

Climate change in the Arctic Ocean: Long-term variability of metocean conditions

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Abstract

The Arctic is responding to climate change more rapidly and intensely than any other region on Earth. Besides the temperature rise and sea ice retreat, surface gravity waves are becoming more energetic, leading to rapid coastal erosion, affecting wildlife, communities and coastal infrastructures. In response to these changes, this research aims to investigate the metocean parameters across the Arctic Ocean over the past decades by numerical modelling, evaluating their climate and long-term variability. It introduces a systematic assessment of sea ice concentration, winds, and waves by computing their monthly averages, higher percentiles and their long-term trends. The trend analyses demonstrated that the sea ice melting has major responsibility for the general increasing trends in significant wave heights across the Arctic Ocean, as trends in wind speeds were milder compared to trends in waves and sea ice concentration. Finally, non-stationary extreme value analyses were applied in order to assess wind and wave extremes taking into account climate change and seasonal cycles in the estimations. Such an approach becomes essential for the evaluation of extreme environmental variables in the Arctic, where the seasonal sea ice coverage and the ice retreat affect the stationarity of the sea state directly. The results show notable seasonal changes and a consistent increase in extreme waves with the largest increasing rates in the Beaufort and East Siberian seas of approximately 60% in areal-average of 100-year return period for significant wave heights over the past decades. At the same time, extreme winds have only increased by 4% in some regions. Therefore, the changes in extreme winds cannot explain the changes in extreme waves. These results make evident that the sea ice melting has primary responsibility for these dramatic changes in extreme waves.

DECLARATION

This is to certify that:

- i) The thesis comprises only my original work towards the PhD;
- ii) Due acknowledgement has been made in the text to all other material used;
- iii) The thesis is fewer than 100,000 words in length, exclusive of tables, maps, bibliographies, and appendices.

Isabela de Souza Cabral
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Chapter 1

Introduction

1.1 Changes in the Arctic

Recent studies have demonstrated metocean changes worldwide. Besides the temperature rise, there is a general global trend of increasing wind speed and wave height (Young et al., 2012). In particular, the Arctic is responding to climate change more intensively and rapidly among any other regions on Earth. In this region, the temperature rises (Steele et al., 2008), and consequently, the sea ice is melting and getting thinner as satellite data have demonstrated since 1979 (Stroeve et al., 2008; Meier et al., 2013). The enlarged ice-free water allows waves to develop beyond pure wind seas and evolve into energetic swells (Thomson et al., 2016).

Concurrently with the delay of the sea ice advance that occurs in the autumn, there is a trend towards stronger and more frequent storms in the same season (Zhang et al., 2004). According to Thomson et al. (2016), sea states along the northern coast of Alaska are becoming higher from 2007 onward and it will continue so in the future, as it is increasingly likely that storms will occur over larger open water areas that persist longer into autumn. This increasing sea state might affect the large-scale evolution of sea ice, the wave forcing on the coasts, the air-sea fluxes and upper ocean properties, and in turn, may influence the response of sea ice to climate change.

The more energetic waves that are one of the main drivers of coastal erosion are contributing to increasing rates of erosion in this region that are already the largest in the world. Recently, mappings of Alaskas shorelines point out huge erosion rates and show the threat of climate change upon the coast. The rates of coastal retreat in the Beaufort Sea have increased from 8.7 m/year in the period between 1979 to 2002 to 13.6 m/year in the period from 2002 to 2007 (Jones et al., 2009). Any increases in already rapid rates of coastal erosion might cause substantial effects on the supply of

freshwater and terrestrial wildlife habitat that depends on the sea ice, life and culture of the communities settled in the coastal areas (Holland-Bartels and Pierce, 2011).

Indigenous communities in the Arctic are directly affected by the prevalence of open water. They now have to travel farther offshore to hunt mammals that live in the icy area, where the ice is getting more unstable and the sea is getting rougher. Besides that, the rapid coastal erosion is already affecting some villages. For instance, the Inupiat community already needs to relocate their village from Sarichef Island just north of the Bering Strait to the mainland (Figure 1.1, The Atlantic (2016)).

Meanwhile, shipping activity during Arctic summer increased over the past two decades in regions for which there is information concurrent with loss of sea ice, as the transits times across the Northern Sea Route have shortened due to favourable ice conditions. Those changes in Arctic ship-based transportation have essential socio-economic and political implications for global trade and economies linked to the traditional shipping paths. They can also be a risk to the marine ecosystems and coastal communities if further action to develop and adequately implement regulations does not keep pace with increased shipping (Meredith et al., 2019).

Increased storm surges can allow gravity waves to propagate further inland, producing greater flooding with sea-water. Some studies have highlighted that fragile Arctic ecosystems can be damaged by severe storm surges (Pisaric et al., 2011; Kokelj et al., 2012). For instance, an unprecedented large storm surge in 1999 dramatically affected the Mackenzie Delta, causing soil salinization, loss of terrestrial vegetation, and changes in formerly freshwater lakes (Pisaric et al., 2011). Vermaire et al. (2013) demonstrated that storm surge is on the rise in the outer Mackenzie Delta as Arctic temperatures increase and sea ice extent declines over the past four centuries by analyzing lake sediment records.

Considering that the rapid sea ice melting is significantly changing the ocean dynamics and the sea state in this part of the planet, researches about the effects of metocean changes become crucial (Overeem et al., 2011). The metocean changes in the Arctic Ocean have significant impacts on the polar ecosystem, coastal infrastructures and morphodynamical effects along the coasts. Assessing such changes is the first step to evaluate, for instance, rates of erosion that are already the largest in the world and are increasing in the last decades. Therefore, this research consists of the assessment of the metocean changes along the Arctic Ocean, providing insight into how the changes of the most significant metocean parameters have been changing over the past decades with the aid of numerical modelling.



Figure 1.1: Coastal erosion in Shishmaref, Alaska (The Atlantic, 2016).

1.2 Research Objectives

This dissertation aims to assess the metocean changes across the Arctic Ocean with the aid of numerical modelling, producing a reliable long-term hindcast of the sea state, evaluating the climate of sea ice concentrations, wind speeds, wave heights and peak periods, computing their averages, and higher percentiles and their long-term trends over the past decades, and performing non-stationary extreme value analyses for assessing wave and wind extremes.

For this purpose, the following research was conducted:

- Assessment of the wave climate in the Arctic Ocean by 28-years hindcast undertaken using WW3 model and ERA5 wind forcing after the full calibration of the wave model and validation against altimeter data. A wave hindcast for the Arctic Ocean has not previously assessed with the recently released ERA5 reanalysis.
- A systematic characterization of the seasonal cycles of the main metocean parameters for 1991-2018 was performed, considering that such an evaluation of magnitudes and seasonal variabilities of the most important metocean parameters in this region have not yet been evaluated together in a consistent way.
- An evaluation of the monthly trends of winds, waves, and sea ice across the Arctic Ocean providing an opportunity to relate our results to existing studies that have demonstrated inconsistencies between trends computed from altimeter data and reanalyses, particularly in the Chukchi, East Siberian, and Laptev Seas

(e.g. Stopa et al., 2016; Liu et al., 2016). A monthly assessment of trends in metocean parameters in the Arctic has not yet performed previously.

- Applying a non-stationary extreme value analysis of winds and wave extremes along the Arctic Ocean taking into account the long-term trends and seasonality in the statistical analysis showing how the magnitude and frequency of extreme waves have changed over the past decades due to climate change. Such an evaluation of extreme winds and waves has not yet been done for the Arctic Ocean.

1.3 Outline of the thesis

Chapter 2 describes a literature review around the previous researches on metocean changes occurring in the Arctic Ocean and the significance of these studies is explained. More specifically, studies about the reduced sea ice coverage, ocean circulation, ocean temperature and salinity, the climate of waves and winds, and morphological changes are presented.

In Chapter 3, the set-up of the wave model used in this research is presented. The calibration and validation of the long-term hindcasts performed are also introduced by comparing the implementation of different input data into the model, different spatial resolutions, the effects of including boundary conditions and ocean currents in the simulations.

Chapter 4 examines the climate of the main metocean parameters: sea ice concentration, wind speeds, and wave parameters for the past 28 years (1991-2018). The monthly average and higher percentiles for each parameter are discussed.

Chapter 5 outlines the trend analysis over these past decades of the same metocean parameters investigated in the previous chapter. It provides insight into how these parameters have changed over this period.

Chapter 6 discusses the non-stationary extreme value analyses of winds and waves, considering the long-term trends and seasonality in the estimations. It provides a deeper understanding of how extreme winds and waves have been changing over the past decades due to climate change.

Finally, Chapter 7 presents some concluding remarks and recommendations for future studies.

Chapter 2

Metocean changes in the Arctic

2.1 Introduction

One of the most robust responses of the climate system to greenhouse gas emissions is happening in the Arctic. In the past two decades, the surface air temperature has increased by more than double the global average (e.g Pithan and Mauritsen, 2014; Huang et al., 2017). For the years between 2014-2018, annual surface air temperature exceeded that of any year since 1900. During the winter months (January to March) of 2016 and 2018, surface temperatures were 6°C above the 1981-2010 average. Besides the temperature rise, this region of the planet has been facing dramatic metocean changes over the past decades. There are several studies around this topic, considering that the changes occurring in the Arctic Ocean can be a risk, for instance, to the ecosystem and coastal infrastructures. However, these changes may also be an opportunity as, for instance, the sea ice reduction opens new ship routes from Europe to East Asia. Most of these studies are based on remote sensing or numerical modelling data, as there is a lack of *in situ* observations in this polar region.

Oceanographic satellites have now been in operation for more than 30 years providing continuous data of sea ice coverage, sea surface temperature, wind speeds, wave heights, and other environmental variables (e.g. Young et al., 2017; Ribal and Young, 2019). Such data have been used extensively in different applications such as investigations on trends of oceanographic variables, validation of numerical models, evaluation of the inter-annual variability and extreme conditions of environmental parameters. Four main instruments used over more than 20 different satellite missions provide global measurements of wind speed and/or wave height are altimeters, radiometers, scatterometers, and synthetic aperture radars (Young et al., 2017). However, the spatial density of those systems is such that extreme meteorological events, for example, storms and cyclones can be missed or underestimated (Young et al.,

2011). To overcome those issues, numerical models have been widely used in order to get reliable and continuous data in higher spatial resolutions to investigate metocean parameters (e.g. Stopa et al., 2016).

This chapter provides an overview of previous studies about changes in the most important metocean parameters in the Arctic. A literature review around the sea ice melting, climatology of winds, waves, ocean circulation, temperature, salinity, and morphological changes in this polar region is presented.

2.2 Sea ice melting

Sea ice plays an important role in the climate affecting human activities, biological ecosystems, ocean circulation, regulating the exchanges of heat, momentum and moisture between the atmosphere and the polar oceans, redistributing salt with the ocean, and affecting the Earth’s albedo, which is a measure of how much light that hits a surface is reflected without being absorbed. Because of its high reflectivity, sea ice reflects the majority of the sun’s radiation back to space. However, as the sea ice cover reduces, the surface albedo decreases, and the sun’s heat absorbed in polar regions amplifies enhancing the ice melting even more. This positive feedback process increases the air temperature in autumn and winter as the ocean returns heat gained in summer back to the atmosphere (Serreze et al., 2009; Stroeve et al., 2012b; Serreze et al., 2016b). For this reason, polar regions are more prone to temperature rises than other regions on Earth.

The Navy’s Special Sensor Microwave Imager (SSM/I) has been providing global maps of radiometric brightness from which sea ice extent, concentration, and type are derived routinely (e.g. Liu and Cavalieri, 1998). Those data provide us with consistent estimates of Arctic sea ice concentration since late 1978. They show a significant downward trend on the sea ice extent (with sea ice concentrations over 15%) of $-82400 \text{ km}^2 \text{ yr}^{-1}$ in September for the period between 1979 to 2019 (Figure 2.1). The changes are more remarkable in summer months with the strongest trends happening in September that is the month with the lowest sea ice cover, as shown in Figure 2.2. In September 2012, the minimum extent of sea ice was 55% lower than detected in the same month of 1980 (Jeffries et al., 2013). Based on linear regression through the measured time series, studies identified a nearly 14% per decade decline in the summer total sea ice extent, but this trend is much stronger (~ 3.5 times) if one considers just the last two decades (Stroeve et al., 2012a; Serreze and Stroeve, 2015). Regionally, sea ice reduction is more dramatic in the East Siberian Sea and

large loss also occurs in the Beaufort, Chukchi, Laptev and Kara seas. Winter ice loss happens in the Barents and Greenland seas (Onarheim et al., 2018).

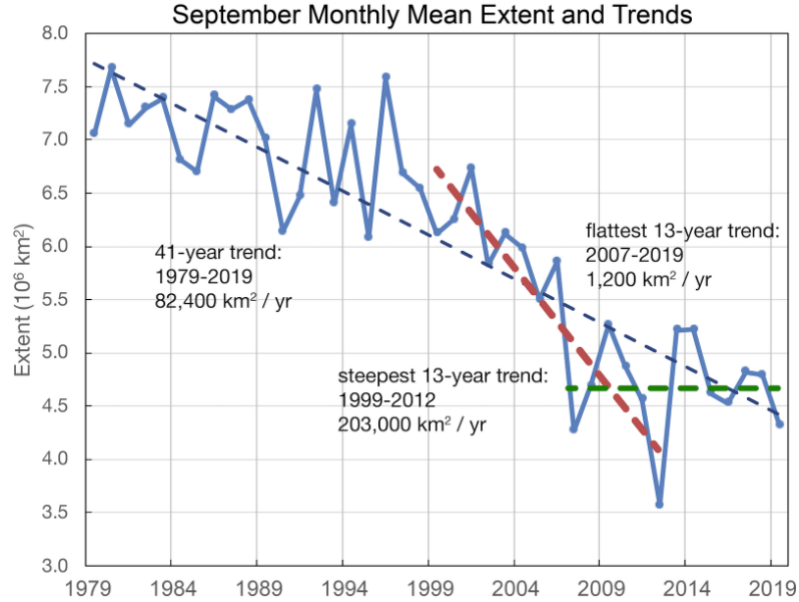


Figure 2.1: September monthly mean trends of sea ice extent in the Arctic Ocean for the period between 1979-2019, showing overall trend and trends for the most recent 13 years, and the steepest 13 years in the 41-year record. Source: National Snow and Ice Data Center - NSIDC.

Previous studies also evaluated the duration of the sea ice melting season and the timing of ice retreat and advance. The pan-Arctic melt season starts three days per decade earlier and ending six days per decade later. This means that the seasonality of sea ice has been changing over the past decades leading to a lengthening of the ice-free season throughout the Arctic (Stroeve et al., 2016; Serreze et al., 2016b). Besides the shorter duration, the sea ice is also getting younger and thinner, which makes it less resilient and more prone to melting and retreat in summer. The observed thinning of the sea ice is consistent with the younger sea ice that has a shorter period of thermodynamic ice growth and thickening from deformation compared to older ice (Maslanik et al., 2007; Stroeve et al., 2012a). The sea ice decline is characterized by a strong variability that is related to fluctuations in surface albedo, clouds and water vapour, surface winds and poleward atmospheric and oceanic energy transport. However, the internal variability of sea ice is primarily driven by atmospheric temperature fluctuations (Olonscheck et al., 2019).

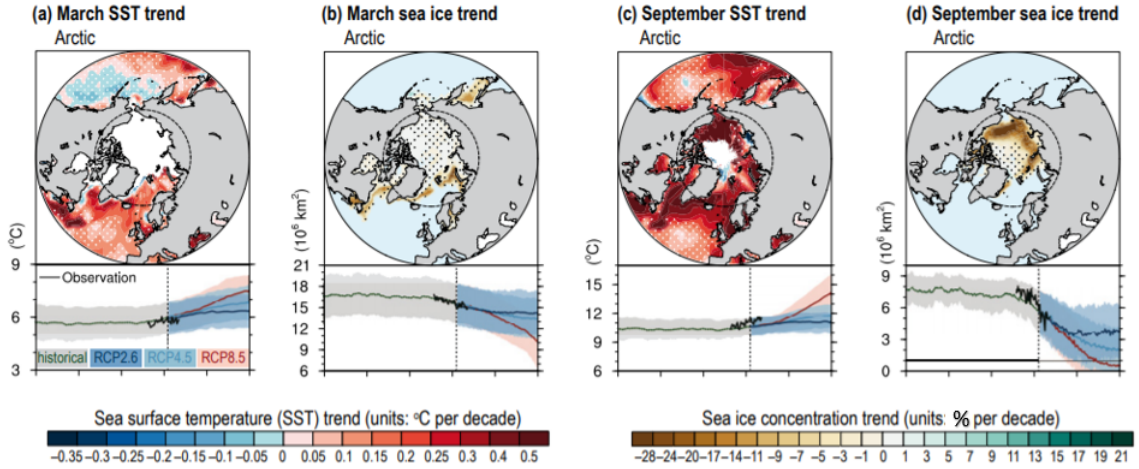


Figure 2.2: Arctic maps of linear trends (in $^{\circ}\text{C}$ per decade) of sea surface temperature (SST) and sea ice concentration (in % per decade) for 1982 to 2017 in March (a, b) and September (c, d) (source: Meredith et al. (2019)).

Sea ice is integral to the marine ecosystems, and its retreat has biological consequences. For some species, those changes are helpful, while it can be a disadvantage for others. For instance, since the sunlight can penetrate more easily in open waters, the primary production tends to increase. Satellite measurements show an increase of approximately 20% in the ocean primary production between 1998 and 2009 (Arrigo and Van Dijken, 2011). However, the other end of the biota size scale, such as walruses, have limited access to sea ice cover areas where they normally rest and get fed (Jeffries et al., 2013).

The changes in sea ice are mostly driven by anthropogenic warming from increasing atmospheric greenhouse gas concentrations (e.g. IPCC, 2013). Notz and Stroeve (2016) quantified the relationship between the total sea ice coverage in the summer Arctic with the cumulative atmospheric CO_2 emissions and demonstrated the importance of limiting the emissions of this gas in the atmosphere in order to keep the summer sea ice cover. Under the 2015 Paris Agreement, different countries agreed to hold the increase of global average temperature to 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5°C . Projections of sea ice coverage under different scenarios confirmed the benefits of going from 2°C to 1.5°C as the frequency of ice-free conditions expected decreases significantly, from once every five years to once every forty years. Whereas under 3°C global warming, permanent summer ice-free conditions are likely to happen (Sigmond et al., 2018). Nevertheless, the current emission reduction policies are expected to limit warming by 2100 to approximately 3°C .

2.3 Arctic Ocean circulation

The Arctic surface circulation is well established as it is shown in Figure 2.3. In sea ice-covered areas, the surface currents follow large-scale patterns of ice drift. The surface circulation is dominated by the Transpolar Drift crossing the Arctic Basin from the East Siberian and Laptev seas to the Fram Strait, and the anticyclonic Beaufort Gyre which is an important ocean and ice circulation pattern that happens in the Canada Basin. This gyre moves in a clockwise direction, fed by an average high-pressure system that promotes anti-cyclonic winds. In the past, sea ice in this gyre could remain in the Arctic for many years, thickening over time. The past decades are characterized by sea ice melting in the southern arm of the gyre, due to the warmer air temperatures and more extensive summer melt north of Alaska and Siberia. The Beaufort Gyre helps to regulate the climate variability in the Arctic as it accumulates a significant amount of freshwater during one anticyclonic climate regime and releases this water to the North Atlantic Ocean during another climate regime (cyclonic) (Proshutinsky et al., 2002).

The Transpolar Drift transports fresh and cold surface water from the Arctic to the Nordic Seas (e.g. Aagaard et al., 1989). It continues down the east coast of Greenland, through the Denmark Strait, and around the southern part of Greenland. North Atlantic water enters the Norwegian Sea and flows northeastward in the Norwegian Atlantic Current that splits into the Barents Sea branch and into West Spitsbergen Current before turning east along the northern Barents Sea shelf break as shown in figure 2.3 (Armitage et al., 2017).

Surface geostrophic currents can be inferred from ocean dynamic height, which is estimated from satellite altimeters or calculated using hydrographic profiles of pressure, temperature, and salinity. However, the estimation of dynamic height from hydrography are limited to long-term means and to deep basins where instruments can safely operate in the Arctic due to lack of data (McPhee, 2013; Armitage et al., 2017).

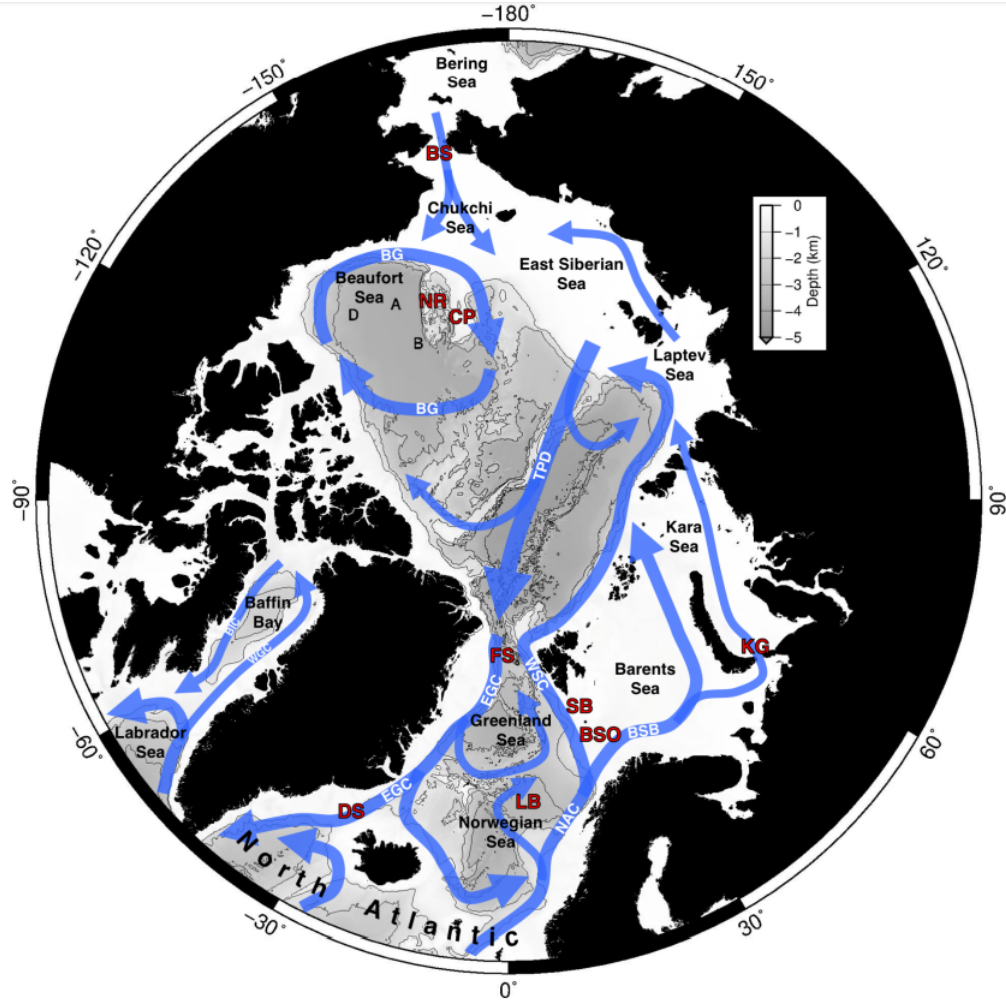


Figure 2.3: Map of the Arctic Ocean of the ocean surface circulation (blue arrows). Depth contours from ETOPO 1. Bathymetric features mentioned in this study are labelled in red as follows: BS, Bering Strait; NR, Northwind Ridge; CP, Chukchi Plateau; FS, Fram Strait; BSO, Barents Sea Opening; SB, Svalbard Bank; KG, Kara Gate; LB, Lofoten Basin; DS, Denmark Strait. Specific currents mentioned in the text are labelled white, with the following abbreviations: BG, Beaufort Gyre; TPD, Transpolar Drift; WSC, West Spitsbergen Current; EGC, East Greenland Current; WGC, West Greenland Current; BIC, Baffin Island Current; NAC, Norwegian Atlantic Current; BSB, Barents Sea Branch. Source: Armitage et al. (2017).

The Arctic Ocean is strongly stratified and receives enormous amount of fresh water from rivers along this region. The stratification is marked by a cold and fresh surface, an intermediate layer of cold and gradually saltier water often called as cold halocline, and a relatively warm and salty Atlantic Waters layer at depth. The fresh surface waters are derived from river runoff, positive net precipitation, relatively fresh pacific inflow, and seasonal ice melt (Rudels et al., 1996; Steele and Boyd, 1998).

Atlantic Waters enter the Arctic Ocean and advect cyclonically around the basin creating an AW layer at depth across the Arctic Ocean (Rudels, 2016).

Winds and ocean surface circulation drive the sea ice drift in polar regions. The drifting sea ice triggers an upper ocean motion, Ekman currents and it transports relatively freshwater at the surface. The heterogeneous distribution of surface freshwater causes horizontal salinity gradients, which in turn tilts the dynamic ocean topography (DOT) in order to the ocean adjusts the geostrophic balance (McPhee et al., 2009). Therefore, changes in sea ice circulation and the upper ocean circulation are tightly coupled. The sea ice drift has been accelerating in the past decades and meanwhile, observations suggest that ocean surface stress has also increased. For instance, in the Beaufort Sea where an accumulation of freshwater is occurring as a result to stronger geostrophic currents and increased Ekman pumping (Proshutinsky et al., 2009; Krishfield et al., 2014).

Armitage et al. (2017) created a record of surface circulation between 2003 and 2014 from satellite-derived estimates of DOT of the Arctic Ocean. They calculated seasonal mean geostrophic currents for that period and also seasonal circulation anomalies relative to the seasonal means for three 4-year periods (see Fig. 3 in Armitage et al. (2017)). Geostrophic current speeds demonstrated a significant increase across almost the entire basin between 2003 and 2010, with most significant changes in the Beaufort Sea. The changes along Beaufort-Chukchi Seas found by Armitage et al. (2017) are consistent with MCPhee (2013), who estimated a 5-6fold increase in current strength along this region. The annual mean current speed calculated by Armitage et al. (2017) in the southern Beaufort Sea more than doubled from 2.8 cm/s in 2003 to 6 cm/s in 2014 (see their figure 4). The overall pattern of changes between 2007-2010 and 2011-2014 shows the Beaufort Gyre shifting to the west with stronger currents in the western portion of the gyre and weaker currents in the southeast part. The southward current in the Fram Strait also demonstrated an increase from 4.6 cm/s in 2003 to a maximum of 7 cm/s in 2011 and 2012, before slowing to 5.1 cm/s in 2014. They also demonstrated that the geostrophic circulation is strongest in winter and weakest in summer. The BG became a more prominent feature of the summertime circulation in later periods evaluated. The strongest currents in the Beaufort Sea occur in October and December and the weakest in August. In the Fram Strait, the currents are strongest in December and weakest in May, August, and September (see their figure 6).

Over the period 2001-2014, the annual volume transport in the Bering Strait from the Pacific to the Arctic Ocean almost doubled from $0.7 \times 10^6 \text{ m}^3 \text{ s}^{-1}$ to $1.2 \times$

$10^6 m^3 s^{-1}$ (Woodgate, 2018). This is the only oceanic input from the Pacific to the Arctic Ocean. Even though it is narrow ($\sim 85 km$ wide) and shallow ($\sim 50 m$ deep), it contributes to approximately one-third of all freshwater entering the Arctic and provides the greatest interannual variability in the Arctic freshwater input. Due to its freshness, the Bering Strait throughflow sets up near-surface (top $\sim 100 - 200 m$) stratification in approximately half of the Arctic Ocean and supplying a cold halocline that protects the sea ice from the warm Atlantic waters below (Woodgate, 2012). Moreover, the volume transport through this strait is also responsible by most of the oceanic properties in the Chukchi Sea (Woodgate et al., 2005). Satellite, *in situ* and modelling results propose that the oceanic heat flux through the strait may explain 68% of the variance in the timing of sea ice retreat in the Chukchi Sea as the correlations suggest that the Bering Strait heat flux is a more efficient estimator than atmospheric forcing such as wind, surface air temperature and radiation (Serreze et al., 2016a).

The Atlantic inflow is generally saltier, warmer and about ten times greater in volume than the Pacific inflow. It occurs through the Fram Strait ($\sim 350 km$ wide, $\sim 2700 m$ deep) and the Barents Sea (mostly via St Anna Trough, $\sim 200 km$ wide, $600 m$ deep). The Fram Strait inflow is about $7 \times 10^6 m^3 s^{-1}$ varying seasonally and in the Barents Sea is roughly $1 \times 10^6 m^3 s^{-1}$ in summer and $3 \times 10^6 m^3 s^{-1}$ in winter. The other inputs to the Arctic consist of Eurasian and Russian rivers ($\sim 0.1 \times 10^6 m^3 s^{-1}$), precipitation minus evaporation ($\sim 0.06 \times 10^6 m^3 s^{-1}$) that together contribute to $\frac{2}{3}$ of the freshwater entering the Arctic Ocean (the other one-third coming from the Pacific inflow). Outflows are all to the Atlantic ($\sim 9 \times 10^6 m^3 s^{-1}$) or via the complex channels of the Canadian Archipelago ($1 - 2 \times 10^6 m^3 s^{-1}$) (Woodgate, 2012). Mesoscales eddies are characterized by horizontal scales of approximately $10 km$ in the Arctic and are important components of the ocean system. In the central basin regions, a statistically significant higher concentration of eddies was sampled in the Canadian Basin compared to Eurasian Basin in the period between 2003 and 2014 (Zhao et al., 2016).

