabilistic forecast with binary values (0 or 100%), making the SPS and IIEE equal in that context.

There are also other verification metrics that can be used to measure the accuracy of a forecast, the most important one being the Modified Haussdor Distance (MHD; Dukhovskoy et al., 2015; Casati et al., 2022). MHD will also be described more in detail in chapter 1, but for a brief description - it is a distance measurement between two ice edges, used to find how far apart the forecasted and observed ice edges are. Measuring the MHD requires determining every point on the two ice edges and measuring the distance between them. However, this is not a trivial operation.

The ice cover is not uniform – it can have pockets of low concentration deep within the ice pack, or be broken up by islands or the coast. Consequently, the ice edge is generally not one continuous line, but consists of several smaller ice floes. Measuring the MHD means we must consider which edge points to include, how to measure the distance between each of them, how to handle the coast or openings in the ice, and how to keep the domain of comparison constant between di erent datasets and dates. In our study, these issues often resulted in us cutting out sections of the data, either spatially or temporally. While we did measure and compare the MHD for the forecasts in chapter 1, we decided in the other chapters to prioritise having a more coherent timeseries of analysis and thus not use MHD. There have been promising developments in new methods for measuring the MHD (Casati et al., 2022) and while it has not been included here, we hope to follow up some of our work by including MHD alongside the other metrics.

For each of the metrics, knowing the verification score or distance gives an idea of how erroneous the forecast is, but does not by itself tell us if it is good enough for our needs. For this reason, verification metrics are more of a tool than the result by itself. We can judge the performance of a model forecast by comparing their resulting metric against that of another model, another version of the same model, or some other 'reference' data. The choice of this reference data in measuring forecast skill is quite important, as a weak reference can lead to overestimation of forecast skill. This search for a simple, reproducible and skillful reference forecast essentially gave birth to this entire thesis.

0.5 Scope of this dissertation

As we have established in the previous sections, this PhD dissertation is focused on the sea ice edge. This is a variable of crucial importance for operational needs and there is strong momentum to verify that both our observations (current and past), as well as forecasts (for the future) are as accurate as possible. This overarching theme has been explored here in three di erent but closely linked ice edge verification studies.

For operational forecasting centers, there has been an increase in user demand for skillful seasonal forecasts of sea ice condition, particularly in the Arctic. Most studies have measured this skill by comparing the forecast performance against two simple references- either historical patterns, or a fixed initial state. While there has been progress in advancing these references by incorporating prior trends or anomalies into them, their application with the ice edge has been limited and the use of probabilistic anomaly has not been explored so far. We describe a simple method of combining the historical probabilities with the anomalies of the initial ice state through Spatial Damped Anomaly Persistence (SDAP), resulting in an ice edge forecast that is skillful enough to be used as a challenging benchmark for sub-seasonal to seasonal (S2S) operational forecasts. It is a very simple method relying solely on historical and initial ice presence, yet the forecast skill is comparable to those of fully coupled dynamical models. This study (published as Niraula and Goessling, 2021) is presented here as **Chapter 1**, with the scientific objectives as follows:

Q1 Can we create a simple reference forecast of sea-ice edge combining probabilistic information from both historical and current ice conditions?

Q2 Can such a forecast perform well in comparison to traditional references and S2S forecasts?

In chapter 1, we find that the ice edge forecasts from the European Centre for Medium- Range Weather Forecasts (ECMWF) are the only ones from the S2S database to perform better than the SDAP benchmark. However, they start with a high initial error, roughly half as high as climatological error. This has also been shown by other studies in the past and motivated us to systematically measure the ice edge error in the initial state of the forecast, alongside the analysis data that was used in the forecast setup (ORAS5, described more within the chapter), against observations from the Ocean and Sea Ice Satellite Application Facility (OSI SAF). We analyse the spatial and temporal patterns in the errors and show that the initial state error is a combination of interpolation error and seasonal bias in both forecast and analysis. This work is presented here as **Chapter 2**, with the following scientific objectives:

Q1 How well do the initial ice-edge states of ECMWF forecasts and ORAS5 analysis agree with observational data from OSI SAF?

Q2 Is there a consistent bias pattern that can explain the error of these ice states?

The results from chapter 1 show significant mismatch in ice edge between the ORAS5 analysis and OSI SAF observations. This has prompted us to ask whether some of the errors actually issue from OSI SAF, and how well does OSISAF itself agree with other observational datasets. What follows is an intercomparison study, where we analyse a collection of satellite derived observational and analysis datasets of sea ice, measuring the pairwise IIEE against each other. These are well established, widely used datasets that represent di erent retrieval algorithms, measurement instruments, and production methods while still having pan hemispheric daily coverage over many years. We compare the bias between the datasets and find regions where certain datasets are substantially further from the consensus. This work is presented here as **Chapter 3**, with a simple scientific objective:

Q1 How well do di erent satellite based observational and analysis datasets of ice-edge agree with each other?

The chapters, as described above, were written as independent manuscripts to be submitted to scientific journals (Chapter 1 has already been published as Niraula and Goessling, 2021). As a result, there is some overlap between them, particularly in the methods, and each chapter has its own Abstract, Introduction and Conclusion sections. Similarly, many important concepts have not been fully discussed in this introduction, but rather left to the chapters. The chapters are presented in a chronological manner, showing how our own ideas regarding ice edge verification have evolved over time. Some of the findings from the latter chapters will therefore challenge the results from earlier, which we will briefly discuss again in the last chapter, concluding this thesis.

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Bimochan बिमोचन