The Arctic Oscillation (AO) influences the variability of Eurasian river runoff, the transpolar drift, and the intensity of Ekman convergence to the Beaufort Gyre. A high AO index means that the bulk river runoff enters the Eurasian shelves and is transported into the Canada Basin and toward the Fram Strait under low AO index (Morison et al., 2012).

2.4 Wind climate

The Arctic atmosphere produces some of the strongest near-surface winds on Earth due to intense mid-latitude cyclones and mesoscale processes, and these strong surface winds have important consequences on the ocean and sea ice processes (Hughes and Cassano, 2015). According to global climate model simulations, the effects of greenhouse gases emissions will be seen first and will be most pronounced in high northern latitudes due to the ice-albedo feedback and the strong stability of the lower troposphere.

Over the period of instrumental records, the Arctic Ocean has demonstrated dramatic variability on interannual, decadal and multi-decadal scales. The so-called North Atlantic Oscillation (NAO) plays an important role in the climate variability of this polar region. It describes mutual strengthening and weakening of the Azores High (AH) and the Icelandic Low (IL), the two centres of action in the atmospheric circulation of the North Atlantic. When AH and IL are strong, NAO is positive. Conversely, when both are weak, NAO has a negative phase. The variations of NAO is associated with high-latitude signals of surface air temperature, cyclone activity, moisture transport, precipitation, sea surface temperatures and ocean heat transport (Serreze and Barry, 2014).

According to Thompson and Wallace (1998), the NAO should be considered as a regional manifestation of the Arctic Oscillation (AO), also known as Northern Annular Mode (NAM), that represents the leading mode of monthly sea level pressure variability poleward of 20 °N and it is associated to the strengthening and weakening of the circumpolar vortex. The major characteristics are the primary centre of action over the Arctic, focusing the area of Icelandic Low, and opposing, weaker centres of action in the North Atlantic and North Pacific. That means, if the pressures are low (high) over the Arctic, they are high (low) over the North Atlantic and North Pacific. During positive (negative) AO, the Arctic shows below (above) normal sea level pressure (SLP), an enhanced (weaken) polar circulation, and a cyclonic (anti-cyclonic) wind anomaly. Both NAO and AO are present year-round but are more evident in winter with similar impacts on the Arctic climate. The NAO/AO have impact on surface air temperature, precipitation, and sea ice cover. A positive shift in the winter season NAO/AO from about 1970 through the mid-1990s was detected, but in the past decades, studies have demonstrated negative NAO. Yet the sea ice has continued to decline and, the Arctic has experienced dramatic climate change (Serreze and Barry, 2014).

Several authors relate the sea ice melting happening in summer Arctic to the presence and phasing of the meridional atmospheric climate pattern called Arctic Dipole (AD) (e.g. Maslanik et al., 2007; Wu et al., 2006; L’Heureux et al., 2008). This pattern resulted in a much faster than expected loss of sea ice in the real world compared to the climate model projections based on anthropogenic forcings. AD anomaly has a dipole field with two centres of action in the Arctic. A negative (positive) AD phase features a higher (lower) SLP on the North American side of the Arctic and lower (higher) SLP on the Siberian side (Overland and Wang, 2010). The AD climate pattern occurs more frequently in its negative phase in the 21st century compared to the late 20th century. Some studies relate the recent summer sea ice melting in part to the presence and phasing of this meridional atmospheric climate pattern, which resulted in a much faster than the expected loss of sea ice in the real world compared to the timing of ensemble mean projections found in climate models based on anthropogenic forcing alone (Stroeve et al., 2007; L’Heureux et al., 2008).

Other climate signals are also well expressed over the extra-tropics, including the Pacific Decadal Oscillation (PDO) and North Pacific Oscillation (NPO). The PDO index is based on the North Pacific sea surface temperature (SST). During positive PDO conditions, SSTs in central North Pacific are relatively cool, while those along the west coast of North America are relatively warm. The negative phase has opposite signals (Serreze and Barry, 2014). Recent studies have evaluated atmospheric reanalyses and they have demonstrated an increasing number of winter storms, and associated moisture intrusions that are contributing to the rapid sea ice loss (e.g Woods and Caballero, 2016; Graham et al., 2017; Rinke et al., 2017). An enhanced downward long-wave radiative is caused by moisture intrusions that transport pulses of warm and moist air from the mid-latitudes into the Arctic. This could explain up to 50% of the recent winter sea ice decline over the Atlantic sector of the Arctic Ocean (Park et al., 2015).

2.4.1 Percentiles

Several studies have presented the wind climatology in terms of percentiles across the Arctic Ocean as it is a useful way to describe the average and extreme conditions from a statistical point of view. For instance, Hughes and Cassano (2015) assessed the climatological distribution of near-surface wind speeds based on four different atmospheric data sets derived from different reanalyses with a focus on extreme winds across the Arctic for 18 years (1990-2007). The ERA-I reanalysis demonstrated weaker wind speeds compared to the other data sets. The horizontal grid played some

role in determining the magnitude of extreme winds, as data sets with similar resolution (CFSR and WRF50) presented similar wind speed statistics. The 50th and 99th percentiles of wind speeds characterized by similar patterns across the Arctic. The largest winds were found close to the Atlantic Ocean. The median winds were about 5-6 *m/s* over the Arctic Ocean, reaching approximately 9-10 *m/s* in Denmark strait and the Barents Sea east of Svalbard. The 99th percentiles were around 15 *m/s* across the Arctic and reaching 25 *m/s* in Denmark strait.

Liu et al. (2016) estimated the overall wind speed average in the Arctic Ocean for the summer period over the last two decades was about 8 *m/s* based on altimeter data. The strongest winds found were around Greenland and Norwegian seas, particularly near Iceland, where average wind heights are approximately 9.5 *m/s*. The 99th percentile of wind speed indicated more spatial variability and showed that the strongest winds occur near the southeast Greenland coast (in Denmark strait).

The seas around southeast Greenland have been known to be a hazard to maritime traffic as a result of extreme winds that occur in the region. In 1970, estimations showed that wind speeds could have reached 90 *m/s* when recorded by an anemometer before it was destroyed indicating mean winds of 54 *m/s* with a gust to 70 *m/s* that devastated a small town of Tasiilaq (Cappelen, 2001). The weather system is forced by the steep topography of the large fjord systems in the region resulting in high-speed wind extremes. The strong katabatic winds triggered by radiative cooling over central Greenland Ice Sheet associated with a deep low-pressure system over the Denmark Strait cause these severe wind conditions (Moore and Renfrew, 2014). According to Liu et al. (2016) estimations, the 99th percentile of wind speed reached approximately 18 *m/s* for the summer months according to altimeter data. The estimations made by Moore and Renfrew (2014) based on ERA-I and ASR-I atmospheric reanalyses for the winter period between 2000 and 2010 showed 95th percentile reaching 24 *m/s* for ASR-I reanalysis and approximately 20 *m/s* based on ERA-I reanalysis.

The region closer to the North Atlantic Ocean characterize higher wind speeds (> 16 *m/s*) than those Pacific-side seas ($\sim$ 13 *m/s*). This is due to more frequent cyclonic weather systems that happen on the Atlantic side (Serreze and Barry, 2014). On the other hand, on the Pacific side, the semipermanent low-pressure centre of action, called Aleutian low, that disappears in the summer period allowing few cyclones to enter the Arctic Ocean (Serreze and Barry, 2014).

2.4.2 Seasonality

Hughes and Cassano (2015) quantified the annual cycle of median and extreme wind

speeds (50th, 95th, and 99th percentiles) calculated from four different data sets (see their figure 5). All data sets showed a sinusoidal pattern for all percentiles with the strongest wind speeds occurring in winter. The extreme winds (99th percentile) are approximately 40-50% faster in winter than in summer. Mean wind speeds vary from 6 to 9 *m/s*, 95th percentile varies from 11 to 18 *m/s* and 99th percentile varies from 13 to 23 *m/s* for the period between 1990-2007.

The wind speeds are stronger in winter and follow a sinusoid for all seas, with the exception of the East Siberian Sea. In this sea, the winds become stronger towards the end of the year (Stopa et al., 2016, figure 4). In most seas, the strongest winds occur in January and the weakest in July. The Nordic-Greenland Seas demonstrated the strongest average wind speeds of roughly 6 to 10.5 *m/s*.

2.4.3 Trends

Liu et al. (2016) estimated the trends in the mean wind speed for the period between 1996 and 2015 for summer months based on satellite data. They demonstrated that the average wind speeds are decreasing across the Arctic. In the East Siberian and Laptev Seas, the decreasing rates were the strongest across the Arctic Ocean of approximately 0.6

$$m/s$$

decade⁻¹ reaching values of 1.2

$$m/s$$

decade⁻¹ in the Laptev Sea. Conversely, some specific regions such as the Alaskan Coast and the southern Baffin Bay experienced an upward trend of roughly 0.3-0.5

$$m/s$$

decade⁻¹ (Figure 2.4).

Stopa et al. (2016) also found trends in average wind speed for the period between 1992 and 2014 for all months together based on altimeter and numerical data, not only for the summer period. Differently from the trends found by Liu et al. (2016), their results show an upward trend ($\sim 0.5 \% \text{ year}^{-1}$) in the region encompassing Laptev and East Siberian Seas. On the other hand, the results of these two studies are in line with each other on the Atlantic side of the Arctic Ocean. Both studies found an increasing trend in the Kara Sea and a downward trend in the Nordic Greenland Sea (Figure 2.4).

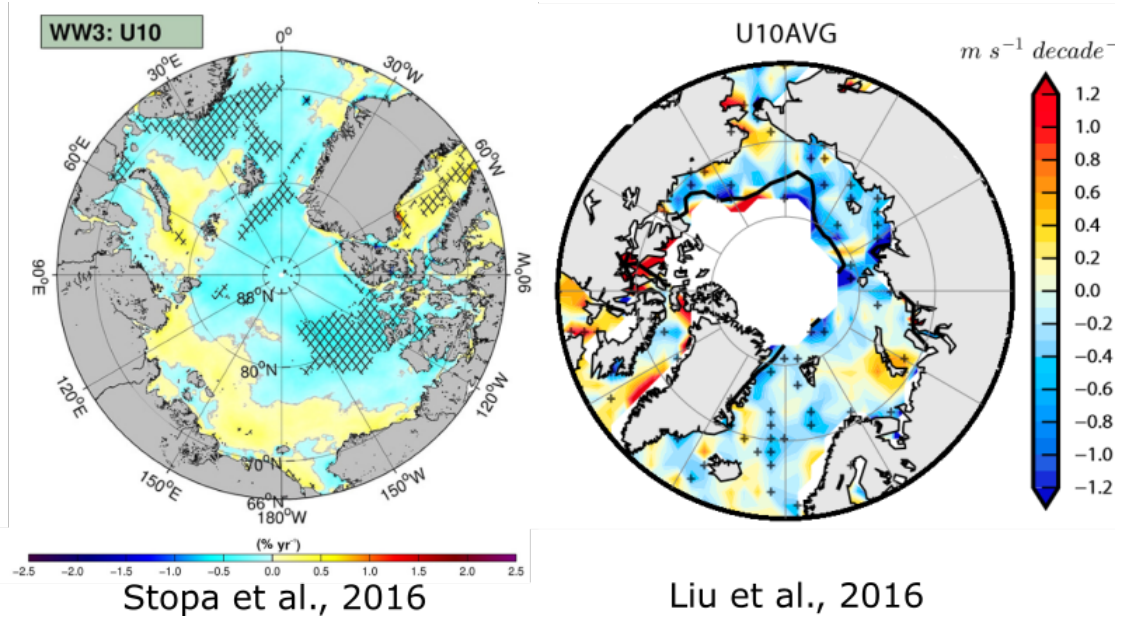


Figure 2.4: Trends in wind speed (U_{10}) for the Arctic Ocean estimated by Stopa et al. (2016) (left panel) based on numerical simulations for the period 1992-2014 and estimated by Liu et al. (2016) (right panel) based on altimeter data measured between 1996 and 2015 in the summer period.

2.4.4 Wind extremes

Extreme value analysis of wind speeds are widely investigated across the globe (e.g. Vinoth and Young, 2011; Breivik et al., 2014; Meucci et al., 2018; Takbash et al., 2019). Such statistical analyses provide the magnitude and frequency of the most extreme winds that can occur in a certain location. Those analyses are based on large historical data sets providing extreme value return period estimates (i.e., wind speeds exceeded on average once every N years, where N is the defined return period). It is desirable long continuous observation records in order to get reliable estimates. However, in practice, such data sets are rarely available. Normally, the estimations are based on satellite data or data derived from numerical simulations. However, there are questions about the accuracy of satellite measurements under extreme conditions (e.g. Young et al., 2017). Vinoth and Young (2011) analyzed the 100-years return period values for wind speeds across the entire globe based on a 23-years satellite dataset. According to their results, the data sets were not long enough to apply a stable extreme value analysis for wind speeds as the distributions that they achieved were extremely noisy. Takbash et al. (2019) attempt a similar analysis with a 30-year satellite dataset. Comparing to Vinoth and Young (2011),

their results demonstrated a smoother spatial distribution. They have applied different extreme value distributions to altimeter and radiometer data. The estimations based on Peaks over Threshold (POT) method applied to altimeter data showed the maximum of U_{10}^{100} of approximately 38 m/s occurring in North Atlantic and North Pacific. In the Denmark Strait, 100-years return period wind speeds reached values of 40 m/s . However, these results did not englobe the entire Arctic Ocean. The estimations based on data obtained from radiometer missions, even though its greater sampling density comparing to altimeter dataset and encompassing the entire Arctic Ocean, showed an unacceptable fair-weather bias for extreme-value applications due to its inability to provide data during rain events.

Breivik et al. (2014) applied ensemble predictions systems to estimate ocean winds and wave extremes predictions to the entire world. They used an ensemble forecast at +240h lead time from the ECMWF Integrated Forecast System. According to this study, the estimations of U_{10}^{100} reach approximately 40 m/s in the Denmark Strait. In Beaufort-Chukchi, Barents seas, and the northern Baffin Bay, the return values are around 25 m/s . In the southern Baffin Bay, the 100-year return values for wind speeds reach approximately 30 m/s . In the Laptev Sea, U_{10}^{100} values are roughly 20 m/s (see their figure 1).

The so-called "weather bombs" are extreme cyclone events that occur approximately 20-40 times per winter season in the North Atlantic section of the Arctic Ocean. Previous studies have demonstrated an increasing trend of approximately six events/decade over 1979-2015 (Rinke et al., 2017). These cyclones transport heat and moisture into the Arctic and they can raise temperatures above freezing conditions causing wintertime sea ice melting or late sea ice growth (Boisvert et al., 2016). The changing climate might be contributing to these extreme cyclones to become more frequent as the storm tracks are shifting poleward and sea level pressure is decreasing at Northern Hemisphere high-latitudes [IPCC, 2013]. The trends of extreme winter cyclones in the Arctic in relation to the sea ice retreat in winter indicates that changes in the frequency of extreme cyclones are related to changes in sea ice and atmospheric circulation (Rinke et al., 2017).

2.5 Wave climate

In the emerging Arctic Ocean, the surface waves are becoming more energetic and storm events are becoming more frequent (Thomson et al., 2016). The sea ice defines the shape and size of the basin controlling the fetch available for the waves to grow

and develop. The enlarged open waters allow waves to grow beyond pure wind seas into energetic swells (Thomson and Rogers, 2014). In the open ocean, sea and swell contribute significantly to the upper-ocean dynamics, exchanges of momentum, heat, and gases. They influence the rich biological cycle and can also be a hazard to navigation and operations at sea. At the coasts, they force circulation and are the main drivers of coastal erosion. As the Arctic Ocean opens, connecting the Atlantic and Pacific Oceans for transportation and commerce purposes, knowledge of the sea state becomes increasingly important (Smith and Stephenson, 2013).

Energetic wave events may be expected to become more frequent in the marginal ice zone (MIZ) that is a highly dynamical region where different physical phenomena take place. In this region, they experience scattering and dissipation by the presence of heterogeneous sea ice concentrations and as a consequence, high-frequency components of wave spectra can be totally reflected or dissipated (Squire, 1995). On the other hand, energetic swells are able to break up ice shields with a thickness of 0.5 and 0.6 m (Collins et al., 2015).

2.5.1 Seasonality

The Arctic Ocean is characterized by a dramatic seasonality due to the freeze-thaw cycles of sea ice throughout the year. In regions where the sea ice cover is reduced, such as Nordic Greenland and the Barents Sea, the waves follow the wind patterns and the seasonality is not as accentuated as in the rest of the Arctic Ocean.

Baffin Bay, Beaufort-Chukchi, East Siberian, Laptev, and Kara Seas experience large seasonal changes with a minimum sea ice cover occurring in September. In these regions, the largest waves occur in October when the sea ice is still reduced, and the winds get stronger (Stopa et al., 2016). In Barents and Nordic Greenland Seas, the winds are stronger and consequently the waves are higher in the period between December and March, as these areas are ice-free during this period. Swells originated in the North Atlantic propagate into these regions with a sheltering in the Barents Sea. It is during this period that the tallest waves of the Arctic occur in the Nordic Greenland Sea. The wind seas are characterized by the cyclonic (anti-clockwise) circulation of the winds common in the North Atlantic sub-basin (Semedo et al., 2015; Stopa et al., 2016).

During the period of minimum ice coverage, between August and October, the waves are generated across the Arctic. In Nordic Greenland and Barents seas, the waves follow the winter's pattern with reduced magnitude. In the eastern Beaufort Sea, the wind seas follow a subtle anti-cyclonic (clockwise) structure while the swells

have opposite direction flowing from the west. In Laptev and East Siberia seas, the wind seas and swells are directed into the sea ice flowing from the east (Stopa et al., 2016).

2.5.2 Percentiles

Significant wave height (H_s) corresponds to the highest third of wave series. Normally, it is computed by four times the square root of the zeroth-order moment (area) of the wave spectrum. Significant wave height percentiles are a convenient way to describe the sea state climate in a statistical point of view. Stopa et al. (2016) evaluated the 50th (median), 95th, and the 99th H_s percentiles across the entire Arctic. Their numerical model results showed the largest wave heights in the Nordic Greenland Sea for all percentiles. In this sea, the median (95th percentile) was around 2.5 m and 99th percentile exceed 8 m with a corresponding mean wave period (T_{m02}) of 9 s. The semi-enclosed seas have smaller wave heights than the region close to the North Atlantic. The median wave heights are commonly about 1.5 m, whereas 99th percentile is around 4 m with a corresponding T_{m02} of 6.5 s. Due to the geometry, the most energetic waves in the Beaufort-Chukchi seas occur when the wind is parallel to the ice edge.

Liu et al. (2016) evaluated altimeter data across three different satellite missions for the summer period between 1996 and 2015. The results were consistent when comparing to the average values found by Stopa et al. (2016). As expected, the 99th percentiles found in these studies are not comparable for the Atlantic side because Liu et al. (2016) just consider the summer months and the highest values in this region occur in winter.

Waves on the Pacific side are dominated by wind sea with a mean wave period of approximately 5 s Wang et al. (2015). Hence, the wave patterns in the Beaufort-Chukchi seas follow wind patterns. Over the other side of the Arctic Ocean, in Barents and Norwegian seas, the waves are dominated by swells coming from southwest and west with longer periods, as demonstrated by altimeter data assessed by Liu et al. (2016).

2.5.3 Trends

Different studies have been evaluating trends in waves and winds across the Arctic. Stopa et al. (2016) assessed the trends with the aid of the Mann Kendall test for ice coverage and significant wave height for the period between 1992-2014. The strongest

trends in ice extent were found in the Barents and Kara seas with roughly eight more ice-free days per year. Some areas such as Greenland, the Amundsen Gulf, and Svalbard have increasing ice coverage with approximately two fewer days per year. Regarding the wave heights across the Arctic Ocean, most of the basin has increasing wave heights demonstrated by both altimeter and model data. Statistically significant downward trends in wave heights were found only in the Nordic Greenland Sea. In the Beaufort-Chukchi seas, the trends were about 1.5 cm/year, which is consistent with the estimated by Francis et al. (2011) (2 cm/year). Wang et al. (2015) computed a difference of approximately 40 cm between 1970-1991 and 1992-2013, which is in agreement with the associated linear rate of 35 cm estimated by Stopa et al. (2016). The largest trends found by Stopa et al. (2016) were higher than 4 cm/year in the Baffin Bay and the Laptev Sea. Those values were large compared to the largest trends estimated by Young et al. (2011) of roughly 2 cm/year.

According to Stopa et al. (2016), the mean wave periods follow the same pattern as the wave heights with an upward trend of roughly 2% per year. The swells have a faster rate compared to wind seas in the Beaufort, East Siberia, Laptev, and Kara seas, which is related to the increase in wave age that is happening across the entire ocean, with a few exceptions such as near the marginal ice zone (MIZ) in the Beaufort Sea.

It is important to mention that trends can be affected by intra-annual oscillations such as the North Atlantic Oscillation (NAO) and the Pacific Decadal Oscillation (PDO). The Nordic Greenland Sea has a strong influence by NAO and the ice and wind dynamics in the Beaufort-Chukchi seas are affected by PDO (Semedo et al., 2015). Stopa et al. (2016) suggested that the negative NAO between 2006-2012 is causing negative trends in wind and waves around the Nordic Greenland and Barents seas encountered in their study.

Thomson et al. (2016) evaluated the sea state of the Beaufort and Chukchi seas, by wave modelling hindcast for the period between 1992 and 2014 for the months of minimum ice cover (August, September, and October). This study has found statistically significant trends for both wave height and peak period, but not for wind speed. Their results are consistent with Wang et al. (2015) that found that changes in wind forcing are insufficient to explain the trends in the waves in Beaufort-Chukchi-Bering Seas. Waseda et al. (2018) evaluated the ERA-Interim 38-year-long reanalysis for the same months evaluated by Thomson et al. (2016). They evaluated the results of this reanalysis for the region encompassing the Laptev, East Siberian, Chukchi and Beaufort seas. On average, the trend of mean wave height found in this study

was around 0.5 cm year^{-1} , which is half of that estimated by Thomson et al. (2016) which is based on 23-year hindcast data. This suggests that the upward trend of the average wave height might be increasing over the last two decades. The results of average wind speed over the ice-free waters do not show any noticeable trend. They also evaluated the maximum wave height, which demonstrated clear upward trends, with the largest trends in October of almost 30% since 1979. The analysis revealed that the areal-maximum wave height has a small correlation with the ice-free water area, and it is highly correlated with the area-maximum wind speed, which has a clear upward trend. This suggests that the increasing trends of the maximum wave heights in these regions are more affected by changes in wind speed than by the enlarged ice-free water area.

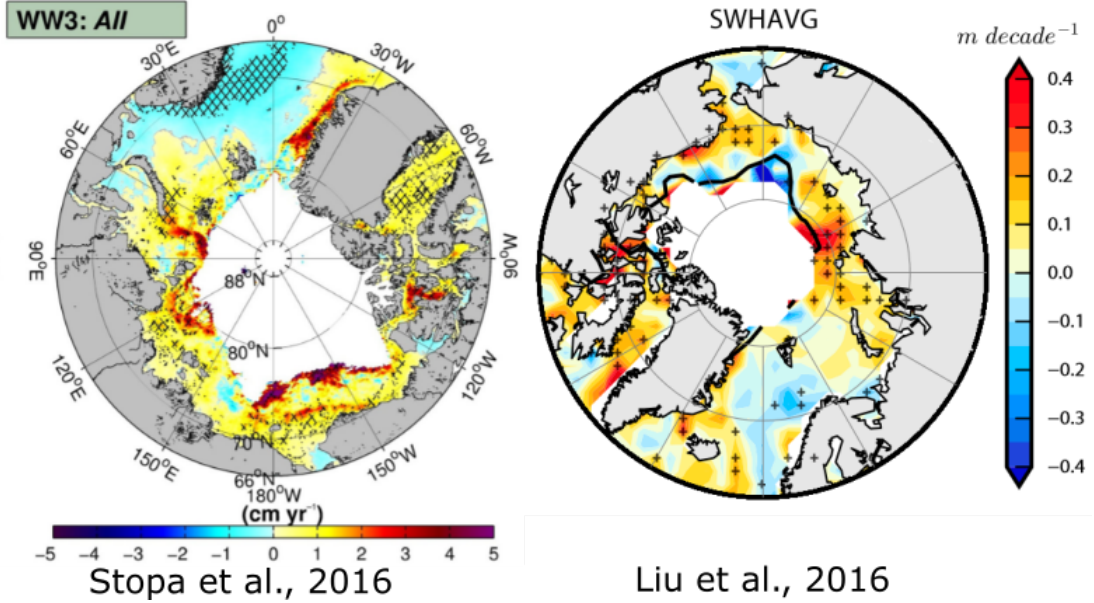


Figure 2.5: Trends in H_s for the Arctic Ocean estimated by Stopa et al. (2016) (left panel) based on numerical simulations for the period 1992-2014 and estimated by Liu et al. (2016) (right panel) based on altimeter data measured between 1996 and 2015 in the summer period.

2.5.4 Wave extremes

There is a number of studies that estimate the extreme wave heights around the globe by applying different extreme value analysis to historical data sets (e.g. Vinoth and Young, 2011; Breivik et al., 2013; Meucci et al., 2018; Takbash et al., 2019). However, as far as we know, no previous research has investigated extreme waves across the Arctic Ocean. One limitation of the established extreme value analysis methods is

the assumption of a stationary time series, which is not suitable for the Arctic Ocean conditions. As demonstrated in the sections before, the Arctic Ocean has a strong seasonality and its sea state conditions are changing dramatically over the past few decades due to climate change. Therefore, an alternative EVA method would be more appropriate, considering the non-stationary condition of the time series. Breivik et al. (2013) applied ensemble prediction systems to estimate wave extremes predictions for the northeast Atlantic Ocean and the North Sea. They compared the extreme ensemble values with estimations based on three different reanalyses. The study demonstrated that the return period values estimated by the ensemble forecasts yield extreme values comparable to the ones found by the traditional EVA from NORA10 but significantly higher than ERA-I and ERA-40. In enclosed areas, such as the North Sea, the upper percentiles are biased low due to the coarse resolution of ensemble forecasts. The results show 100-year return values of significant wave heights of 10-15 m in the North Sea and 18-22 m in the northeast Atlantic Ocean (Figure 2.6).

The highest wave conditions globally are found in the northeast Atlantic (e.g. Alves and Young, 2003; Semedo et al., 2015). Therefore, evaluating the wave extremes on the Atlantic side of the Arctic is particularly interesting and stress the importance of considering the swell propagation from the Atlantic into the Arctic Ocean in the wave simulations.

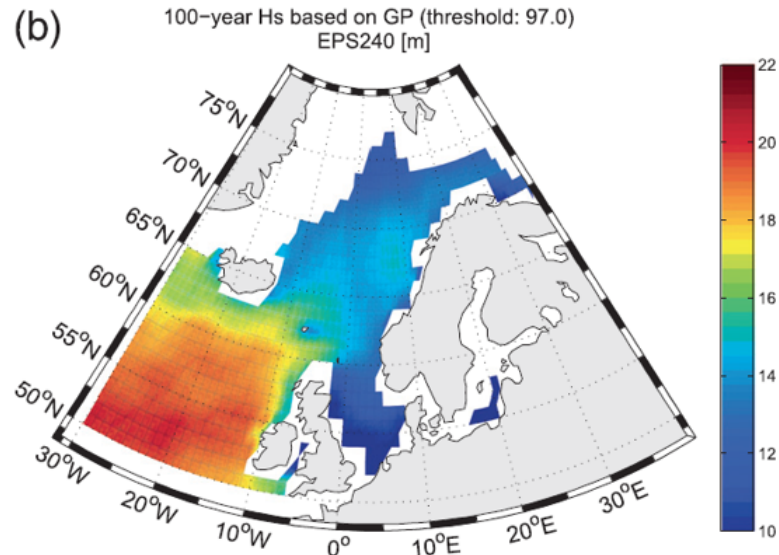


Figure 2.6: 100-year return period values for H_s in the North Atlantic (Breivik et al., 2013)

2.6 Ocean Temperature

Ocean temperatures and associated heat fluxes have an important influence on sea ice (e.g. Carmack et al., 2015). In the summer, the surface waters are warmer and contribute to the sea ice melting. Once the sea ice melts, it produces a cold and fresh layer at the surface resulting in an underlying near-surface temperature maximum (NSTM) layer. The heat of this layer, which is originated from the local incoming summer solar radiation, is trapped and stored due to stratification. Those warm water layers deeper than the NSTM play a crucial role in the heat budget of the Arctic Ocean affecting the sea ice cover (e.g. McPhee et al., 1998).

The surface temperature has got warmer across the entire Arctic Ocean. There is evidence that the Atlantic sector started warming since the 1970s and in the period between 1993 and 2007, the Canada Basin surface waters temperatures have significantly increased. Some ice-free regions in summer have experienced an increase of approximately 0.5°C per decade over 1982-2017 (Timmermans et al., 2017). This ocean warming is an evident consequence of the sea ice loss, changing the albedo and increasing the absorption of solar radiation. Estimations based on the decrease in Arctic Ocean’s albedo over 1979-2011 show that the growth of sea ice might reduce by up to 25% in both Eurasian and Canadian basins due to more solar energy input to the ocean of approximately 6.5 W/m^2 (Timmermans, 2015).

The warm (temperature higher than 0°C) and salty intermediate depth (150-900 m) Atlantic Waters (AW) play an important role in establishing the thermal state of the Arctic Ocean. The AW is transported cyclonically (counterclockwise) along the deep Arctic Basin and its heat is able to melt the sea ice numerous times if eventually released to the surface. There has been evidence that this layer has been expanding farther northeast and its stratification is becoming weaker (Årthun et al., 2012; Lind et al., 2018). The total heat content in the AW layer temperatures continues to increase since 2008 and, at the same time, it reduces its variability. There has been an increase of winter ventilation as the sea ice is melting, the halocline is getting weaker, and the Atlantic Water layer is becoming shallower. Those changes are contributing to making this region similar to the western Eurasian Basin resembling traits of the Atlantic Ocean in a so-called “atlantification” of the Eurasian Basin which is reducing the sea ice thickness along the continental slope off Svalbard (Polyakov et al., 2017).

As the volume flux and temperature rises, the heat transport of the Pacific inflow through Bering Strait has increased by 60%, from around 10 TW in 2001 to 16 TW in 2014 (Woodgate, 2018). In the Canadian Basin, the maximum temperature of

the Pacific Water Layer increased by approximately 0.5°C between 2009 and 2013 (Timmermans et al., 2014). The reduction of the sea ice coverage led to a fivefold increase of the summer solar heat absorption by the surface waters with a doubling in integrated heat content over 1987-2017 in the Beaufort Gyre halocline, that is associated with anomalous solar heating of surface waters in the northern Chukchi Sea (Timmermans et al., 2018).

2.7 Ocean Salinity

Salinity plays an important role in polar ocean density, stratification, circulation, and mixing. It varies with net precipitation (snow, rain, and evaporation), freshwater runoff from rivers and land ice to the ocean, sea ice growth and thaw, and advection of mid-latitudes waters from the Pacific and Atlantic Oceans. Recent estimations yield a freshwater increase (relative to the salinity 34.8 on the Practical Salinity Scale) of $600 \pm 300 \text{ km}^3\text{yr}^{-1}$ for 1992-2012 and consequently decreasing of salinity and thickening of the freshwater layer across the Arctic (e.g. Carmack et al., 2016). The amount of freshwater in the Beaufort Gyre has increased by approximately 40% due to the dominant clockwise wind patterns over the Canadian Basin (Proshutinsky et al., 2015).

Even though Woodgate (2018) demonstrated a significant increase of the freshwater flux coming from the Pacific Ocean with a positive trend of $30 \pm 20 \text{ km}^3\text{yr}^{-1}$, mainly due to the increasing volume flux between 1991-2015, Armitage et al. (2017) estimated a decrease of freshwater content of roughly 180 km^3 over 2003-2014, in the East Siberian, Laptev, Chukchi, and eastern Kara seas. They illustrated a convergence of surface freshwater in the Beaufort Gyre concurrent with regional reductions in sea surface height in those seas, mainly contained shoreward of the 50 m isobath. This freshening of the Beaufort Gyre and deepening of isopycnals carried more saline deepwater further up in surrounding shelf seas. Freshwater content in the upper 100 m of the northern Barents Sea declined by about 32% during the 2000s, from a mean of 2.5 m (relative to the salinity of 35) in 1970-1999, to 1.7 m in 2010-2016 (Lind et al., 2018).

Freshwater release from rivers is increasing due to the permafrost thaw and loss of ground ice. Ice rich permafrost areas where impacts of ice melting are evident include Yukon in Canada and the Yedoma deposits in Siberia, Alaska (Schirmer et al., 2011). Discharges of glacial ice from Greenland are also increasing significantly that might have consequences on the formation of water masses that represent the

headwaters of the Atlantic Meridional Overturning Circulation. Increasing freshwater fluxes also influence local circulation with the fjords by freshening the surface layer and affecting the estuarine circulation (Kjeldsen et al., 2015).

2.8 Morphological changes

Arctic permafrost coasts represent approximately 34% of Earth’s coastlines and are influenced by the presence of landfast and sea ice coverage (Lantuit et al., 2012). Recently, mappings of Alaskas shorelines point out huge erosion rates and show the threat of climate change upon the coast. The rates of coastal retreat in the Beaufort Sea have increased from 8.7 m/year in the period between 1979 to 2002 to 13.6 m/year in the period from 2002 to 2007 (Jones et al., 2009). The extension of ice-free conditions occurred at a similar rate in the same period (factor of ~ 1.5 increase). However, rates of annual fetch and wave height are slightly bigger (factor of 1.8 increase). The hypothesis is that the more frequent storms in the fall (Atkinson, 2005) might be counteracted by the lower ocean temperature that occurs at this time of the year. The erosion of the bluffs of the Beaufort Coast can be fast even during relatively calm sea states, as bluffs have high interstitial ice content (64%) having high mechanical strength, but limited resistance to thermal erosion (Overeem et al., 2011). This way, Overeem et al. (2011) assert that future studies should focus on the treatment of both thermal evolutions on the ocean and also storm surges on which the increased waves ride and may accelerate yet more strongly the coastal erosion in this area.

These high coastal rates together with a large amount of organic matter frozen in permafrost (Schuur et al., 2015) are resulting in an annual release of up to 14.0 Tg (1012 grams) of particulate organic carbon into the nearshore zone (Wegner et al., 2015). This feedback might accelerate the impacts of climate change, but the concentration of greenhouse gas emission from these regions is still uncertain (Schuur et al., 2015).

Coastal evolution in the Arctic is driven by a combination of relative sea-level rise, climatic variability aspects, and morphosedimentary features of the coast (Manson and Solomon, 2007). At the Tuktoyuktuk tide gauge, the rate of sea-level rise was $3.5 \text{ mm} \cdot \text{a}^{-1}$ (Manson and Solomon, 2007), however, it incorporates the submergence due to glacial isostatic adjustment of $1.68 \text{ mm} \cdot \text{a}^{-1}$ and correction for ice-mass changes (James et al., 2014). Projections of mean sea level elevations at the end of the 21st century vary from 0.26 m to 0.98 m. However, taking into account the atmospheric

changes and increases in freshwater inputs, the rate of relative sea-level rise in the Arctic might be even higher (IPCC, 2013).

The rates of coastal erosion are expected to accelerate due to the increasing fetches that allow waves to become more energetic and storms caused by the reductions of sea ice (Forbes, 2011). This might increase the annual coastal delivery of sediment, carbon and nutrients and may alter the biochemical properties on the upper coasts in the Arctic (Wegner et al., 2015).

Reduced landfast ice and increased storm surges can allow gravity waves to propagate further inland, producing greater flooding with sea-water. Some studies have highlighted that fragile Arctic ecosystems can be damaged by severe storm surges (Pisaric et al., 2011; Kokelj et al., 2012). For instance, an unprecedented large storm surge in 1999 dramatically affected the Mackenzie Delta, causing soil salinization, loss of terrestrial vegetation, and changes in formerly freshwater lakes (Pisaric et al., 2011; Vermaire et al., 2013) demonstrated that storm surge is on rise in the outer Mackenzie Delta as Arctic temperatures increase and sea ice extent declines over the past four centuries by analyzing lake sediment records.

The erosion in the coastal region of the Beaufort Sea is known to be among the highest in the world (Survey et al., 1988; Jorgenson and Brown, 2005). The high interstitial ice content of the coastal sediments in this region contributes to the strong erosion rates reaching values greater than 18 m/yr in the American part of the Beaufort Sea coastline (Gibbs et al., 2015). This coastline is protected by landfast sea ice from processes responsible for coastal erosion such as waves, winds, and currents all year round except the summer months (July–September). It is during the ice-free period of the year that coastal erosion occurs. Generally, ice-rich bluffs erosion is a thermo-mechanical process that depends on the open water season duration, the number and magnitude of storms impacting the coastline, sea-level, and summertime sea surface temperature (SST). The spatial variation of the erosion rates along the coastline also depends on the bluffs height, sediment composition, degree of ice-richness, near-shore bathymetry, and the presence of barrier islands (Survey et al., 1988; Jorgenson and Brown, 2005; Solomon, 2005).

The changes that occur in the Arctic shelves are systematically under-studied due to harsh conditions. For instance, ice-breaking research vessels tend to avoid the coastal waters in those polar regions, and there is a lack of shore-based research infrastructure (Fritz et al., 2017). Any increases in already rapid rates of coastal erosion in the Arctic coastal regions might cause substantial effects on the supply of freshwater and terrestrial wildlife habitat, life and culture of the communities settled

in these coastal areas can be a risk to petroleum infrastructures (Holland-Bartels and Pierce, 2011), and can potentially impact the global carbon budget by transferring organic carbon from terrestrial to marine storage zones (Ping et al., 2011).

2.9 Conclusion

Recent studies have demonstrated significant metocean changes in the Arctic Ocean. This ocean is characterized by accentuated seasonal cycles in most of the environmental parameters due to the retreat-expansion cycles of sea ice. As discussed before, several researchers have assessed wind and wave climate, but there were some inconsistencies between their results.

The metocean parameters in this region have not yet been assessed together in a consistent way. A systematic evaluation of the main metocean parameters of the Arctic Ocean would provide a better understanding of the changes occurring in this region. The main drivers of the dramatic coastal erosion occurring in some regions are not yet well understood.

In addition, there is a gap of knowledge about extreme waves and winds across the entire Arctic Ocean. Previous studies have only evaluated these parameters in the Atlantic sector of the Arctic Ocean.

Chapter 3

Wave hindcast

3.1 Introduction

Over the past few years, recent studies have demonstrated that the waves are changing in a consistent way across the Arctic (e.g. Liu et al., 2016; Stopa et al., 2016). However, there is still a lack of knowledge about the changes in extreme waves in this region. There is also a deficiency of reliable measured data. Besides the temporal limitation of satellite observations, there is also the spatial restriction as most of the altimeter data currently available do not span latitudes higher than 82° .

The use of inaccurate and inconsistent data on the metocean properties of the Arctic Ocean can halt the understanding of the changes that are happening in the region. In order to obtain reliable data that is consistent in time and space of the sea state in the Arctic Ocean, a 28-year wave hindcast was performed with the WAVEWATCH III (WW3) model in this study. In order to ensure accurate model results, a calibration process was carried out by comprehensively analyzing the performance of the model against buoy and altimeter data for August and September of 2014, assessing different input data, spatial resolutions, boundary conditions, and comparing the most recent source terms available in the wave model adjusted by different wind-wave growth parameters. Once the best set-up was achieved for the Arctic domain, the model results were validated for the period between 2012 and 2016 against altimeter data. Stopa et al. (2016) compared the performance of CFSR and ERA-Interim wind data sets in the WW3 model for the Arctic Ocean. According to this study, ERA-Interim matched the variability of the buoy data better than the CFSR wind. However, it has demonstrated an underestimation of energetic waves. In this study, taking into account that the ERA-Interim reanalysis is consistent in time and therefore, more recommended for climate change studies than CFSR data, there has been made an effort to improve the wave model results with this dataset by using different

source terms and wind-wave growth parameters in the model. In addition to that, an evaluation with the recently released ERA5 atmospheric reanalysis, which is also consistent in time, was carried out.

The sea ice concentrations play an important role in the evolution of the sea state in the Arctic as it defines the available fetch for waves to grow and develop. It means that as the sea ice extent decreases, the waves become higher. Therefore, the performance of the wave model was evaluated by comparing different sea ice concentration data sets as input for the simulations. This section outlines an overview of the WW3 model and introduces the calibration and validation results for the long-term wave hindcasts for the Arctic Ocean performed in this study.

3.2 Overview of Wave Model

The wave simulations are performed with the WW3 model (version 6.07) which is a third-generation spectral wave model (Tolman, 2009). This wave model is a phase-averaged model for wind-generated surface gravity waves that includes physical processes like non-linear wave-wave interactions, wave-ice interactions, dissipation due to whitecapping, and bottom friction. It uses the third-order spatial and spectral advection scheme. The evolution of the wave spectrum is described by the spectral action balance equation and is given by

$$\frac{\partial N}{\partial t} + \frac{\partial c_x N}{\partial x} + \frac{\partial c_y N}{\partial y} + \frac{\partial c_\sigma N}{\partial \sigma} + \frac{\partial c_\theta N}{\partial \theta} = \frac{S}{\sigma} \quad (3.1)$$

Where x and y are the spatial coordinates, t is time, σ is the relative radian frequency, θ is the direction normal to the wave crest, $N(\sigma, \theta, x, y, t)$ is the action density spectrum which is defined as the wave energy density (E) divided by the relative frequency $\{(N = E/\sigma)$, c_x and c_y are the group velocities in x and y directions, representing the propagation of the action density in geographic space in the second and third terms of the action balance equation. The fourth term represents the shifting of the relative frequency due to variations in depth and currents with the propagation speed c_σ in σ space. The fifth term represents depth- and current-induced refraction with c_θ in direction space. The term $S(\sigma, \theta)$ is the source and sink term based on energy density, representing the effects of generation, dissipation, and nonlinear wave-wave interactions. It represents different physical sources and fluxes of wave energy, including the wind input term S_{in} , wave breaking term S_{ds} , nonlinear wave-wave interactions S_{nl} , and swell decay S_{swl} (Cavaleri et al., 2007).

The wind input term in spectral wave models operates traditionally on the friction velocity u^* , which is parameterised in terms of the wind speed at 10 m above the sea surface (U_{10}) by considering the wind profile is logarithmic. The energy input from the wind is commonly represented by $\frac{(u^*)}{c_p} \cos \phi$ (e.g. Komen et al., 1984) where c_p is the wave phase velocity and ϕ is the angle between wind and wavenumber vectors.

3.2.1 Source terms

There are four different physical formulations available in the WW3 model that describe the wind input, wave breaking due to whitecapping, and swell dissipation. The ST2 source term developed by Tolman and Chalikov (1996) and updated by Tolman (2002) combines a dissipation consisting of one term for low frequency and another for the high-frequency tail of the spectrum and a wind input based on the numerical model airflow above waves by Chalikov and Belevich (1993). The ST3 source term is the ECMWF WAM described by Bidlot (2012) that combines the wind input term originally based on the wave growth theory of Miles (1957) with the feedback on the wind profile parameterised by Janssen (1991).

The ST4 source term described by Ardhuin et al. (2010) and further updated by Leckler et al. (2013) was developed around a saturation-based dissipation, a cumulative effect that dissipates short waves due to the breaking of long waves, and a swell dissipation that converts from non-linear in turbulent conditions to linear in the viscous regime. The wind input is based on Janssen (1991) parameterisation with a reduction at high frequencies in order to achieve a balance with the whitecapping term and reduce unrealistic large drag coefficients under strong wind conditions, but removing the age dependence in the wind stress (Stopa et al., 2016).

The ST6 source term based on Zieger et al. (2015) was derived by the 3-year field experiment carried out in Lake George, New South Wales in Australia (Young et al., 2005; Donelan et al., 2005) that provided various novel features of wave dynamics. According to Donelan et al. (2006), the wind input term S_{in} is a nonlinear function of the wave spectrum as the growth rate depends on the steepness and hence the spectrum itself. The growth rate slows down in extreme conditions due to the flow separation, which means that the wave growth still increases if the winds increase, but not as fast as one would expect by extrapolating the measurement in moderate wind-forcing. According to Babanin et al. (2007), the wind input doubles over a breaking wave and hence can increase if the breaking rates are substantial. Regarding the whitecapping term (S_{ds}), the threshold for inherent wave breaking demonstrates

its existence in terms of wave steepness and a dimensionless value for such threshold was established by Babanin and Young (2005) across the entire spectrum. The two-phase behaviour of S_{ds} takes into account that the breaking can happen due to inherent reasons, but above the spectral peak, the breaking is enhanced as longer waves influence shorter ones. This source term also considers the direct dependence of S_{ds} on the wind speed when U_{10} exceeds 14-15 m/s (Manasseh et al., 2006) and the bimodal nature of the directional distribution of S_{ds} (Young and Babanin, 2006).

According to Stopa et al. (2016), ST6 and ST4 perform similarly with the most significant differences in higher-order wave parameters and low wave heights. ST4 demonstrated the lowest significant wave height biases, but it overestimates swell and wind waves in some regions. On the other hand, the ST6 source term produces more accurate swell heights, but it overestimates the high-frequency tail. Liu et al. (2019) recalibrated the ST6 term by increasing wind input S_{in} and tunable parameters of S_{ds} and the results demonstrated improvements on the simulated high-frequency energy level and provided better predictions of bulk wave parameters. This happens because a relatively stronger input allows a higher dissipation, which in turn pulls the overestimated spectral tail down to the correct energy level. In this dissertation, a comparison of the two most recent source terms was carried out: ST4 and ST6 parameterisations. Wind-wave growth parameters can adjust both models: β_{max} in ST4 and CDFAC in ST6.

3.2.2 Nonlinear wave-wave interactions

Nonlinear wave-wave interactions (S_{nl}) can be modelled using the Discrete Interaction Approximation (DIA Hasselmann et al., 1985). This parameterisation is a crucial component in third generation wave models that overcomes the time-consuming methods for computing the nonlinear wave-wave interactions such as the Webb-Resio-Tracy (WRT) method that computes the exact solution of the redistribution of wave energy over the spectrum resulted from a resonant wave-wave interaction described by Hasselmann (1962) or the GMD approach developed by Tolman (2013). The DIA method accounts for interaction contributions for a single representative quadruplet, making the numerical simulations several orders of magnitude more efficient and retaining the dominant features of the exact solutions (Tolman, 2013).

3.2.3 Wave-ice interactions

Recent efforts have been made toward including wave-ice interactions in the WW3 model. Some of the new parameterisations were first described in Rogers and Orzech (2013). Observation data sets measured during the Sikuliak cruise (Rogers et al., 2016) and other data (e.g. Ardhuin et al., 2016) contributed to some improvements and tuning of such parameterisations. Recent developments are presented in the WAVEWATCH III manual (WW3DG, 2019).

The wave-ice interaction schemes available in the WW3 model (Thomson et al., 2018) include:

- IC0 partial blocking, scaled by ice concentration and high concentration treated as land;
- IC1 Simple dissipation, uniform in frequency;
- IC2 Basal friction, laminar and/or turbulent;
- IC3 Ice as viscoelastic layer (Wang and Shen, 2010), frequency-dependent ;
- IC4 Assorted parametric and empirical formulae, most being frequency-dependent;
- IC5 Ice as viscoelastic layer (extended from Fox and Squire (1994) frequency-dependent;
- IS1 Simple conservative diffusive scattering term;
- IS2 Floe-size dependent conservative scattering, combined with ice break-up.

Although those recent efforts, there is still a lack of robust physics that describe the attenuation of waves in ice-covered seas properly in such models. There is a strong need to develop better model coupling that simulates the air-sea-ice-wave processes altogether. For instance, pancake formation, or almost any other ice type, is not included in those wave-ice schemes. Laboratory experiments have been performed in order to better describe the wave-ice interaction physics (e.g Bennetts et al., 2015; Toffoli et al., 2015) and new findings should be incorporated in those models. Similarly, recent physics representing the wave-forced breakup of ice into specific Floe Size Distributions (Montiel and Squire, 2017) has yet to be implemented in any wave-ice model. Besides that, the details of wave and wind coupling in ice-covered seas are not yet fully understood (Li et al., 2015).

3.2.4 Wave-current interactions

As described previously, the WW3 wave model is a third-generation wave model that operates on the conservation of wave action. The wave action spectral density varies in space, time, wave number, and wave direction as described in equation 3.1. The ocean currents affect both the left and the right side of the equation. It is assumed that the current field varies slowly in space and time with respect to wave length with respect to wavelength and wave period, which is reasonable considering that the changes in currents are controlled by tides and geostrophic balance (Peregrine, 1976).

On the left side, which describes the wave kinematics and dynamics, surface currents are included by modifying the velocities of propagation which advect wave action in geographical and spectral spaces. The wave group velocity is affected by the ocean currents in terms of the frequency Doppler shift, i. e., $\sigma = \omega - k \cdot U$, where σ is the wave radian frequency, k is the wave number, U is the surface current speed, and ω is the absolute frequency or the frequency in a frame or the reference moving with the Earth. The total velocity at which the wave action is advected in space becomes directly proportional to the currents, i. e. $U + cg$. The wave number changes as a function of current spatial gradients in the wavenumber direction $\frac{\partial U}{\partial s}$ and the waves are refracted by transverse current spatial gradients $\frac{\partial U}{\partial m}$, where s and m are coordinates parallel and orthogonal to the k -vector. Under conditions where the wave linear dispersion applies and where the wave currents are known, the wave kinematics are well simulated by the action balance equation (Chawla and Kirby, 2002). However, under circumstances where the non-linearity plays an important role in the wave-current interactions (e.g. Babanin, 2011), the model accuracy is compromised in opposing currents and near blocking regions (Ardhuin et al., 2012; Rapizo et al., 2017).

As a consequence of the conservation of the wave action, the waves that propagate over collinear currents with negative (positive) shear in the along wave direction will experience increase (decrease) in wave number and, consequently, wave energy.

The right-hand side of the equation 3.1, that represents the positive and negative source of energy as well as its distribution in spectral space, has been historically subgrouped by the energy input, dissipation, and nonlinear wave-wave interactions. However, the currents have been considered only in the input term S_{in} . The dissipation due to breaking and nonlinear interactions do not take into account the mean water flow. However, as described by Chawla and Kirby (2002), opposing currents can increase the probability of breaking waves as a consequence of the wave steepening. This way, spectral models can lead to an overestimation of the dissipation rate by misrepresenting the dissipation rate. Besides that, nonlinear interactions and the

development of a spectral tail can be affected by varying current fields (Waseda et al., 2015).

The WW3 model incorporates the ocean currents in the wind input by a simplified vector balance between local wind and current that can be expressed as $u_e(z) = u(z) - aU$, where $u(z)$ is the wind vector at a certain level z , U is the surface current vector and u_e is the resultant effective wind vector. When $a = 1$, the currents have the largest effect.

There are some limitations of this simplistic formulation of current-induced effects in wave models. As described before, the only term that is affected by currents on the right-hand side of the action balance equation is the wind input source term. Whereas in the left-hand side the implications of currents are all derived from the modified Doppler-shifted frequency (Rapizo et al., 2018).

The WW3 model can be coupled to ocean models. For instance, in COAWST modelling system (Warner et al., 2010), the WW3 simulations are affected by the results of the ocean model such as by changes in water levels, currents, and alterations in bathymetry and bottom roughness (to simulate morphological changes due to sediment transport on the sea floor). The ocean surface currents (u_s and v_s) have an impact on the wave action balance by two different ways. First, the source term uses the components of 10 m wind speed (U_{wind} , V_{wind}) from the atmosphere model modified by the local current ($U_{wind} - u_s$, $V_{wind} - v_s$) thereby modifying the wind stress. The other way is modifying the group velocities ($c_x + u_s$, $c_x + v_s$) which affect the wave number to allow current-induced refraction (Holthuijsen, 2010; Warner et al., 2010). The ROMS model (Shchepetkin and McWilliams, 2005) is also affected by WW3 simulations, as wave fields are utilized to compute forcing in the form of radiation stress gradients which allow wave-driven flows, being able to compute Stokes velocities, to provide correct mass flux transport, and to compute wave-enhanced bottom stresses.

3.3 Set-up of the wave model

The spectral domain has been divided into 32 frequency and 24 directional bins (directional resolution of 15°). The minimum frequency was set at 0.0373 and the frequency increment factor has been set at 1.1, providing a frequency range of 0.0373-0.715.

3.3.1 Physics packages

The physics packages used in the wave simulations with the ST6 (Zieger et al., 2015) and the ST4 (Ardhuin et al., 2010) source terms were the same, except for the flux computation methods:

- FLX4 For ST6 simulations the flux computation with friction velocity according to the following equation for flux computation was used (Hwang, 2011):

$$C_d \times 10^4 = 8.058 + 0.967U_{10} - 0.016U_{10}^2 \quad (3.2)$$

- FLX0 - For ST4 simulations, the package with no routine for flux computation is chosen
- NL1 DIA approximation (Hasselmann et al., 1985) for non-linear interactions.
- BT1 JONSWAP bottom friction formulation (Hasselmann et al., 1973) with no bottom scattering.
- LN1 Cavaleri and Rizzoli (1981) for linear input source term
- DB1 Battjes-Janssen shallow water depth breaking (Battjes and Janssen, 1978) with a Miche-style shallow water limiter for maximum energy.
- UQ ULTIMATE QUICKEST (Leonard, 1979, 1991; Davis and Moore, 1982) propagation scheme with averaging technique for Garden Sprinkler alleviation (Tolman, 2002).
- IC0 No damping by sea ice
- IS0 No scattering by sea ice
- REF0 No reflection
- RWND Correct wind speed for current velocity.
- WNT1 Linear interpolation method for wind interpolation
- CRT1 Linear interpolation method for current interpolation
- TR0 No triad interactions used.

In the source term ST6, the bulk adjustment to the wind forcing can be achieved by calibrating the drag parameterisation FLX4 through the CDFAC parameter. This has a similar effect to tuning variable β_{max} in ST4 source term package.

Considering the ultimate goal of this study of evaluating the more energetic waves in the open water region and the lack of robust physics in the available parameterisations of wave attenuation due to ice, the ice-covered sea was considered as land where the ice concentration was over 25%.

3.3.2 Computational domains

In order to generate the boundary conditions for the Arctic domain, especially to get reliable results of the swells generated in the North Atlantic Ocean and propagate through the Arctic Ocean, a global model with 1 x 1 degree of spatial resolution was calibrated and validated with the same input data used for the Arctic domain. The simulations were performed in one-way nesting, where the first step was to run the global model and get the wave spectra for the points located in the boundaries of the Arctic domain.

3.3.2.1 Global domain

The GRIDGEN (Chawla and Tolman, 2007) was used to generate the global domain used in the WW3 model. It is a tool in MATLAB that was specifically developed to generate grids that can be used in this wave model. The bathymetry used to create this computational domain was ETOPO1 (Amante and Eakins, 2009) that has a horizontal resolution of 1 arc-minute and integrates land topography and ocean bathymetry. Besides generating the files with the information with the bathymetry and the land boundaries, this tool also generates the obstruction grids that are needed to remove energy from unresolved islands (Chawla and Tolman, 2008).

For this global domain the maximum global time step, the maximum CFL time step for x-y, and for k-theta were the same (3600 s) and the minimum source term time step was 30 s.

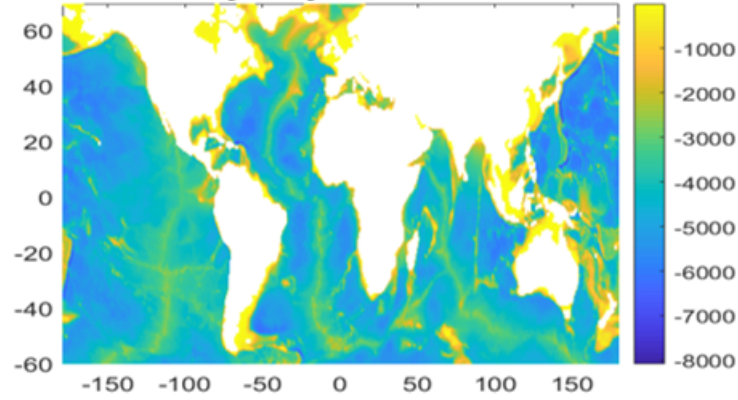


Figure 3.1: The bathymetry in meters from ETOPO1 for the global domain with 1x1 degree of horizontal resolution.

3.3.2.2 Arctic domains

The use of curvilinear grids is well-suited and more efficient choice in simulations for polar regions as it maintains the geographic distance between nodes more realistic (Rogers and Orzech, 2013).

Three different model domains were compared for the Arctic wave simulations. The horizontal resolution, minimum latitude, and number of grid points of each grid point are shown in Table 3.1. These grids were generated with a Python library called PYROMS for generating curvilinear grids in the format that is used by the ocean model called Regional Ocean Modelling System (ROMS) and further converted to the format that is required by WW3 model using a MATLAB script. After generating the files with the bathymetry information and land masks, the obstruction grids were generated with the aid of GRIDGEN.

The coarser grid was used to perform the hindcast as the results of those grids were the same as shown in section 3.5.2.1. This grid has a horizontal resolution varying from 9 to 22 km with 400 x 300 grid points (minimum latitude of $53.17^{\circ}N$) as shown in figure 3.2. It is in the Arctic Polar Stereographic Projection. As in the global model, the bathymetry used to create this computational domain was the ETOPO1. For this domain, the maximum global time step was 600 s, the maximum CFL time step for x-y was 300 s, for k-theta was 150 s and the minimum source term time step was 10 s.

Table 3.1: Configurations of each Arctic domain used for the wave simulations with the WW3 model.

	Horizontal resolution (km)	Maximum latitude (°)	Grid points
Grid 1	9-22	54.66	400x300
Grid 2	6-16	53.17	550x450
Grid 3	4-12	52.85	800x600

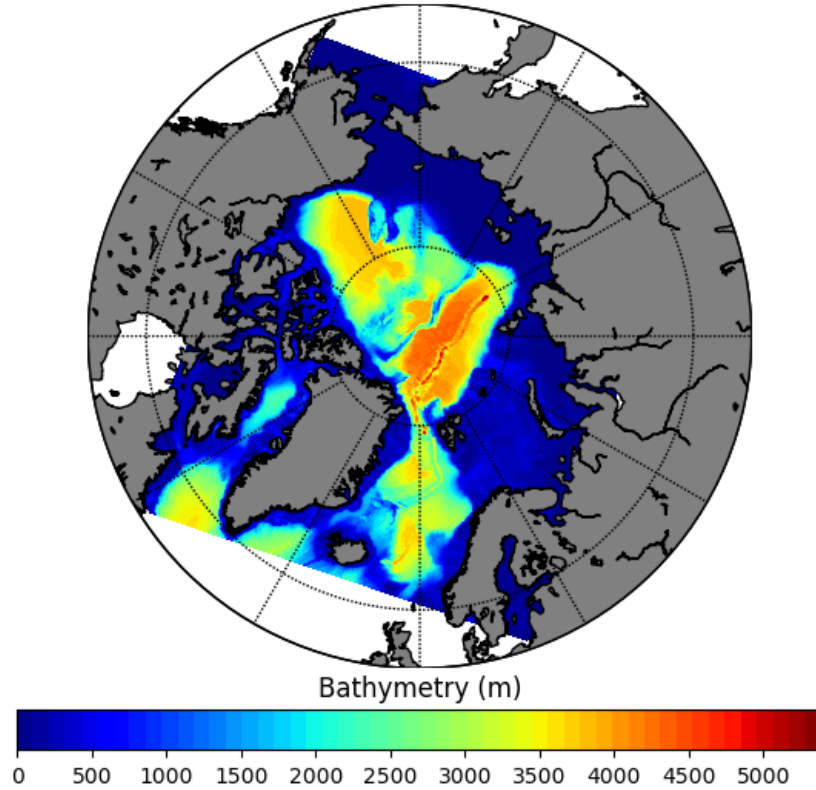


Figure 3.2: The bathymetry in meters from ETOPO1 for the Arctic domain with 9-22 km of horizontal resolution in the Arctic Polar Stereographic projection.

3.3.3 Input data

3.3.3.1 Atmospheric Forcing

Atmospheric reanalyses that consist of observations and numerical modelling results have been widely used for assessing ongoing changes within the Arctic System (Stroeve and Notz, 2018). In this study, three different atmospheric reanalyses were used as an input for the wave model and the performance of the model with each wind input was compared against buoy and altimeter observations.

The ERA-Interim global reanalysis of the European Centre for Medium-Range Weather Forecasts (ECMWF) is a source of the atmospheric forcing as it has demonstrated good performance for the Arctic when comparing to other atmospheric reanalyses (Jakobson et al., 2012). This reanalysis has a resolution of 0.75 degrees and 60 vertical levels and covers the period from 1979 onwards and continues to be extended forward in near-real time. It consists of the data assimilation of satellite data, *in situ* observations, and forecast modelling. This reanalysis estimates parameters that are consistent with the laws of physics as well as with observations. It is achieved by using forecast models, assimilating and comparing observations of different types and from multiple sources. It provides information from locally observed parameters to unobserved parameters at nearby locations, and it can also propagate this information forward in time (Dee et al., 2011).

It is crucial to consider that the polar amplification has been the strongest during the more recent decades (Screen and Simmonds, 2010) and time-varying biases have been reported in the ERA-Interim reanalysis owing to the rapid increase in satellite observations beginning in the 1990s (Dee and Uppala, 2009). So even though the reanalysis span over a longer period (since 1979), the analysis performed in this study will use data since 1991.

The atmospheric forcing of the NCEP Climate Forecast System Reanalysis (CFSR) was also used as an input for the wave model. The first version of this reanalysis comprises the period between 1979 and 2010 and the second version of the reanalysis from 2011 to the present. The second version differs from its predecessor in terms of assimilation of satellite data, higher spatial resolution and coupling between ocean, atmosphere, land surface, and sea ice model (Saha et al., 2010, 2014). Jakobson et al. (2012) have compared four different reanalyses against observations in the central Arctic Ocean: ERA-Interim, NCEP-CFSR, NCEP-DOE, and NASA-MERRA. Despite large errors encountered by all reanalyses, ERA-Interim got the highest overall ranking, especially for air temperature and wind speed. Its largest errors included moist bias throughout 890 m layer and warm bias of up to 2°C in the lowermost 400 m.

In 2018 the ECMWF launched its 5th generation climate reanalysis dataset called ERA5, which has a horizontal resolution of 31 km and 137 vertical levels, and a temporal resolution of 1 hour (Hersbach et al., 2019). It is based on the advancements implemented on the ECMWFs operational forecasting system called Integrated Forecasting System (IFS) that serves as the climate model for the production of reanalyses such as ERA-Interim and ERA5. The ERA5 atmospheric analysis is based

on a hybrid incremental 4-dimensional variational data assimilation (4D-Var) system (Hersbach et al., 2018).

Graham et al. (2019) evaluated the performance of five atmospheric reanalyses (ERA5, ERA-Interim, CFSRv2 Japanese 55 Re-analysis - JRA-55, and Modern Era Retrospective analysis for Research and Applications version 2 - MERRA-2) in an Arctic gateway during late summer. They used radiosonde observations from two cruises in the Arctic to evaluate these data sets. This research demonstrates that the recently released ERA5 performs best with the largest improvements in the wind and temperature fields. The clearest improvement in ERA5 for the wind field is possibly related to the higher vertical resolution of this reanalysis. Mean wind speed biases and RMSEs are smaller in ERA5 than ERA-I and correlation coefficients are higher at every level.

Dullaart et al. (2019) also evaluated the performance of ERA5 and ERA-Interim in storm surge modelling. They found an RMSE in tropical cyclone wind speed by 58% lower in ERA5, compared to ERA-Interim. And the validation of 10-m winds (U_{10}) shows that for tropical cyclones the negative bias of wind speed is reduced from 28.0% for ERA-Interim to 2.5% for ERA5.

3.3.3.2 Sea Ice Data

In the wave simulations with the WW3 model, the ice concentrations of different sources were evaluated. The data sets assessed include the Global Ocean Physics Re-analysis (GLORYS2v4), the sea ice concentration given by ERA-Interim and ERA-5 reanalyses, the satellite data from IFREMER/CERSAT, and also the sea ice concentration provided by the National Snow and Ice Center (NSIC) of NOAA.

The Special Sensor Microwave/Imager (SSM/I) is a seven-channel, four-frequency, linearly polarized passive microwave radiometer system. Its brightness temperatures accurately estimate sea ice concentrations (Liu and Cavalieri, 1998). The IFREMER-CERSAT is delivered from high-frequency channels of SSM/I that are used to estimate daily average on a horizontal resolution of 12.5 km sea ice concentration and it is able to reproduce important features of the marginal ice zone (MIZ) (Ezraty et al., 2007).

The NOAA/NSIDC Climate Data Record is based on passive microwave data delivered from the Defense Meteorological Satellite Program (DMSP). They are provided in a 25 km grid and they are produced using an algorithm that joins ice concentrations from two established algorithms developed at the NASA Goddard Space Flight Center (GSFC): the NASA Team (NT) algorithm (Cavalieri et al., 1984) and the Bootstrap (BT) algorithm (Comiso, 1986).

GLORYS2v4 is derived by the sea ice model LIM2 coupled to NEMO 3.1 ocean model and assimilates satellite data from the IFREMER/CERSAT. These data sets are derived by Special Sensor Microwave/Imager (SSM/I) which provides brightness temperatures for estimation of sea ice concentrations and they are provided daily with a spatial resolution of 12.5 km (Ezraty et al., 2007).

ERA-Interim sea ice concentration is derived from the same input data used for ERA-40 described by Fiorino (2004) for dates prior to 2002, and changing for daily operational NCEP products from 2002 and most recently for the OSTIA (Stark et al., 2007).

The daily sea ice concentration available in the ERA5 reanalysis is derived from different high-resolution sea surface temperature/sea ice cover products: the UK Met Office Hadley Centre HadISST2 product for SST and sea ice, the EUMETSAT OSI-SAF reprocessed product for sea ice, and the UK Met Office OSTIA product for SST and sea ice. HadISST2 is considered for the historical period, while OSTIA would support the near-real-time reanalysis. The sea ice cover errors are taken from the spread within the range of available products (Hersbach et al., 2019; Hirahara et al., 2016). The aim was to produce a merged dataset that is as accurate as possible at each moment in time without significant discontinuities, and that can be reliably updated close to real-time.

3.3.3.3 Ocean currents Data

The Global Ocean Physics Reanalysis GLORYS2v4 (Ferry et al., 2012; Garric et al., 2017). This reanalysis has a horizontal resolution of 0.25 degrees and 75 vertical levels. It is based on the version 3.1 of NEMO (Nucleus for European Models of the Ocean) ocean model (Madec, 2015) and assimilates observed data from the altimetric sea level anomaly, temperature, and salinity *in situ* profiles, sea-surface temperature observations, and sea ice concentration. This reanalysis is available for the period between 2013 to present.

3.4 Wave Data for calibration and validation

Data measured by three different buoys located in the Beaufort and Chukchi Seas and available from the National Data Buoy Center (NDBC) were used in the calibration of the wave simulations. Significant wave height measurements are available from July through October (of selected years between 2012 and 2014) in depths less than 50 m. The locations of the buoys are shown in figure 3.3.

Significant wave heights can be also measured by satellite altimeters from active sensor microwave sensors typically in the Ku and Ka bands. Altimeters have now been operated since 1985, providing global data of oceanic wind speed and wave height. This data is usually calibrated and cross-validated to ensure that it represents a stable database over a determined period of time. Once the data are quality controlled and sensor biases are removed, H_s are comparable to buoy measurements (e.g. Zieger et al., 2009).

In this study, the merged dataset of (Queffeuilou and Croizé-Fillon, 2015) was used in the calibration and validation of the wave model. These altimeter databases were fully calibrated and validated and they consist of data across six satellite missions, namely European Remote-Sensing Satellites 1 and 2 (ERS-1/2), Environmental Satellite (Envisat), Geosat Follow-On (GFO), Altika SARAL and CryoSat-2. The merged dataset spans the period between 1993 and 2016. The northern latitude limit is 81.4°N for Geosat Follow On, 82°N for ERS1, ERS2, ENVISAT, and SARAL, and 88°N for CRYOSAT-2. They also have different repeat mission period, which is the time until satellite repeats the same ground track. The repeat cycle is 17 days for GFO, 30 days for CRYOSAT-2 and 35 days for ERS1, ERS2, ENVISAT, and SARAL. ERS1, ERS2, ENVISAT, and Cryosat-2 were launched by the European Space Agency. Altika Saral was launched by Indian Space Research Organisation and CNES, and GFO was a US Navy satellite mission.

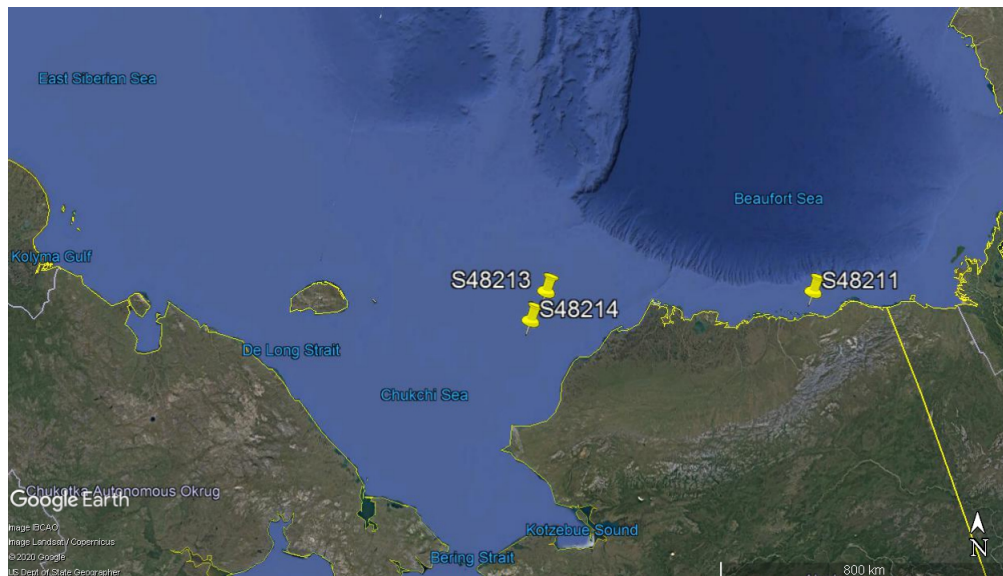


Figure 3.3: Buoy locations provided by NDBC.

3.5 Calibration

Taking into account the necessity of calibrating and validating the wave model for the region of interest, different wind forcing reanalyses, sea ice input data, and different source terms were evaluated in this study. The results of the wave models were compared against buoy and altimeter data described in detail in section 3.4. The simulations were carried out for August and September 2014. The wave model set-up that performs better agreement with observations was selected for the 28-year hindcast implementation.

Stopa et al. (2016) compared the wave model results against buoy and altimeter observations using CFSR and ERA-I winds for the Arctic Ocean. The significant wave height error metrics of ERA-I showed better agreement with buoy data. However, the CFSR wind was able to resolve better the large sea states. In their implementation, they just used one source term described by Ardhuin et al. (2010) using a fixed β_{max} on each simulation with different winds. Taking into account the importance of resolving the extreme waves, they chose CFSR winds to run the 23-years hindcast. However, it is important to mention that the CFSR winds are not consistent in time as the second version of this reanalysis, which covers the period from 2010 to the near present and has a spatial resolution of 0.2° , has upgrades to nearly all aspects of the data assimilation and forecast model components of the system compared to its predecessor, which is available from 1979 to 2010 and it has a spatial resolution of 0.3° (Saha et al., 2010, 2014). Therefore, considering the discontinuous features of these reanalyses, caution must be taken when using them to evaluate the climate.

In this study, to establish a better-suited wave model set-up in the Arctic, besides different wind data sets, the accuracy of the model was also evaluated by comparing different dissipation source terms available in WW3: ST4 described by Ardhuin et al. (2010) and ST6 based on Zieger et al. (2015).

Taking into account the ultimate goal of this study of evaluating the more energetic waves in open waters and considering the lack of robust physics in the available parameterisations of wave attenuation due to ice, the ice-covered sea was considered as land where the ice concentration was over 25% in the wave simulations. Different sea ice concentration data were also evaluated as an input for the wave model: ERA-Interim sea ice cover (Dee et al., 2011), Global Ocean Physics Reanalysis GLORYS2v4 (Ferry et al., 2012), National Snow and Ice Data Center (NSIDC/NOAA), satellite-derived ice concentrations from IFREMER/CERSAT (Ezraty et al., 2007), and ERA5 reanalysis (Hersbach et al., 2019).

Wave observations available from the National Data Buoy Network (NDBC) and altimeter measurements across six satellite described in section 3.4 are used to calibrate and validate the wave simulations undertaken in this study.

Standard error metrics are used to evaluate the model including bias, root mean square error (RMSE), scatter index (SI), and correlation coefficient (R):

$$BIAS = \frac{\sum_{i=1}^n (m_i - o_i)}{n} \quad (3.3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (m_i - o_i)^2}{n}} \quad (3.4)$$

$$SI = \frac{\sqrt{\frac{\sum_{i=1}^n (m_i - \bar{m}) - (o_i - \bar{o})^2}{n}}}{\bar{o}} \quad (3.5)$$

$$R = \frac{\sum_{i=1}^n (m_i - \bar{m})(o_i - \bar{o})}{\sqrt{\sum_{i=1}^n (m_i - \bar{m})^2 \sum_{i=1}^n (o_i - \bar{o})^2}} \quad (3.6)$$

where m represents the model, o represents the observation, and n is the number of data pairs.

3.5.1 Global model

Taking into account that energetic swells coming from the Atlantic Ocean can propagate through the Arctic Ocean, it is important to implement boundary conditions into the wave simulations. In order to get reliable boundary conditions, a global model of 1-degree spatial resolution was calibrated with the ST6 source term and different CDFACs forced with ERA5 atmospheric forcing and ERA5 sea ice concentration. The comparison between the results of the calibration of these global simulations and altimeter data is shown in Table 3.5.1. The best performance was achieved with a CDFAC of 1.19.

Table 3.2: Standard error metrics for global simulation results with ERA-5 wind forcing and sea ice concentration and ST6 source term in WW3 model with different CDFAC parameters.

		N	NBIAS (%)	RMSE (m)	SI (%)	R
	CDFAC 1.18	1523365	-0.17	0.42	17.33	0.96
ST6	CDFAC 1.19	1523365	0.49	0.4	16.42	0.96
	CDFAC 1.20	1523365	1.89	0.46	19.05	0.96

3.5.2 Arctic model

3.5.2.1 Spatial resolution

In order to evaluate the performance of the model by using different spatial resolutions, a comparison of the model results against buoy data was carried out using the three different computational domains described in section 3.3.2. The time steps were selected according to each horizontal resolution. The computational costs varied significantly and the results demonstrated practically the same results for each grid, as shown in Figure 3.4. Therefore, the coarser model domain that has a more efficient computational cost and a horizontal resolution varying from 9 km to 22 km (minimum latitude of 53.17°N) was chosen for the long-term hindcasts performed in this study.

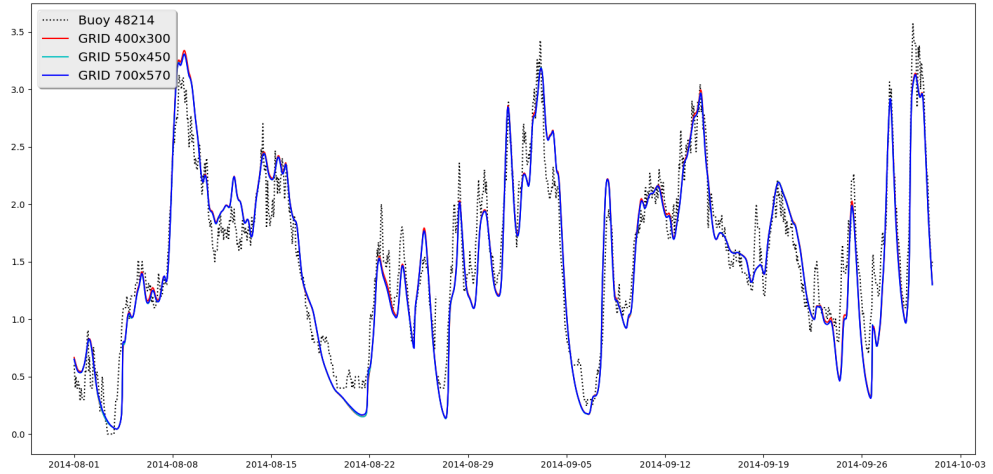


Figure 3.4: Significant wave height time series for August and September of 2014. The black dashed line represents the buoy data, and the solid lines represent the WW3 model results with different spatial resolutions.

3.5.2.2 Boundary Conditions

The spectral boundary conditions produced by the global model previously described were included in the simulations with the best set-up of the Arctic model using the ST6 source term, CDFAC of 1.23, ERA5 wind forcing and ERA5 sea ice concentration. The results of the simulations with and without boundary conditions are displayed in Figure 3.5. The results showed substantial enhancement of the wave hindcast results for the Arctic Ocean. The results without boundary conditions were underestimated

with a normalized bias (NBIAS) of -3.78% and this problem was solved by adding the boundary conditions obtaining a new NBIAS of just 0.28%. In addition, the overall correlation also significantly improved from 0.92 to 0.96 and the RMSE reduced by 14 cm (from 45 cm to only 31 cm). It can be noted by looking at the scatter plots between the results and altimeter data that the model underestimates quite a few energetic waves by up to 8.3 m without boundary conditions. Such underestimations are solved when including the boundary conditions obtained by the global simulations.

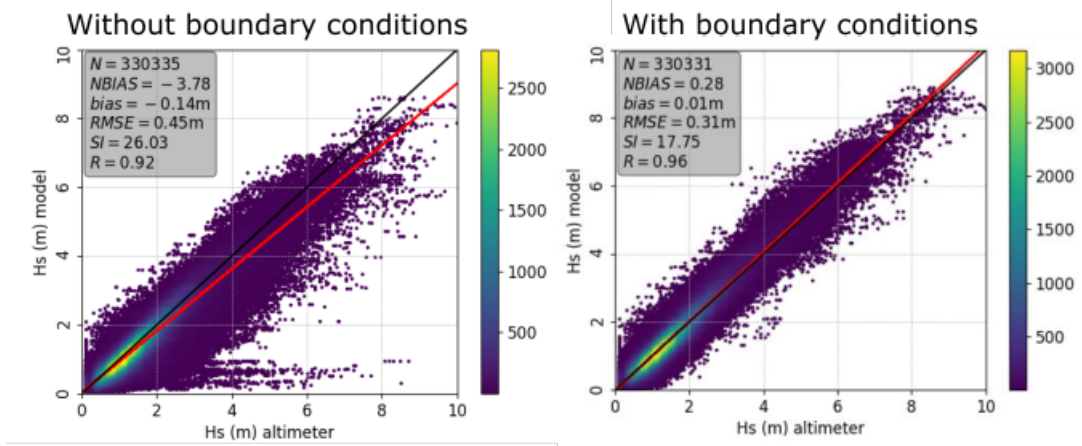


Figure 3.5: Significant wave height comparison for the hindcast results of the best fit for model results with (left panel) and without (left) boundary conditions versus co-located data from altimeters for significant wave heights for August and September of 2014. The colour scales of the scatter plots denote the number of observations. The standard error metrics are shown in the text box. The lines shown are the 1:1 agreement (black diagonal line) and the linear regression (red line).

3.5.2.3 Source term versus wind forcing

The comparison of different wind inputs and different source and sink terms were performed concurrently in this study. The results of different wind inputs (CFSR, ERA-Interim, and ERA5) were evaluated by using the two most recent source and sink parameterisations available in the WW3 model (ST4 and ST6). The performance of ERA-Interim and ERA5 wind input were evaluated by comparing different wind-wave growth parameters for each source term: BETAMAX for ST4 and CDFAC for ST6. The parameters that were set for the CFSR wind were already validated on previous studies (e.g. Stopa et al., 2016; Zieger et al., 2015).

The simulations for the calibration were performed for August and September of 2014 and they were compared to the observations of the buoy S48214 of NDBC. Table 3.3 shows the significant wave height error metrics for the simulations with

different winds, source terms, and wind-wave growth parameters. The model set-up that achieved the best agreement was using ERA5 with the ST4 source term with a β_{max} of 1.9. However, the best fit for both source terms (ST4 and ST6) with this atmospheric forcing were very similar. Thus, further analysis is recommended.

It can be noticed that the ERA-Interim model performs better for higher values of CDFAC than the default (CDFAC of 1.00) solving the problem of underestimation in H_s using this wind forcing described by Stopa et al. (2016). The best performance was achieved with CDFAC of 1.35 as shown in Table 3.3.

Table 3.3: Standard error metrics for the results of the WW3 model using different atmospheric forcing data sets and source terms and different wind-wave growth parameters.

			Bias (m)	RMSE (m)	SI (%)	R
CFSRv2	ST4	BETAMAX 1.25	0.02	0.25	15.95	0.94
	ST6	CDFAC 1.00	-0.092	0.31	20.55	0.93
ERA-I	ST4	BETAMAX 1.45	-0.09	0.26	16.9	0.94
		BETAMAX 1.50	-0.06	0.25	16.34	0.94
		BETAMAX 1.55	-0.09	0.26	16.82	0.94
	ST6	CDFAC 1.30	-0.411	0.48	31.28	0.94
		CDFAC 1.35	0.001	0.24	15.52	0.95
		CDFAC 1.40	0.056	0.25	16.4	0.95
ERA5	ST4	BETAMAX 1.8	-0.3	0.24	14.8	0.96
		BETAMAX 1.9	0.11	0.23	14.6	0.96
		BETAMAX 2.0	0.73	0.26	16.82	0.96
	ST6	CDFAC 1.22	-0.411	0.23	15.2	0.96
		CDFAC 1.23	0.12	0.24	14.9	0.96
		CDFAC 1.24	0.32	0.24	16.4	0.96

The time series of H_s and T_p of the buoy data and the results of the best fit of each source term are shown in Figure 3.6. Both simulations show great agreement with buoy data for H_s and T_p . The error metrics demonstrate very similar results for each source term. Therefore, taking into account the very similar performance of these source terms, a deeper comparison will be further discussed by comparing

the results of these two different configurations when they are applied to a long-term hindcast (1991-2018).

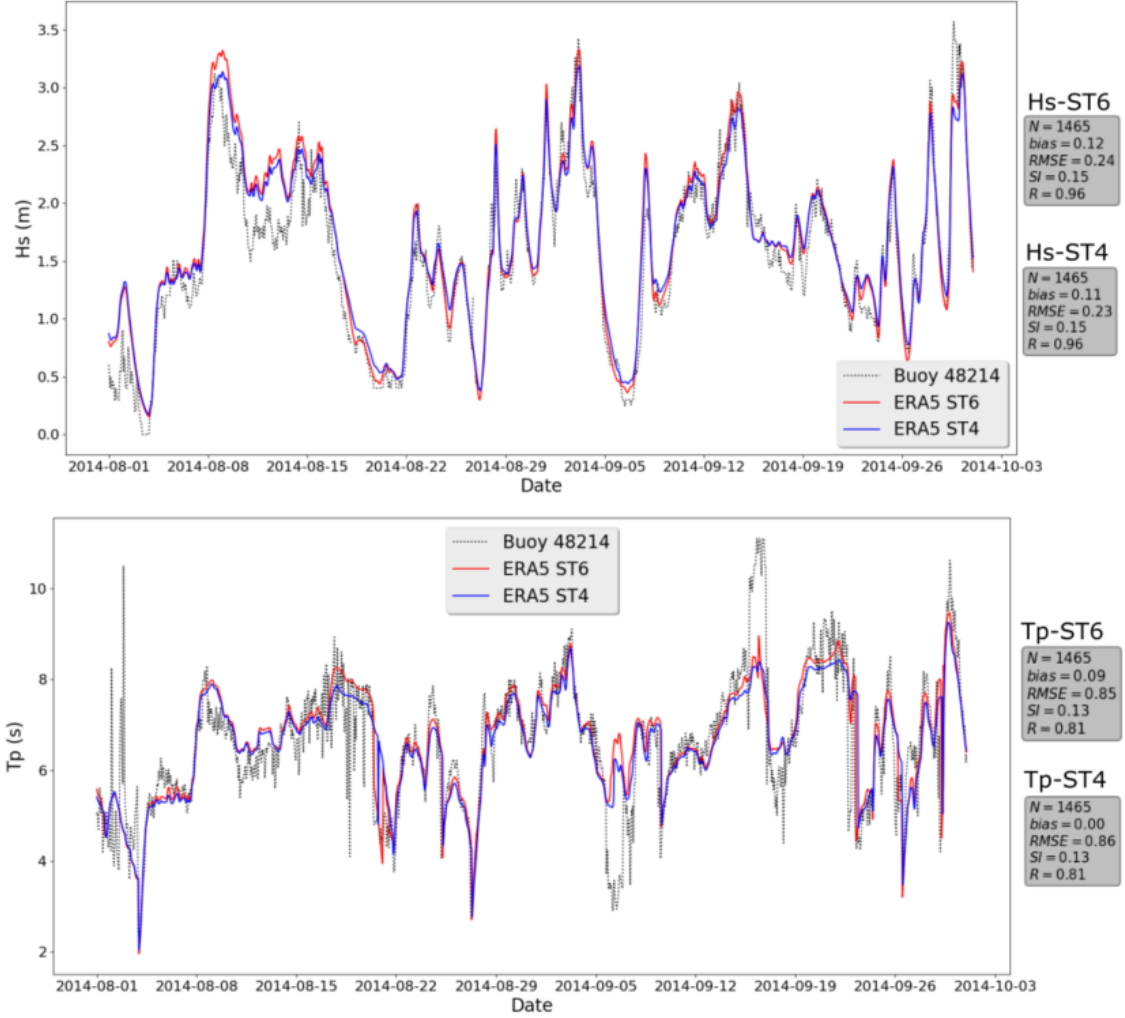


Figure 3.6: Time series of H_s (top panel) and T_p (bottom panel) for August and September of 2014. The black dashed line represents the buoy observations, and the solid lines represent the WW3 model results with ERA5 wind forcing and different source terms: ST4 (blue) and ST6 (red). The standard error metrics are shown in the text box.

In order to ensure good results across the entire Arctic Ocean, the calibration of the wave model by implementing the ERA5 wind forcing was performed comparing the results against not only buoy observations but also altimeter data. Table 3.4 displays the results of the standard error metrics of the model results for each source term and different wind-wave growth parameters against altimeter data for the period between August and September of 2014 throughout the Arctic Ocean. One can note that the

best fit for both source terms achieved very similar results. The correlations were the same, the RMSE and SI of the ST4 source term were slightly better, whereas the normalized bias was better for the best fit of the ST6 source term. Taking into account the similar performance achieved by these two different source terms, a further comparison was undertaken by performing two different long-term hindcasts and then validating them against altimeter data for a longer period (2012-2016). The results will be discussed in the following section of this study.

Table 3.4: Standard error metrics for the results of the WW3 model using ERA5 wind forcing with different source terms and wind-wave growth parameters against altimeter data.

			N	NBIAS (%)	RMSE (m)	SI (%)	R
ERA5	ST4	BETAMAX 1.8	303047	-0.44	0.29	18.6	0.95
		BETAMAX 1.9	303047	0.46	0.28	18.3	0.95
		BETAMAX 2.0	303047	0.78	0.30	18.7	0.95
	ST6	CDFAC 1.22	303047	-0.58	0.31	19.5	0.95
		CDFAC 1.23	303047	-0.07	0.30	18.7	0.95
		CDFAC 1.24	303047	0.17	0.31	18.8	0.95

3.5.2.4 Sea ice concentration

A comparison of the performance of the wave model by using different sea ice concentration data sets as input for the simulations is outlined in this section. Four different sea ice sources were compared in a first stage of the calibration before the release of the ERA5 reanalysis: CERSAT and NSIDC satellite data, GLORYS2v4 and ERA-Interim reanalysis. These data sets are described before in section 3.3.3.2. After the release of ERA5 reanalysis, the sea ice concentration dataset that achieved the best performance was further compared with this recently released reanalysis.

Figure 3.7 displays the time series for the results of the simulations for August and September of 2014 and buoy observations. It can be noticed similar results between the four different input data. However, a slightly better agreement for the CERSAT dataset that is a satellite-derived data with a spatial resolution of 12.5km.

Table 3.7 shows standard metric errors for each simulation. It demonstrates quite similar results. But it can be noticed a better performance by using the CERSAT satellite data.

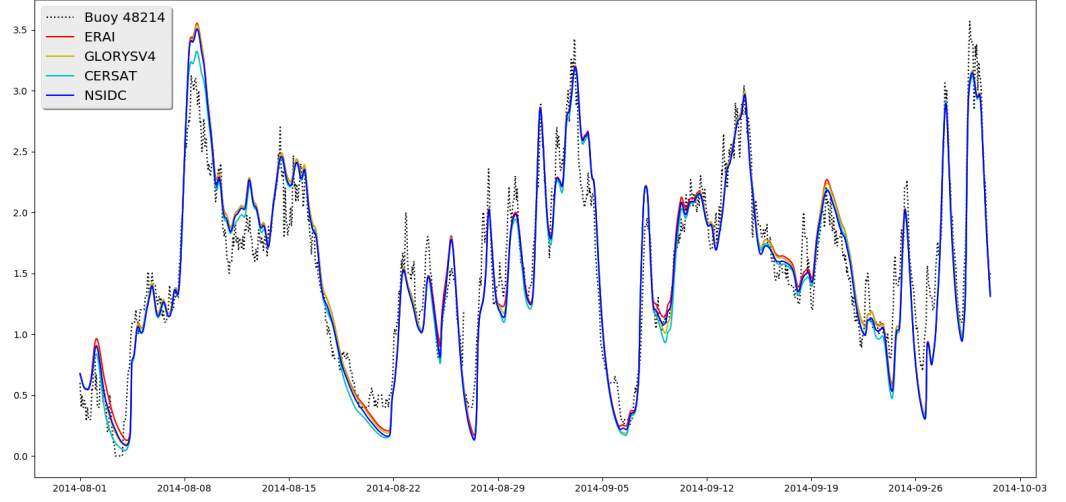


Figure 3.7: Significant wave height time series for August and September of 2014. The black dashed line represents the buoy data, and the solid lines represent the WW3 model results with different sea ice inputs (ERA-Interim, GLORYSV4, CERSAT, and NSIDC).

Table 3.5: Standard error metrics for the results of the WW3 model using different sea ice concentration sources.

	bias (m)	RMSE (m)	SI (%)	R
ERA-Interim	0.001	0.24	15.52	0.95
GLORYS2v4	0.01	0.24	15.3	0.95
CERSAT	-0.04	0.23	15.1	0.96
NSIDC	-0.02	0.24	15.4	0.95

The performance of the wave model with the sea ice concentration of ERA5 was also then compared to the CERSAT satellite-derived sea ice concentration. Figure 3.8 displays the results of the simulations with these two sea ice concentrations against altimeter data. One can note that the results were quite similar. However, the ERA5 sea ice concentration performed slightly better. Therefore, this sea ice dataset was chosen for the long-term simulations performed in this research.

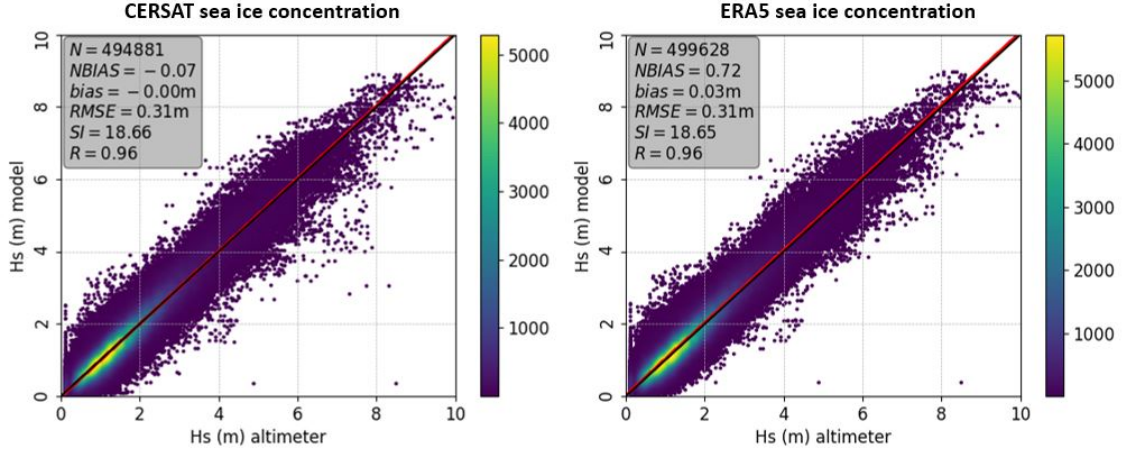


Figure 3.8: Significant wave height comparison for the hindcast results with different sea ice concentration data sets versus altimeter data for September and August of 2014. The colour scales of the scatter plots denote the number of observations. The standard error metrics are shown in the text box.

3.5.2.5 Ocean surface currents

The ocean currents data provided by MERCATOR called GLORYS2v4 was used as an input for the model. After adding the data, it was necessary to recalibrate the wind-growth parameter. However, even after the calibration, the results that were found by adding the ocean currents were less accurate than without them, as shown in Figure 3.9. It can be noticed that the model underestimated the wave heights in various points by including the ocean surface currents on the simulations.

In order to investigate the causes of those results, the differences between the wave simulations with and without ocean currents were investigated by plotting maps every three hours over one month (September 2014). There were significant differences in coastal regions, whereas in deep-water, the results were very similar (e.g. Figure 3.10). As described by previous studies, the ocean currents in the Arctic basin are not strong enough to affect the offshore waves significantly. The unrealistic wave heights close to the coasts might be explained by the coarse resolution of the ocean reanalysis and its not so accurate results especially close to the shores where different processes need to take into account. In addition to that, it is worth considering that in large scale wave modelling, the depth-induced effects are also neglected. This might be one of the causes of the unsatisfactory results close to the coast. Therefore, the ocean currents were not included in the long-term simulations performed in this study.

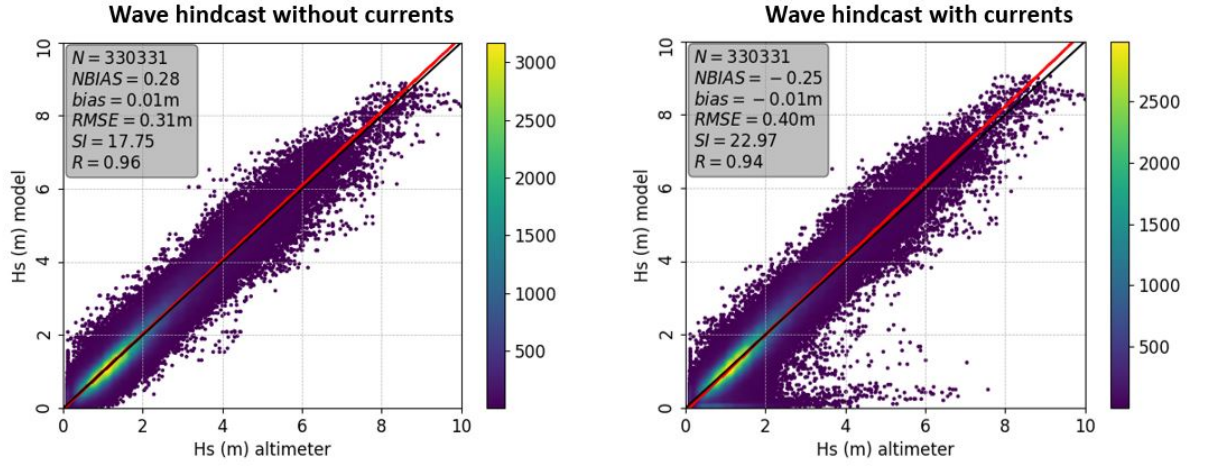


Figure 3.9: Significant wave height comparison for the hindcast results with (right) and without (left) superficial ocean currents data versus altimeter data for September and August of 2014. The colour scales of the scatter plots denote the number of observations. The standard error metrics are shown in the text box.

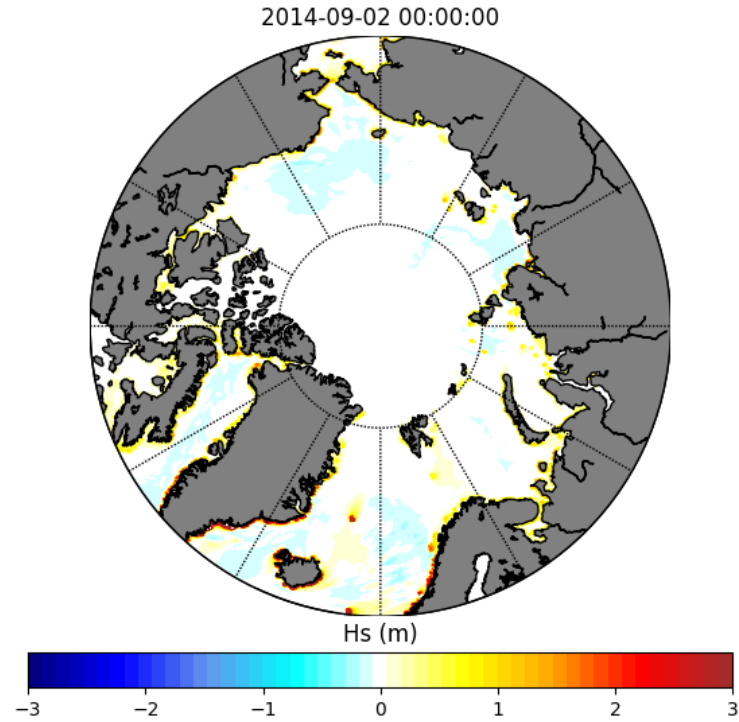


Figure 3.10: Sample of the discrepancy between model results with and without ocean surface currents on the simulations for a specific time (02/09/2014 00:00).

3.6 Validation

Validation is a process to check the calibrated model. There is a lack of observed data across the Arctic Ocean. The NDBC network provides data across the entire globe, but in this polar region, it provides buoy data for only three locations in a minimal amount of time. Therefore, satellite data is a good way to overcome this problem and make a way to validate the wave model properly evaluating the performance for the entire domain.

After the calibration, 28-year hindcasts were performed for the period between January 1991 and December 2018 using the best set-up achieved for both source terms evaluated in this research. The performance of the model was further validated against altimeter observations across six different satellite missions merged and calibrated previously and provided by IFREMER (Queffeulou and Croizé-Fillon, 2015) and described in section 3.4. The altimeter dataset consists of wave measurements from European Remote Sensing satellites 1 and 2 (ERS1 and ERS2), Environmental Satellite (ENVISAT), Geosat Follow On (GFO), CRYOSAT-2, and Altika SARAL. The results were interpolated temporal every 30 min and spatially every 2km. The results were compared for five years (between 2012 and 2016, except for August and September 2014 that was the period utilised in the calibration process). The error metrics described in section 3.5 were computed for each point and then an overall error metrics were computed for all the co-located points.

3.6.1 Global Model

After achieving the best fit of the global model, 28-year hindcast was performed for the period between 1991-2018 producing spectral wave data for each point of the Arctic domain. The validation of these global simulations show great agreement with altimeter data for 2012-2016 as shown in Figure 3.11. The overall correlation was 0.96, RMSE of 0.51 m, normalized bias of just -0.68% and SI of 18.75%.

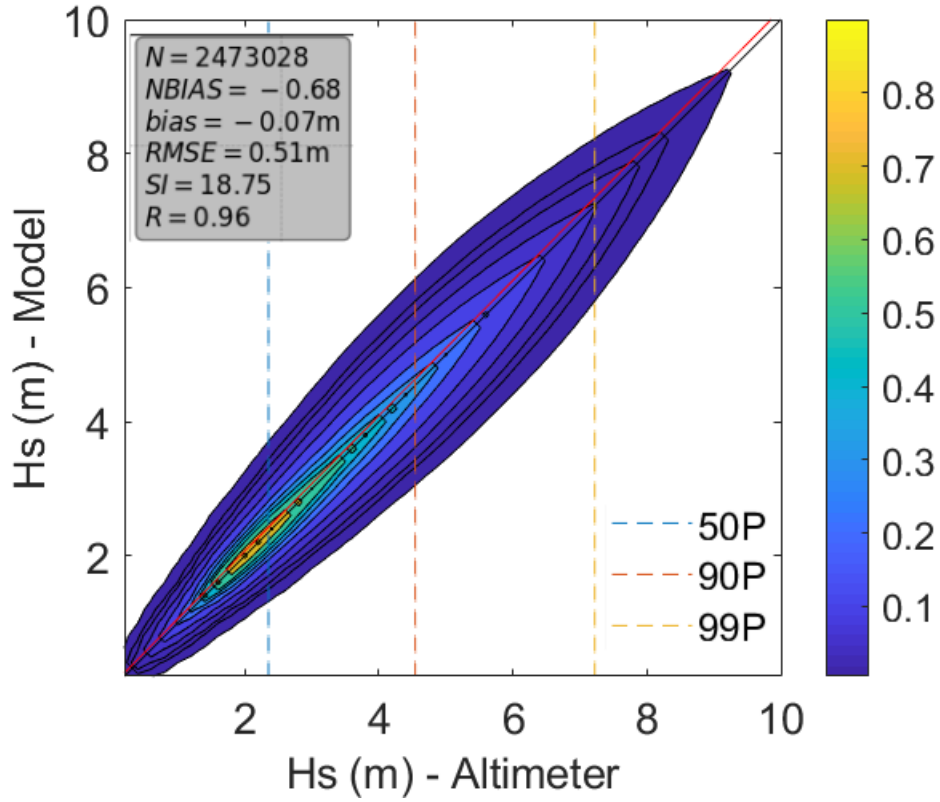


Figure 3.11: Contour plots of hindcast results with global hindcast results versus co-located data from altimeters for significant wave heights for 2012-2016. Contours show the density of data points which has been normalized such that the maximum value is 1.0. The lines shown are the 1:1 agreement (black diagonal line) and the linear regression (red line). The standard error statistics are also presented.

3.6.2 Arctic Model

Figure 3.12 shows the contour plots between the altimeter and the model for significant wave heights for both hindcasts with the two most recent source terms available in the WW3 model (ST4 and ST6). The results for both simulations were in excellent agreement with satellite data. The accuracies of the models were quite similar. The standard error metrics for ST6 source term results obtained an overall correlation of 0.97, a normalised bias of 0.43%, root mean square error of 0.38 m, and scatter index of 15.99%. For ST4 simulations, the correlation was the same, but the overall SI, RMSE, and NBIAS were slightly better (NBIAS of 0.2%, RMSE of 0.37 m, SI of 15.34%).

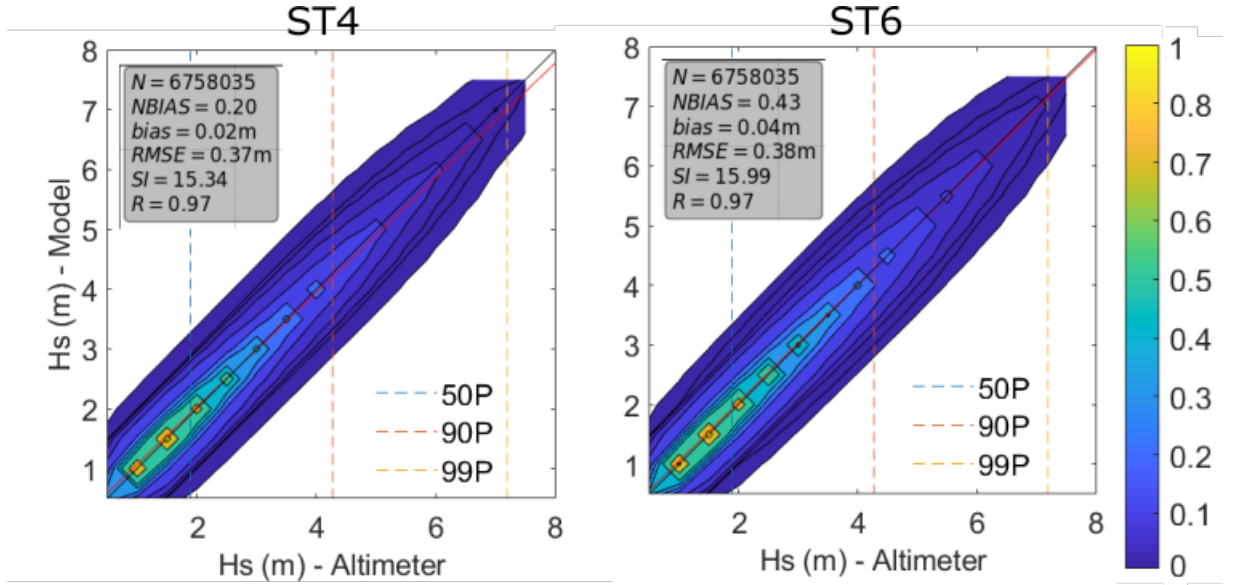


Figure 3.12: Contour plots of hindcast results with the ST4 (left) and ST6 (right) source terms versus co-located data from altimeters for significant wave heights for 2012-2016. Contours show the normalized density of data points. The lines shown are the 1:1 agreement (black diagonal line) and the linear regression (red line). The standard error statistics are also presented in the text box.

Figure 3.13 displays the standard error metrics in maps for the ST6 source term hindcast. The correlations were higher than 0.95 in most parts of the Arctic. The normalised biases were less than 2% across the domain, the root mean square error was approximately 0.35 m through most part of the Arctic Basin and finally, the scatter index (SI) was approximately 16%. Those results were better than the ones found by Stopa et al. (2016) forced with CFSR wind data. These results are evidence of the better quality of the ERA5 atmospheric forcing. The linear regression (in red) was very close to the 1:1 agreement line in black, which means that the overall data did not substantially under or overestimate. Based on these comparisons, it can be noticed that the wave hindcast results are quite satisfactory with excellent error metrics when comparing to altimeter data, showing that the model is reliable on estimating the wave heights for the Arctic Ocean.

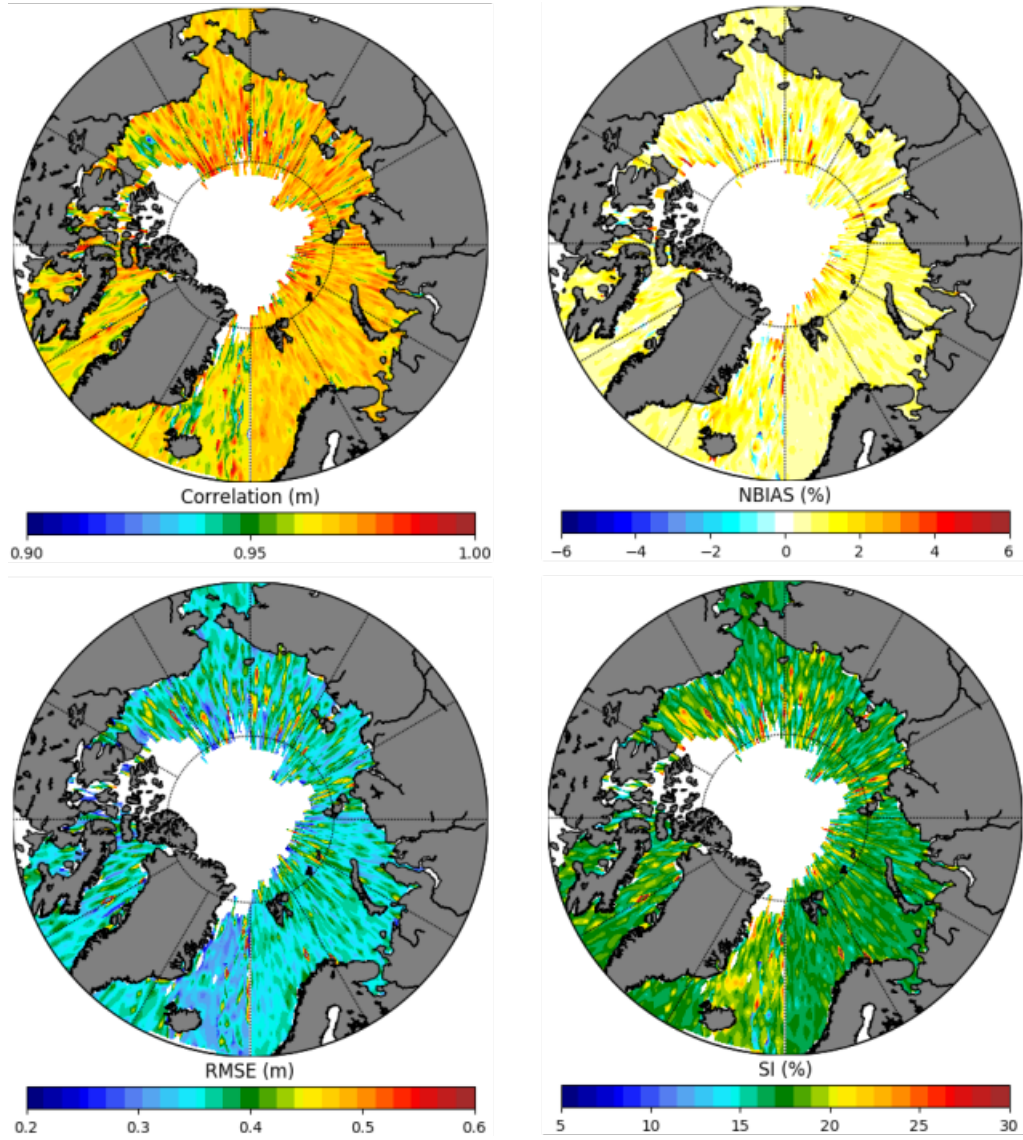


Figure 3.13: Comparison between model results and altimeter observations (European Remote Sensing satellites 1 and 2 - ERS1 and ERS2, Environmental Satellite -ENVISAT, Geosat Follow On, CRYOSAT 2, and Altika SARAL) for 2012-2016 based on the error metrics: correlation, root mean square error (RMSE), normalised bias (NBIAS), and scatter index (SI).

It is worth mentioning that altimeter data are not entirely reliable on measuring extreme waves as previous studies have demonstrated (e.g. Young et al., 2011). Meanwhile, numerical models such as WW3 also tend to underestimate the higher percentiles of wave heights. In this research, the overall normalised bias shows a slight overestimation of the wave heights simulated in the hindcast, but those results are not based on the extremes, it considers the entire time series of each grid point. Therefore, the computation of the same error metrics were also computed for the

higher percentile (90th percentile) as shown in Figure 3.14. One can note that the standard error metrics for the most energetic waves are substantially worse than the overall ones, with the exception of the scatter index ($\sim 5\%$ lower than the overall one). Therefore, caution must be taken when considering the results of these hindcasts in practical engineering solutions, for instance, in the design an offshore structure and evaluating risks of coastal infrastructures.

Once again, the results for both source terms were quite similar. Nevertheless, one can note that the error metrics for the higher percentile that is the focus of this research were slightly better with the ST6 source term – especially the normalized bias indicating that this source term underestimates less the results. Thus, this source term was selected in the subsequent analyses undertaken in this study, such as the climate evaluation of wave parameters, the trend analyses, and the non-stationary EVA. In the last chapter of this thesis, an evaluation of the non-stationary EVA applied to the model results of these two different source terms will be compared.

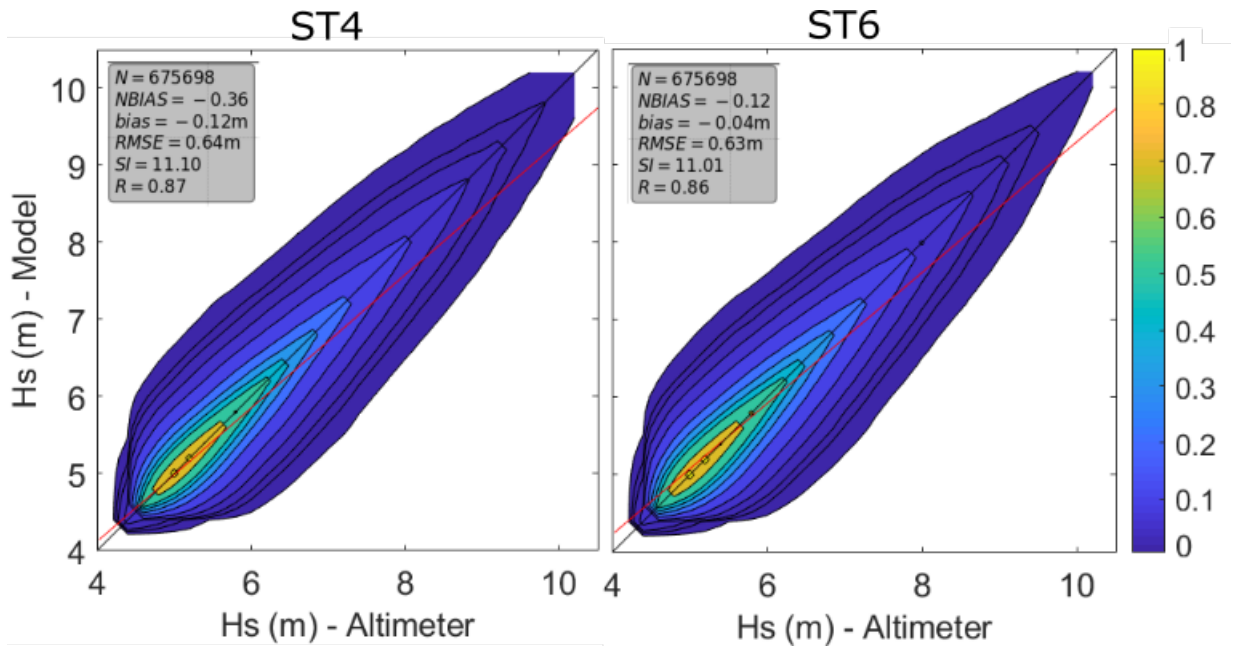


Figure 3.14: Same as Figure 3.12, but for the 90th percentile.

3.7 Conclusions

The specific objectives of this research chapter include the calibration and validation process of the WW3 model applied to the Arctic Ocean. The calibration process was undertaken by comparing the model results against buoy and altimeter data. The

comparison of different atmospheric forcing reanalyses (CFSR, ERA-Interim, and ERA5) concurrently with two different source terms available in the WW3 model demonstrates the better performance of the model forced with ERA5 wind speeds. These results show that this recently released atmospheric reanalysis is expressively more reliable than its antecessors. The results of each source term were quite similar. However, for the higher percentiles of significant wave height, the performance of the model using the ST6 source term was slightly better.

The comparison of the sea ice concentration data sets (NSIC/NOAA, IFREMER/CERSAT, GLORYS2V4, ERA-Interim, and ERA5) show very similar results, but a small improvement was achieved with ERA5 sea ice concentration. Similarly, the comparison of different spatial resolutions demonstrated very similar accuracy. The finer spatial resolutions did not contribute to any enhancement of the performance. Therefore, the coarser grid utilized in this research was selected for the long-term hindcasts.

In addition to that, an evaluation of the inclusion of the boundary conditions was also carried out. In order to get reliable boundary conditions, a global model of 1-degree spatial resolution was calibrated with the ST6 source term and different CDFACs using the same inputs used for the Arctic model. The final results showed substantial enhancement of the wave hindcast results for the Arctic Ocean.

The inclusion of ocean surface currents (GLORYS2V4 reanalysis) was also assessed. However, the results were not satisfactory when comparing to altimeter data. The performance of the model got worse when ocean currents were incorporated into the wave simulations. These results make evident the limitations of the simplistic formulation of current-induced effects in wave models and also the necessity of more reliable ocean reanalyses for this polar region. Two different hindcasts of 28 years (1991-2018) were performed using different source terms (ST4 and ST6). The validation of both hindcasts showed excellent agreement with altimeter data, with results significantly superior to previous hindcasts performed in previous studies by comparing statistical errors such as bias, correlation and RMSE (e.g. Stopa et al., 2016). Taking into account that the simulations with the ST6 source term achieved better performance for the higher percentile of significant wave height, the climate evaluation and trend analyses undertaken in this study were based on the results with this source term. In addition, in Chapter 6, the differences in extreme wave estimations using these two different source terms in the wave model are also assessed.

Chapter 4

Metocean Climate

4.1 Introduction

The metocean conditions of the Arctic Ocean have been investigated in the past few years, as discussed in Chapter 2 (Hughes and Cassano, 2015; Stopa et al., 2016; Liu et al., 2016). However, the most significant parameters, such as sea ice concentration, wind speeds, wave heights and peak periods, have not yet been fully described in a consistent way taking into account the remarkable seasonal cycles and considering not only their average but also their higher percentiles. In this study, a systematic evaluation of monthly intensities of each parameter and an evaluation of how their averages and higher percentiles change seasonally are performed.

In order to quantify the seasonal cycles of the main metocean parameters, the climate of sea ice concentrations, wind speeds, significant wave heights, and peak periods were evaluated monthly by 50th, 90th and 99th percentiles (10th and 50th percentiles for sea ice concentration) for 1991-2018 based on the ERA5 reanalysis and the long-term wave hindcast performed in this study. Furthermore, the differences between joint distributions of H_s and T_p over the past decades were also evaluated. These results are the first step to understand the metocean changes that the Arctic Ocean has experienced.

4.2 Sea ice

The freeze-thaw cycles of sea ice in the Arctic Ocean play an essential role in the ocean dynamics and seasonality of this region. In order to give an insight into how the sea ice coverage varies throughout the year, this section discusses monthly averages and 10th percentile of the sea ice concentration over the past decades. The selection of the 10th percentile was taken considering that it is under minimum ice coverage

conditions that extreme ocean events occur, such as the most energetic waves that will be discussed in the following sections.

Figure 4.1 shows the monthly results for the 10th percentile based on the daily sea ice concentration ERA5 dataset. One can note the substantial seasonal differences in the sea ice concentration during the year. The months with minimum ice coverage are August and September. In October, the sea ice starts freezing, and in June the sea ice starts retreating considerably.

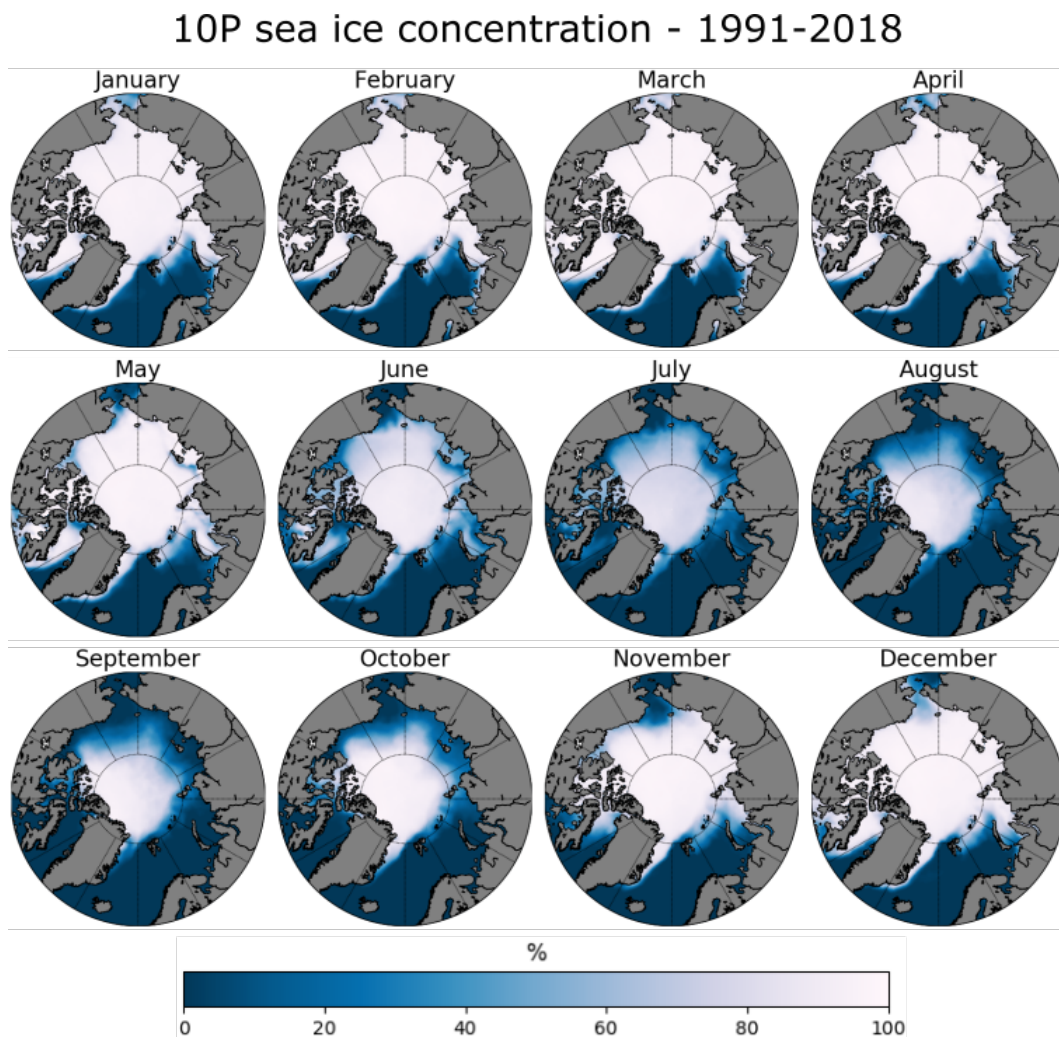


Figure 4.1: Monthly 10th percentile of sea ice concentration from 1991-2018 based on ERA5 dataset

Figure 4.2 shows the monthly results for the average sea ice concentration for the same period of 28 years. The results are quite similar to the 10th percentile in Figure 4.1, indicating that the daily results of each month do not vary significantly. Most of the Arctic Ocean is covered by sea ice almost all year round. The region encompassing

the Beaufort, Chukchi, East Siberian, and Laptev seas have ice-free open water areas in just a few months of the year (August, September, and October).

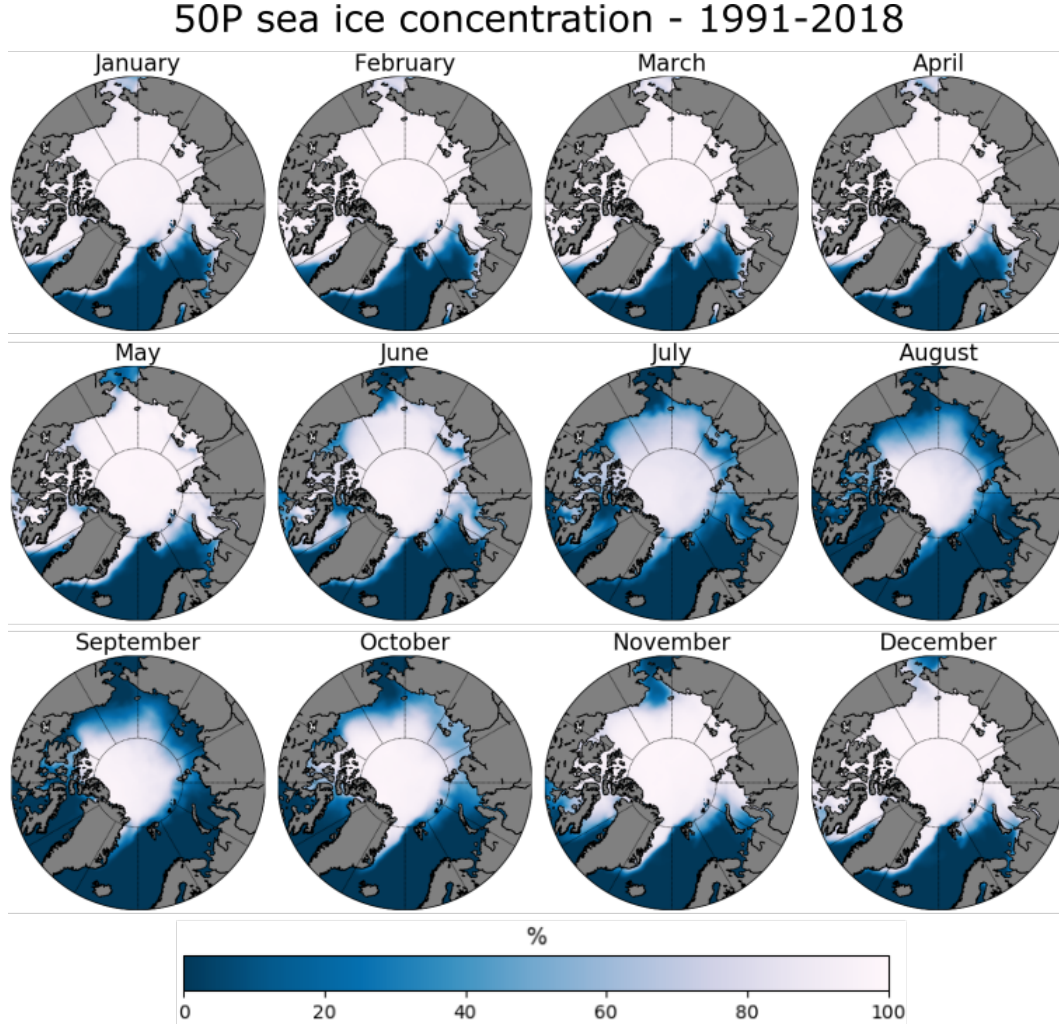


Figure 4.2: Same as Figure 4.1, but for average sea ice concentration.

Taking into account that the sea ice is changing significantly over the past decades, an evaluation of the first (1991) and the last year (2018) of the period evaluated in this study is presented. Figure 4.3 shows the monthly averages of sea ice concentration for 1991 with the limits of the marginal ice zone (MIZ): the red lines correspond to the 15% sea ice concentration and the green lines represent the 80% sea ice concentration contours. The Marginal Ice Zone (MIZ) is a highly dynamic region where important physical phenomena, such as atmosphere-ice-ocean interactions, and biological processes take place. It is in this region where the waves are attenuated by the sea ice coverage, while the sea ice is formed and can be broken by the presence of waves.

The MIZ is often limited by the concentrations used in this study (15% - 80%) (e.g Strong, 2012; Strong and Rigor, 2013).

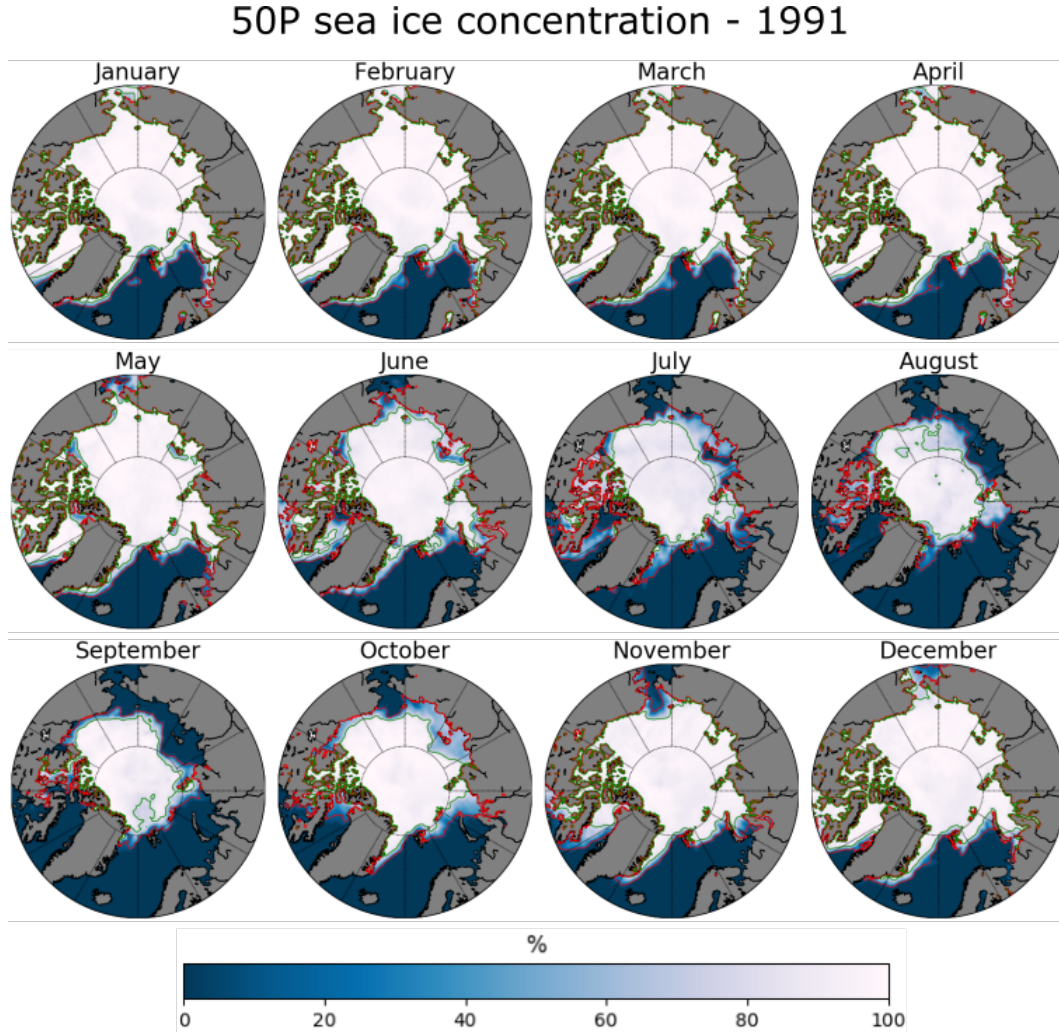


Figure 4.3: Monthly average sea ice concentration for 1991. Limits of the MIZ marked by red (15%) and green lines (80%).

The monthly averages of sea ice concentration for 2018 (Figure 4.4) were significantly different from the ones for 1991 (Figure 4.3). Besides the sea ice retreat, the differences of the MIZ widths between these two years is also evident. In most months of 2018 (except for February, March, and April) these transition regions were quite larger compared to the ones in 1991. These results demonstrate that besides the reduction of sea ice extent, the sea ice is becoming more fragmented, possibly due to the more severe environmental conditions such as more energetic winds and waves. These results are in agreement to the ones found by Strong and Rigor (2013) that indicated a downward trend in MIZ widths in the cold season (Feb-Apr) in the

period between 1979-2011 with a 15% narrowing over the record, whereas a significant increasing trend in the warm season (Jul-Sep) with 39% widening over the same period.

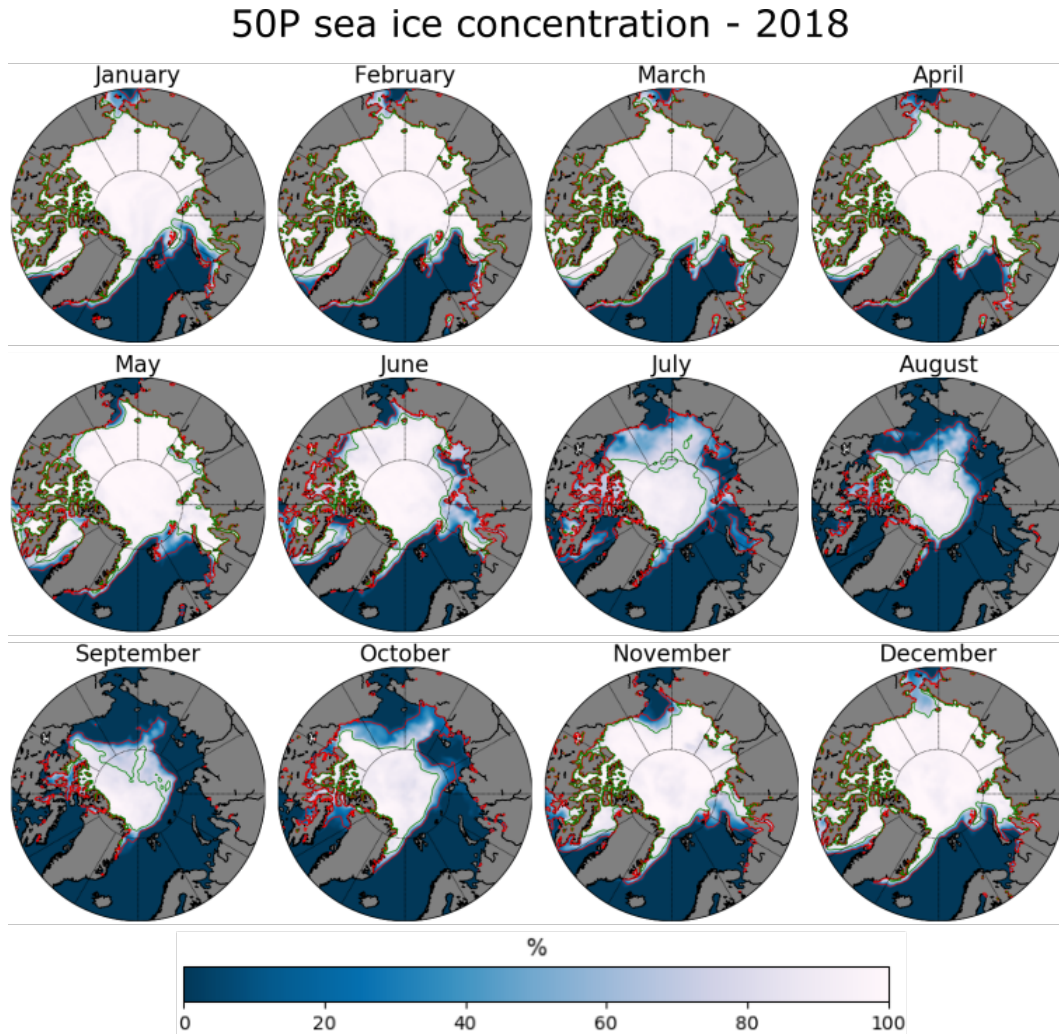


Figure 4.4: Same as Figure 4.3, but for 2018.

The differences in sea ice concentrations between 1991 and 2018 make evident the sea ice melting that it is occurring in the past decades (Figure 4.5). The regions that are experiencing the most significant changes in summer months include Beaufort, Chukchi, East Siberian, Laptev, Kara, and Barents seas. The Barents Sea is the only region that is experiencing a retreat in all months of the year. The Bering Sea was covered by sea ice the first 5 months (January - May) of 1991, and it became essentially an ice-free area in 2018.

Discrepancy in sea ice concentration 1991-2018

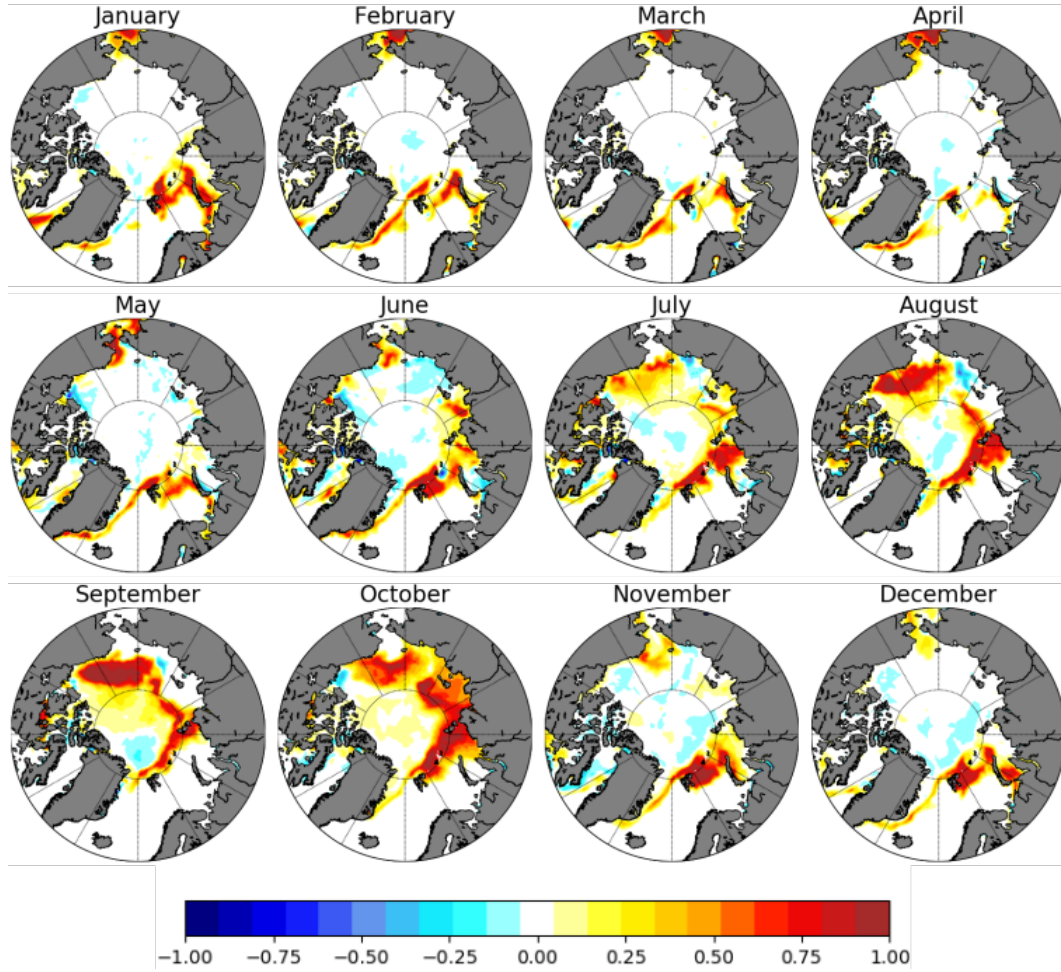


Figure 4.5: Discrepancy of sea ice concentration between 1991 and 2018.

4.3 Winds

This section discusses a monthly evaluation of different percentiles (50^{th} , 90^{th} , 99^{th}) of the wind speed 10 m above sea level (U^{10}) from the ERA5 reanalysis. The seasonal results show significant seasonal differences in wind speeds, marked by two well-defined cycles: the cold (Dec-March) and warm (June-August) seasons.

In winter, the winds are notably more energetic: the 50^{th} percentile reaches values of 13 m/s on the Atlantic side of the Arctic Ocean (Figure 4.6) and approximately $5 - 7 \text{ m/s}$ in the rest of the ocean. In the Bering Sea, the average winds were also quite high, reaching values of 10 m/s .

In summer, the average wind speeds decrease significantly to values of approximately 7 m/s on the Atlantic side. In the Chukchi Sea, the average wind speeds

are approximately 5 m/s in summer and 9-10 m/s in winter. Other seas, such as Laptev, East Siberian, and Beaufort seas do not experience significant seasonal changes throughout the year with average wind speeds varying from 5-7 m/s .

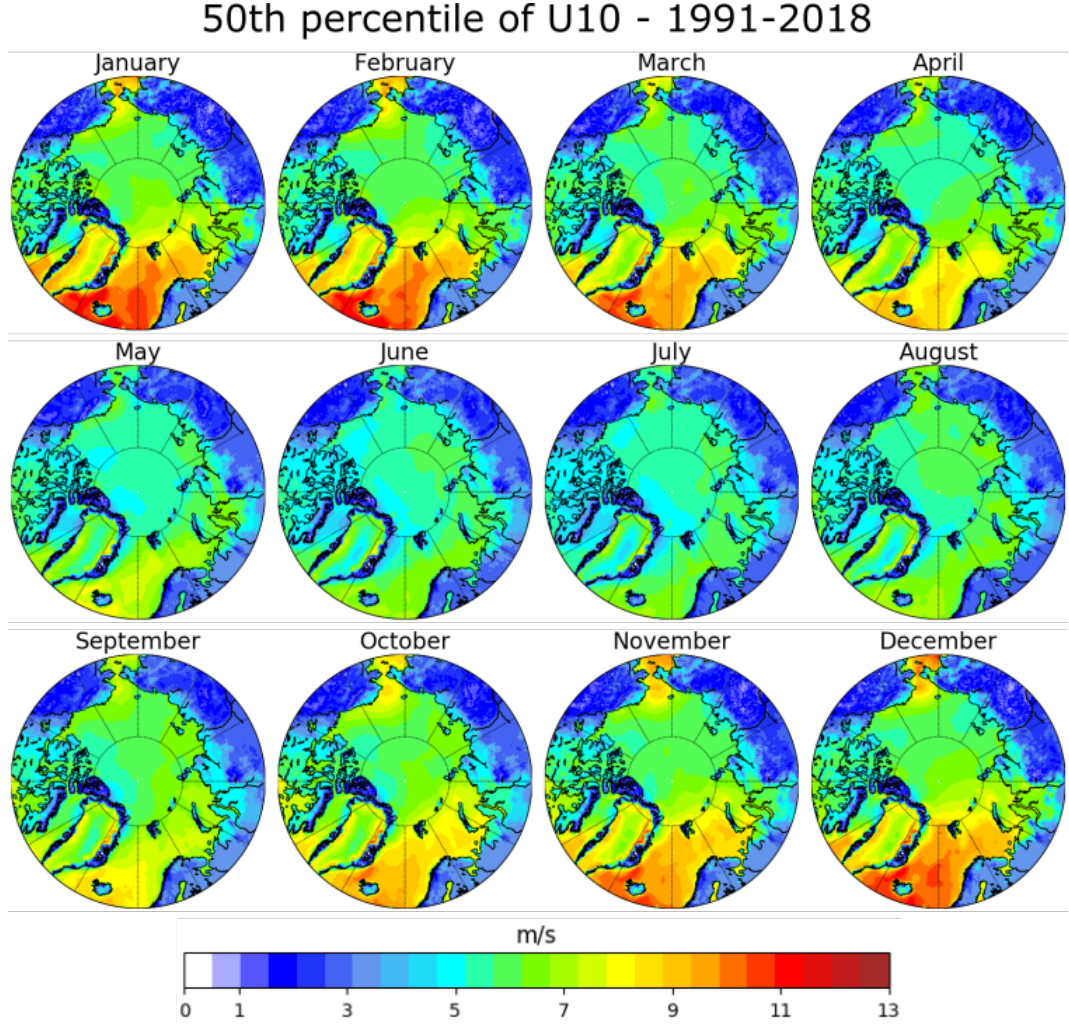


Figure 4.6: Monthly average U_{10} (m/s) from 1991-2018 based on ERA5 dataset.

The results for the monthly 90th percentile of wind speeds for 1991-2018 are shown in Figure 4.7. Similarly to the results for the average wind speeds (Figure 4.6), there are two distinct patterns: one for the summer period and another one for winter. In order to facilitate the comparison of the results for the higher percentiles, the results for this percentile are shown with the same colorbar as in Figure 4.8 for 99th percentile results.

In winter, the strongest winds have the 90th percentile speeds of approximately 21 m/s on the east coast of Greenland. In the rest of the Greenland Sea, the Norwegian Sea, and the Bering Strait the 90th percentiles are roughly 17-19 m/s , whereas in

the rest of the ocean is around 10-14 m/s for winter months. In summer months, the results are slightly lower with values varying from 9 to 13 m/s across the entire ocean.

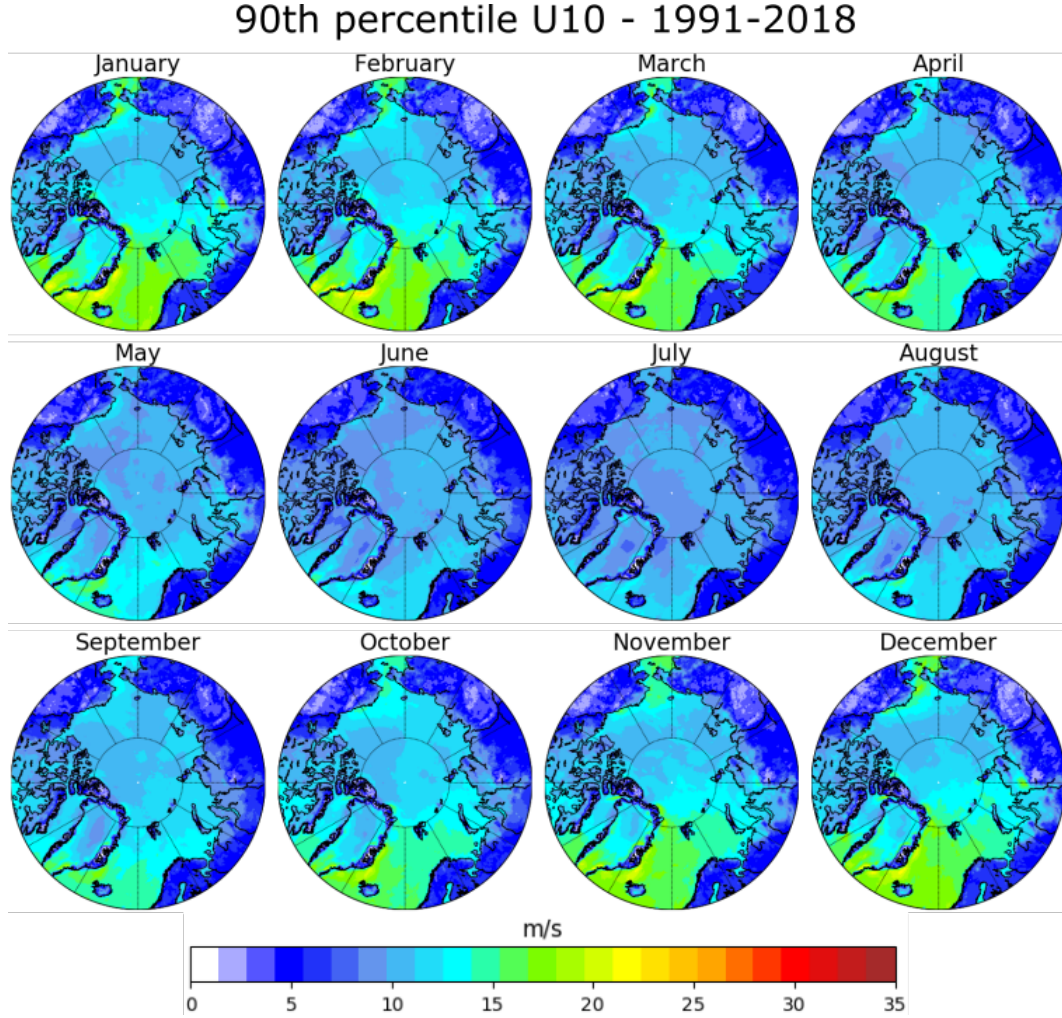


Figure 4.7: Same as Figure 4.6, but for 90th percentile of U_{10} (m/s).

Finally, Figure 4.8 shows the results for the 99th percentile of U_{10} . It is evident the differences between the magnitudes of the two higher percentiles evaluated in this dissertation (90th and 99th) by comparing the figures 4.7 and 4.8 with the same colorbar. The results for the 99th percentile of U_{10} are generally twice faster than the median wind speeds and 30-40% stronger than the 90th percentile. However, similarly to the other percentiles shown previously, the results for most energetic winds also demonstrate two distinct seasons. In winter months, the highest values reached up to 35 m/s in the southern part and the east coast of Greenland. In the Norwegian and Barents seas and the Bering Sea, the strongest wind speeds were roughly 22-26 m/s in

winter and 15-17 m/s in summer. In the rest of the Arctic Ocean, the 90th percentile of wind speeds varies between 13-18 m/s in summer and 15-22 m/s in winter.

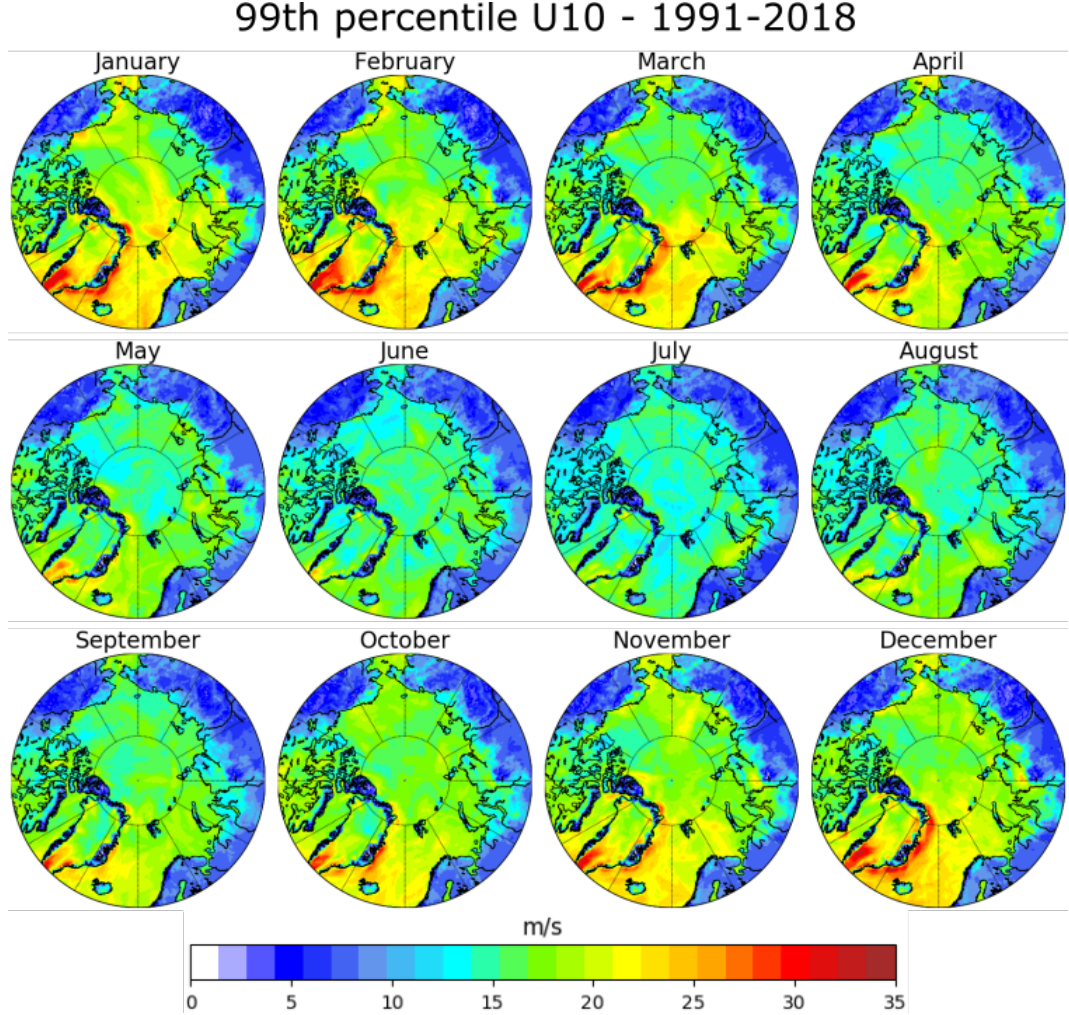


Figure 4.8: Same as Figure 4.6, but for 99th percentile of U_{10} (m/s).

4.4 Waves

In order to evaluate the sea state in the Arctic Ocean, this section quantifies the monthly significant wave height and peak periods based on the 28-years hindcast performed with WW3 model applying ST6 source term to the ERA-5 reanalysis described in Chapter 3. The joint distribution for H_s and T_p for specific points across the Arctic Ocean are also assessed.

4.4.1 Significant Wave Height

The monthly averages of H_s (50th percentile) change significantly throughout the year, as shown in Figure 4.9. As expected, the most energetic wave heights occur in the region of the Arctic Ocean closer to the North Atlantic, due to energetic swells coming from this ocean and also due to the more energetic winds that occur in this region as shown in the previous section of this study. In this region, the average H_s in winter is approximately two times more energetic than for summer months ($\sim 4\text{--}5$ m in winter and ~ 2 m in summer). On the other side of the ocean, where it is covered by ice in a significant part of the year, the average H_s reached values of only 1.2 m in summer (Figure 4.9).

As most of the Arctic Ocean is covered by sea ice from November to June, the waves can only propagate in ice-free areas and they are attenuated in the marginal ice zone. It is worth mentioning that in the wave simulations that generated the results shown here, the marginal ice zone was considered as land (where the sea ice concentration is over 25%) as explained in Chapter 3. This way, the wave heights in the regions close to the ice edge are not expected to be as accurate as in the open water regions. Note, however, that the aim of this research is an evaluation of the wave climate in open waters rather than in the MIZ.

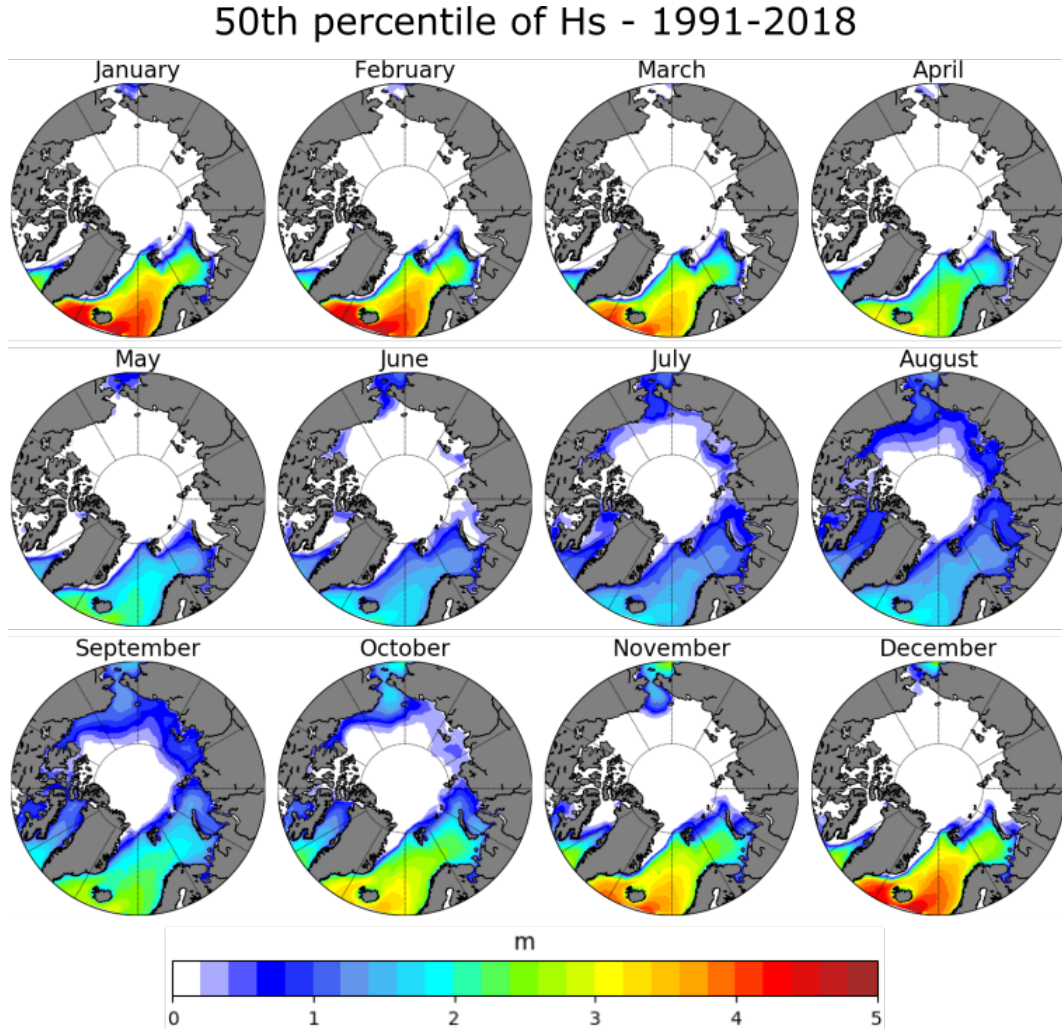


Figure 4.9: Monthly average H_s (m) from 1991-2018 based on the 28-year wave hindcast.

Similarly to the results for wind speeds in the previous section, the results for the higher percentiles of H_s are presented with the same colorbar as shown in figures 4.10 and 4.11. The values of 90th percentile of H_s on the Atlantic side are approximately 8-9 m and on the Pacific side vary between 2-5 m in summer (Figure 4.10). These results are approximately twice higher than average H_s and at the same time they are quite small compared to the 99th percentile shown in Figure 4.11 (~ 30 -40% smaller).

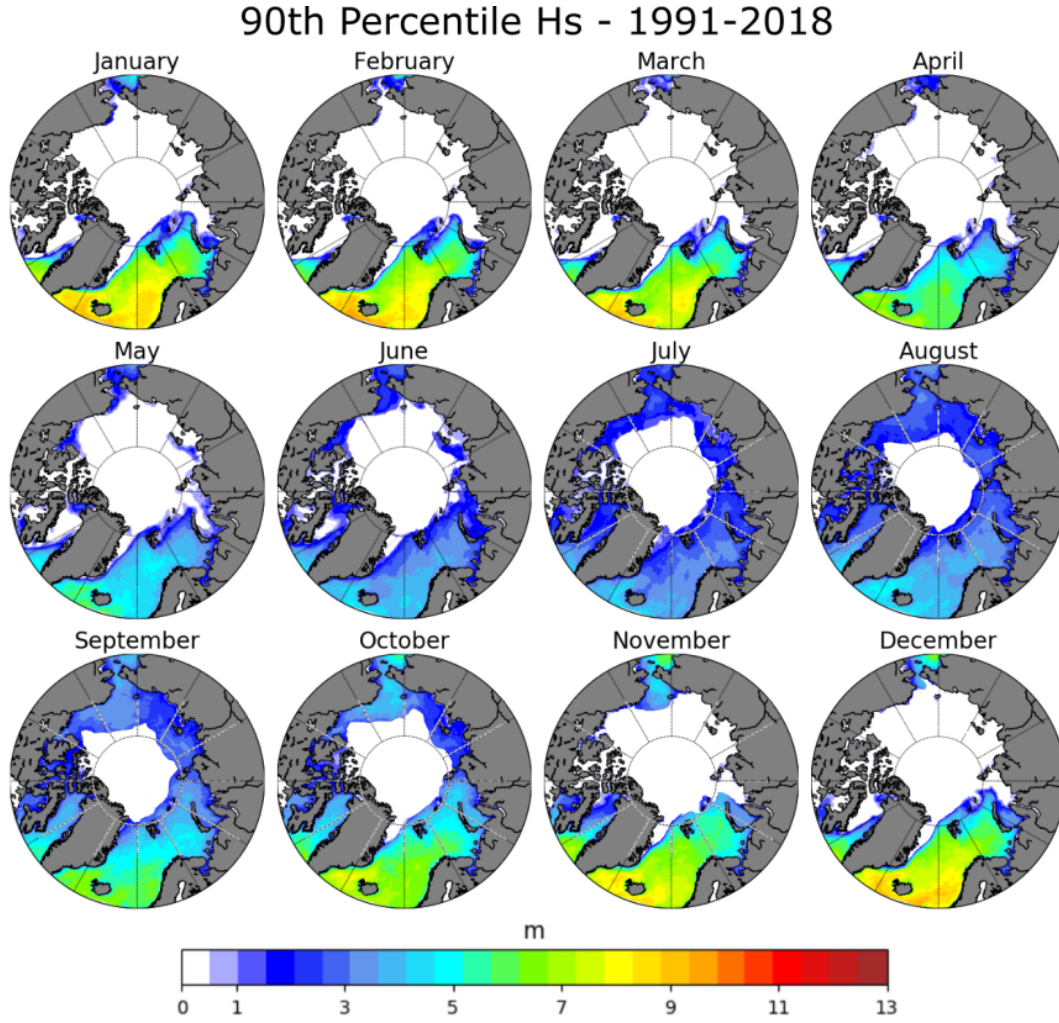


Figure 4.10: Same as Figure 4.9, but for 90th percentile of H_s (m).

It is interesting to note that the apparent minimum ice coverage for the higher percentiles appear to be significantly smaller than for the average values. These results make sense taking into account that for these higher percentiles computations, just the most extreme waves are considered and there are no waves almost all year round in those regions explaining the average wave heights equal to zero.

The most extreme waves that occur in the Arctic Ocean have values of 99th percentile of H_s reaching 13 m in the Norwegian and Greenland seas, as shown in Figure 4.11. The highest waves that occur in the region encompassing Beaufort, Chukchi, and East Siberian seas vary between 5-8 m in October. In the Barents Sea, the results vary from ~ 5 m in summer to ~ 9 -11 m in winter.

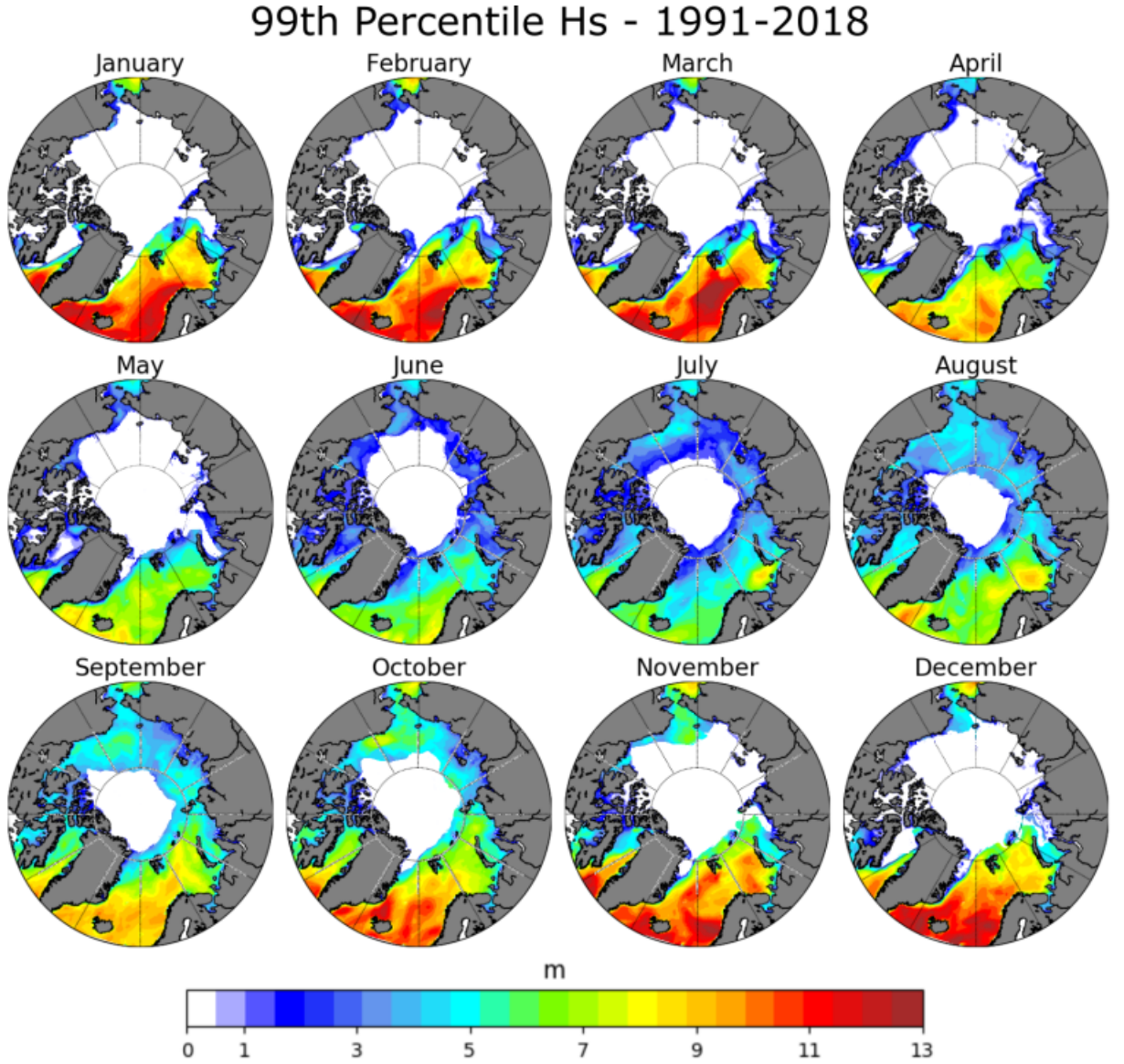


Figure 4.11: Same as Figure 4.9, but for 99th percentile of H_s (m).

4.4.2 Peak period

Another important wave parameter often used to quantify the sea state in a specific region is the wave peak period (T_p). In this session, the results for the average and higher percentiles over the last decades are discussed.

Figure 4.12 shows the monthly results for average T_p (50th percentile). The temporal and spatial variabilities of the peak period are not so significant as for significant wave height shown previously. Similarly to the wind patterns, the results for this wave parameter have two different well-defined patterns: one for the cold season and another one for warmer months. The monthly results for 90th percentile of T_p show

values reaching 13 s in the Norwegian and Greenland seas in winter. In the same region, the longest average peak periods achieve values of 10 s in summer months. On the Pacific Side, the highest average values are ~ 8 s in the Bering Sea and 5-7 s in Beaufort-Chukchi seas.

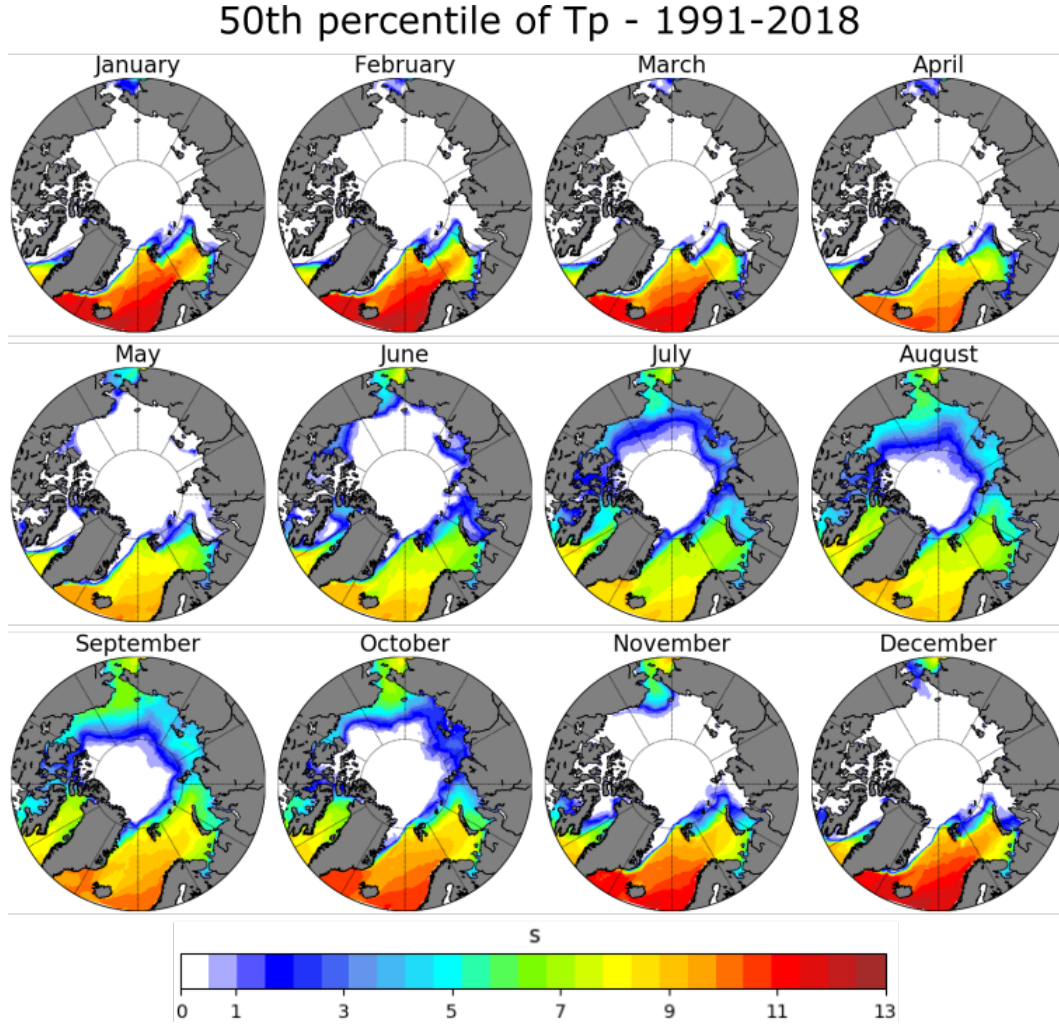


Figure 4.12: Monthly average T_p (s) from 1991-2018 based on the 28-year wave hind-cast.

The results for 90th percentile of T_p are shown in Figure 4.13. They have similar patterns, like the average T_p shown in Figure 4.12. However, the longest values are found a bit further away from the North Atlantic Ocean in the Barents Sea, reaching values of approximately 17-18 s. On the other side of the ocean, the values reach around 8-10 s in September and October.

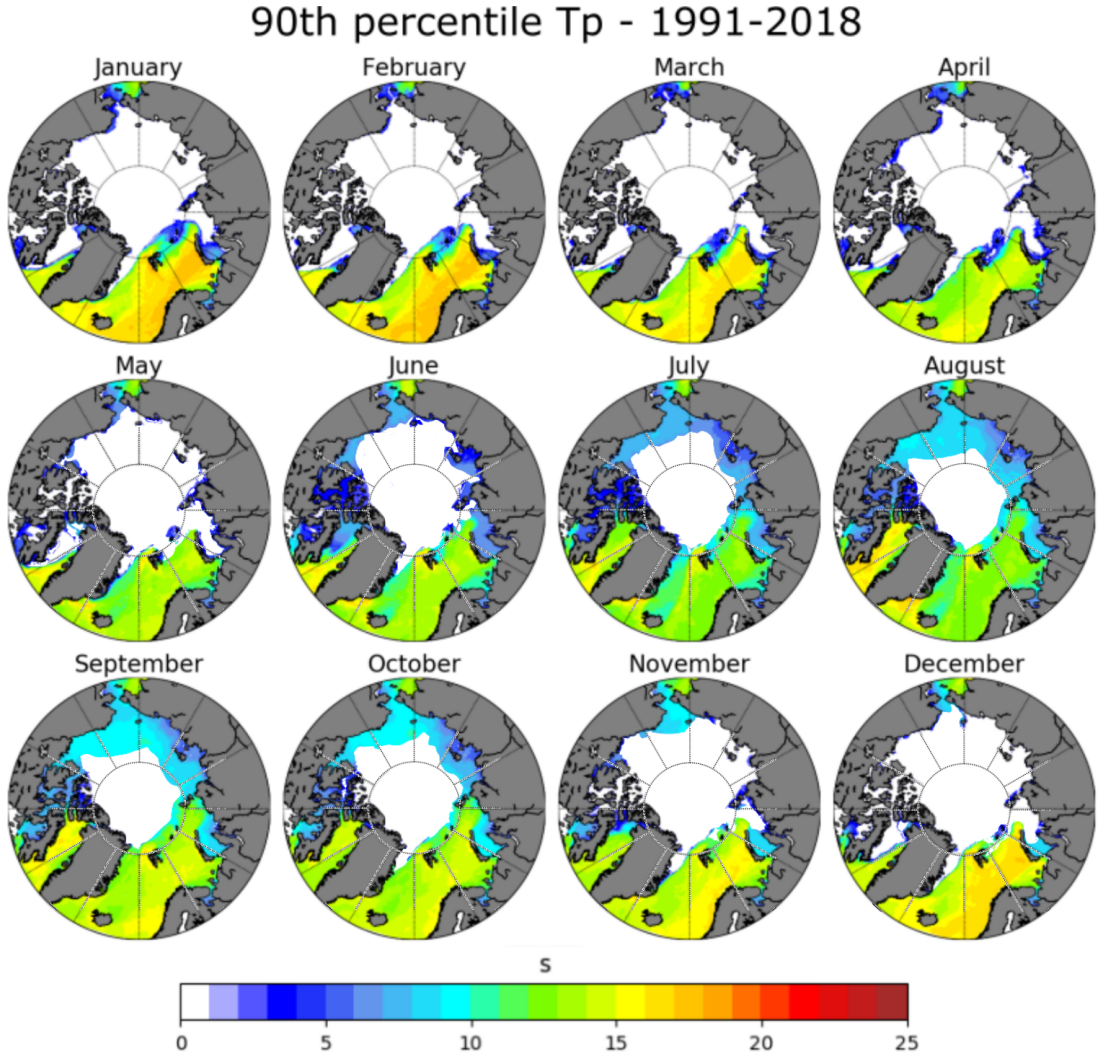


Figure 4.13: Same as Figure 4.12, but for 90th percentile of T_p (s).

The results for the longest (99th percentile) wave peak periods that occurred over the record are shown in Figure 4.14. The patterns for this percentile are very similar to the patterns for the 90th percentile for T_p (Figure 4.14), but with significantly higher values. The results reach 25 s in the Barents Sea in January, that is approximately 40% higher than 90th percentile results. The longest T_p in the Beaufort-Chukchi seas occur in September and October reaching values of 13 s at some points.

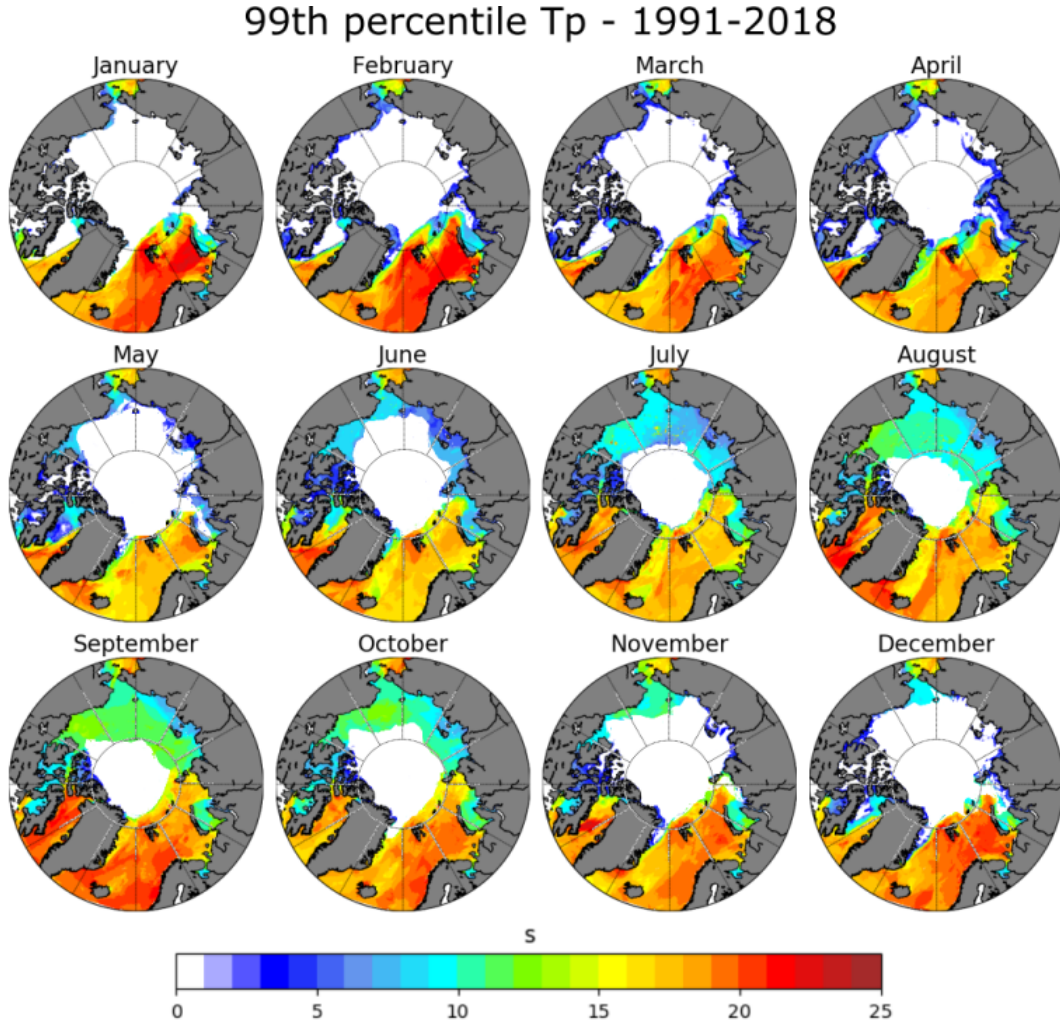


Figure 4.14: Same as Figure 4.12, but for 99th percentile of T_p (s).

4.4.3 Joint Distributions

The joint distribution of significant wave heights and peak periods provides an informative description of the whole sea state in a specific location and it is essential for many practical applications in coastal and offshore activities (Memos and Tzanis, 2000). They are often evaluated to assess, for instance, the steepness of ocean waves in a certain location. They also indicate the existence of an upper bound for the wave shape and how likely the waves can break (Toffoli et al., 2010). The design of offshore structures based on probability usually requires joint distributions to describe the long term wave climate (Mathisen and Bitner-Gregersen, 1990). Therefore, six points, representing locations with distinct wave patterns, were selected across the Arctic Ocean, in order to provide an idea of how the joint distributions of H_s and T_p have been changing over the past decades (Figure 4.15).

The joint distributions for each point are shown in Figure 4.16. The contours represent the probability levels for the 28 years (1991-2018), and the first (1991) and last (2018) years separately. The differences between the results for these two years are evident, especially for points 2 to 5, located close to the ice edge in the Barents, Kara, and East Siberian seas. It is evident that in the first year, those points were covered by ice during most of the year explaining the low occurrence probability of wave heights different than zero and peak periods of around 2 s (lower limit of the wave model simulations is 1.4 s). As the sea ice melts, the waves can develop and reach those areas in 2018 (right panels of Figure 4.16). The upper curves in these graphs represent the steepest waves that occur at some point. The steeper this curve, the steeper the waves are. It can be noticed that the waves at point 1 located in the Norwegian Sea are becoming slightly steeper by looking at the upper curve of the joint distributions of 1991 and 2018. The upper curve for 2018 is steeper than for 1991. One can also note that the waves are becoming more energetic and longer as the curves are shifting up and to the right for all points comparing the results for 28 years (left panels) and 2018 (right panels). These changes might affect the coasts enhancing sediment transport and causing more dramatic coastal erosion in the region.

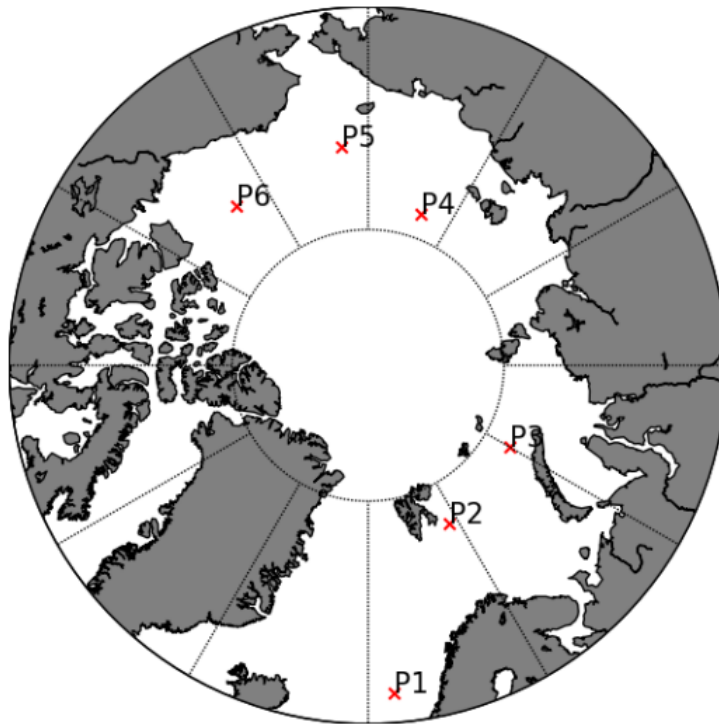


Figure 4.15: Location of the points chosen for joint distribution analysis.

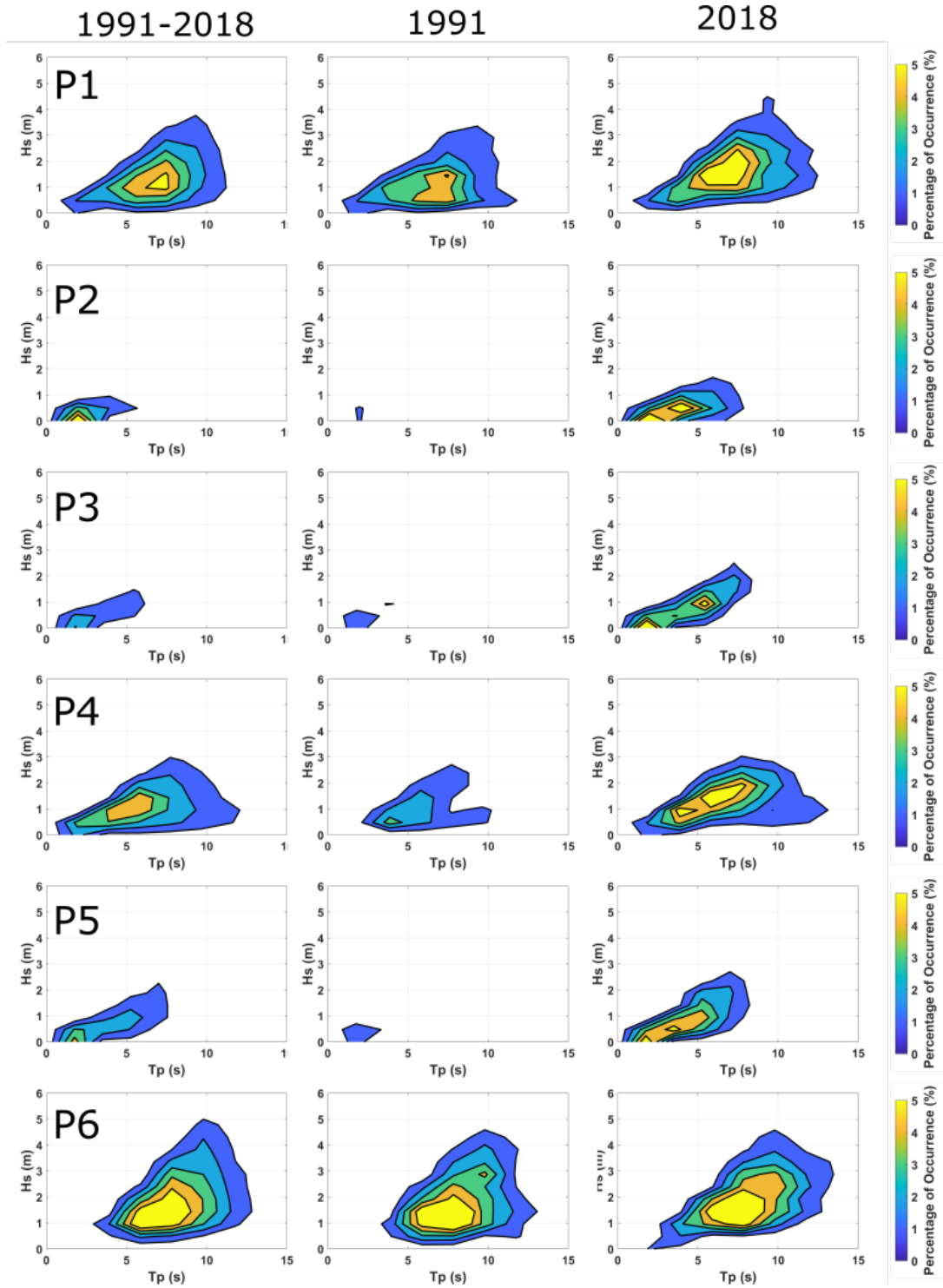


Figure 4.16: Joint distributions of H_s (m) and T_p (s) for the period between 1991 and 2018 (left panels), for the year 1991 (middle panels), and for 2018 (right panels) for six points located in the Arctic Ocean.

4.5 Areal-averages

In order to obtain more details on the variability of each sea over the years, the regional averages were computed for 50th, 90th, 99th percentiles of H_s and U_{10} for the months with minimum sea ice coverage (August and September) during the whole duration of the dataset. Figure 4.17 provides details of the areal-averages for the Pacific sectors of the Arctic Ocean, whereas Figure 4.18 shows the time-series for the seas in the Atlantic sectors. A notable feature in these time series is the interannual variability of winds and waves. For instance, the regional average for 99th percentile of wind speeds for the Norwegian Sea varied from 16 m/s in 2005 to 13 m/s in 2006. No significant long-term variability can be noted from the time series of winds in any sea.

The variabilities in waves follow the wind variability. However, differently from wind results, the time series for regional averages of H_s on the Pacific sector show significant long-term variability, particularly in the Beaufort, Chukchi, East Siberian, and Laptev Seas (Figure 4.17). On the other hand, the seas in the Atlantic sector did not present significant long-term trends in the time series, with the exception of the Kara Sea. A more detailed discussion on trends is reported in Chapter 5.

These regional results are generally in agreement with the results found by Liu et al. (2016). Their estimations based on altimeter data for August and September for 1996-2015 demonstrated similar ranges and variability for the Chukchi, Laptev, and Barents seas for the same percentiles computed in this study (Fig. 9, Liu et al., 2016). For instance, both studies demonstrated that the areal-average of 99th percentile of H_s reached ~ 5 m in 2010 and dropped to 3 m in 2011 in the Barents Sea. However, some differences can be noted. For example, in the Kara Sea, the 99th percentile of wind speeds obtained from ERA5 reanalysis varied from 9 to 11 m/s and the ones obtained by Liu et al. (2016) were around 11-16 m/s . Similarly, the 99th percentile of H_s obtained from the wave hindcast results for the Laptev Sea varied from 0.5 to 3 m, whereas the results based on altimeter data showed variability from 2 to 3.5 m in this sea for the same period. Such differences are comprehensible, taking into account the accuracy of altimeters and model results, and the possible differences in selecting the limits of each sea for the regional averages computations. In addition to that, it should be mentioned that altimeters have no temporal and spatial consistency, whereas the model results are obtained hourly for every grid point of the computational domain.

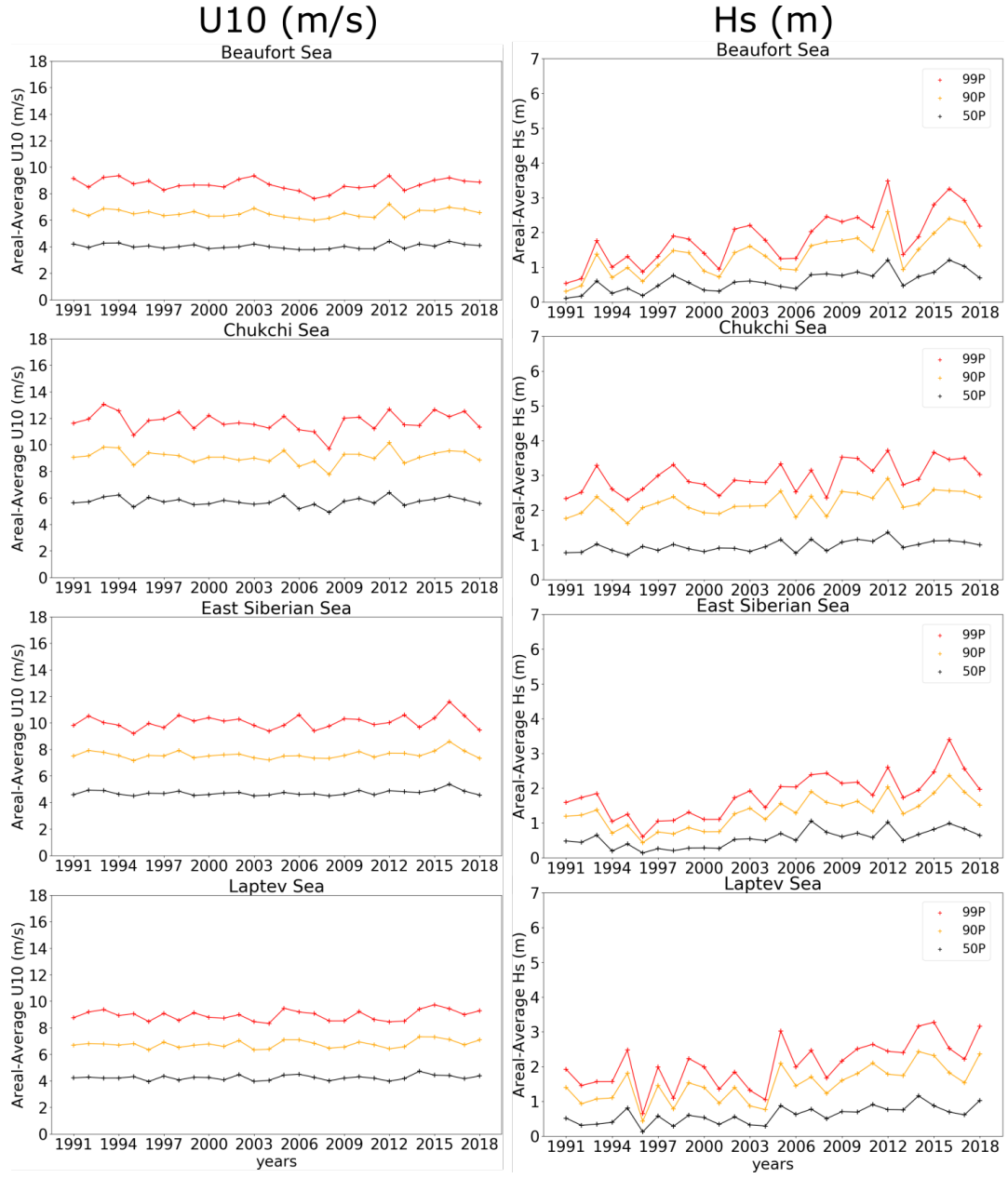


Figure 4.17: Areal-averages for U10 (left panels) and H_s (right panels) for August and September of each sea on the Pacific sector of the Arctic Ocean.

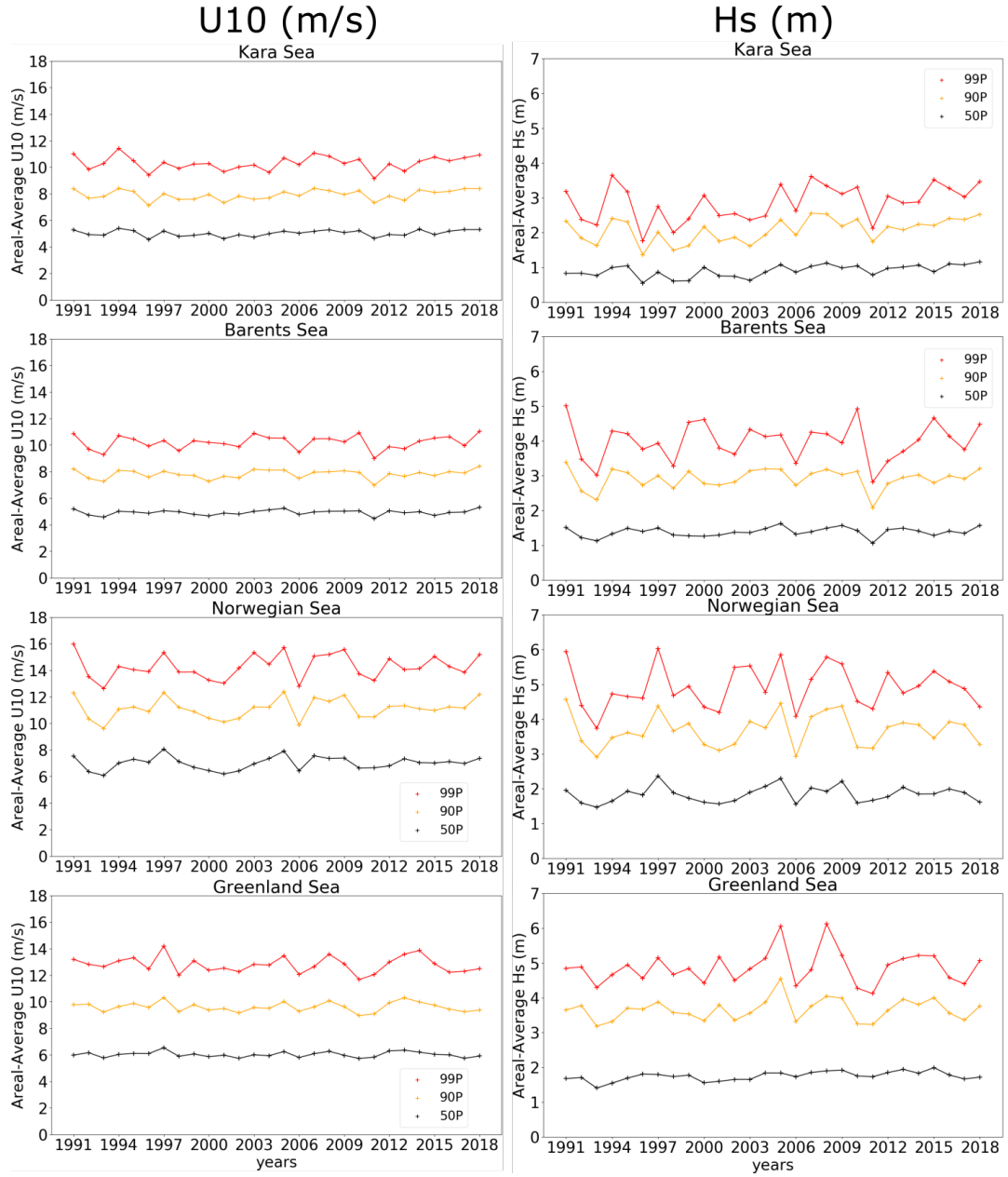


Figure 4.18: Same as Figure 4.17, but for the seas on the Atlantic sector of the Arctic Ocean.

4.6 Conclusion

This chapter provides a general overview of essential climatic properties of the Arctic Ocean. It discusses the monthly averages and higher percentiles of the most significant metocean parameters in the Arctic Ocean over the past decades. The results for monthly sea ice concentrations show significant seasonal differences all year round.

The sea ice starts to freeze in October and it melts from June to September when the sea ice coverage is minimal. The differences between 1991 and 2018 demonstrated a widening MIZ throughout the year, except for the cold season (Feb-Apr). The regions that experienced more considerable differences between these two years evaluated include all the seas that are covered by ice during most of the year. The Barents Sea was the only sea that has experienced sea ice melting in all months. The Bering Strait was covered by ice in 1991 for the first five months of the year, and this sea became mostly ice-free in 2018.

The wind speeds show two distinct seasons for all percentiles: the cold season with stronger winds and the warm season characterized by milder winds. The strongest winds were found around the Greenland and Norwegian seas due to more frequent cyclonic weather systems that often take place in this region, as discussed in (Serreze and Barry, 2014). On the other hand, the semi-permanent low-pressure systems on the Pacific side called Aleutian low are responsible for the weaker winds in this area.

The descriptive sea state in the Arctic Ocean based on the 28-year wave hind-cast performed in this study shows substantial seasonal and spatial differences for significant wave heights across this region. The significant wave heights in winter are approximately two times higher than in summer on the Atlantic side. On the other hand, the spatial and temporal variabilities of peak periods are generally not so dramatic as for significant wave heights. However, they are still quite evident. The peak period results in winter show waves $\sim 40\%$ longer than waves in summer in the Atlantic sector. Similarly to wave heights, the wave period on the Atlantic side is twice longer than for the Pacific side.

The areal-averages estimated for each sea provided more details of interannual variability of winds and waves. It could be noticed substantial interannual variability in winds, and consequently in waves. The waves in the Pacific sector of the Arctic Ocean demonstrated significant long-term variability that was not found for the winds.

Chapter 5

Trend Analysis

5.1 Introduction

Assessing environmental variables as a function of time is useful to detect changes in the climate. Such changes can be periodic, such as the annual seasonal cycle or the interannual variability (e.g. the North Atlantic or ENSO/Southern oscillations), or monotonic such as a steady increase in monthly values over time (Fu and Cazenave, 2000). In order to determine the magnitudes of long-term fluctuations or trends, different mathematical techniques can be applied, such as simple linear regression based on the least-square fitting approach. In this study, changes in the Arctic Ocean wave extremes are identified by performing the Mann-Kendall test (Mann, 1945; Kendall, 1948) for randomness against trends assessing the significance of the trend. This procedure is particularly useful to address non-normal distributions, seasonality and missing values from monthly time series. The estimation of the trend slope was based on the method proposed by Sen (1968). This chapter discusses the trend estimations of sea ice concentration, wind speeds, wave heights, and wave periods for 1991-2018.

5.2 Methodology for trend analysis

A broad range of different methodologies for trend analysis can be used to infer changes in environmental parameters. In ocean climate fluctuations, interest is commonly focused on describing seasonality and interannual to multi-decadal cycles. According to Zieger (2010), among many different techniques available to detect trends or long-term fluctuations on time series of different environmental variables, there are three most common techniques: (i) model-based approaches, (ii) non-parametric approaches, and (iii) singular spectrum analysis (SSA). Model-based approaches include

simple and multiple linear regression (Montgomery et al., 2015). Non-parametric techniques include trend estimations analysis such as Mann-Kendall test (MKT) (Sen, 1968) and Seasonal Kendall test (SKT) (Hirsch et al., 1982; van Belle and Hughes, 1984). SSA algorithms work in a similar way to principal component analysis (PCA) for multivariate data but applied to a one-dimensional time series (Alexandrov, 2009). More recently, De Leo et al. (2020) proposed a methodology that combines different trend estimators modifying the estimation of linear trend slope minimizing the weight of possible outliers.

In the present analysis, trend estimations analysis such as Mann-Kendall test (MKT) and Seasonal Kendall test (SKT) are applied as they were found to be the most suitable based on the nature of the time series used in this study. The scientific community widely uses MKT and it is particularly useful to address non-normal distributions and missing values from monthly time series. SKT is a modification of the MKT test applicable for time series exhibiting strong seasonality, which is the case of the Arctic region.

5.2.1 Mann-Kendall Test (MKT)

The Mann-Kendall test (MKT) has been extensively applied in estimating trends of wind speed and wave climate (e.g Zieger, 2010; Liu et al., 2016; Stopa et al., 2016; Wang and Swail, 2002). The test is derived from a rank correlation test (Kendall's τ), taking into account the correlation between the rank order of the observed values and their order in time. The null hypothesis for randomness states the time series $X = (x_1, \dots, x_n)$ of n independent and identical distributed randomly ordered variables, i.e. there is no trend under the null hypothesis. The statistic test S is defined as

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n a_{kj}, \quad (5.1)$$

where

$$a_{kj} = \text{sgn}(x_j - x_k) = \begin{cases} 1 & x_k < x_j \\ 0 & x_k = x_j \\ -1 & x_k > x_j \end{cases} \quad (5.2)$$

Under the null hypothesis that X is an independent and randomly ordered time series, the distribution of S tends to normality for large n , with median and variance for the case of no ties is given by

$$E(S) = 0 \quad (5.3)$$

$$var(S) = \frac{n(n-1)(2n+5)}{18}. \quad (5.4)$$

For tied observations the variance of S can be determined by the following equation to avoid overestimation:

$$var(S) = \frac{1}{18} \left[n(n-1)(2n+5) - \sum_{j=1}^v u_j(u_j-1)(2u_j+5) \right], \quad (5.5)$$

where u_j represents the number of elements in a single set of ties and v is the total number of sets of ties in the time series X (Sen, 1968).

A two-sided test for trend can then be performed by comparing the following statistic

$$Z_{MKT} = \frac{(S - sgn(S))}{\sqrt{var(S)}}. \quad (5.6)$$

If the absolute number of the statistic Z_{MKT} does not exceed the critical value of standard normal distribution function ($\frac{\alpha}{2}$ level), the null hypothesis of X is accepted, i. e. the data are random and there is no trend. Conversely, if it exceeds this level, the null hypothesis is rejected if

$$|Z_{MKT}| > norm_{\frac{\alpha}{2}}. \quad (5.7)$$

Rejecting the null hypothesis of X implies a statistically significant trend with a positive value of Z_{MKT} indicating an upward trend and negative value of Z_{MKT} a downward trend.

A statistically significant trend can be described by a standard simple linear regression model

$$f_{MKT}(t) = \beta_1 + \beta_2 t + \epsilon, \quad (5.8)$$

where β_1 is the intercept and β_2 is the slope and they are constant coefficients. The term t represents time and ϵ is a random error component with zero mean and unknown variance. In addition to identifying time series that exhibit trend, Sen (1968) proposed a slope estimator to quantify the magnitude of such trend. The study suggested an estimator for the regression coefficient slope (trend) including estimates for the confidence intervals, which can be determined using Kendall's rank correlation (Kendall, 1948). The set of slopes is given by

$$B_{ij} = \frac{(x_j - x_i)}{(t_j - t_i)}, \quad (5.9)$$

where t_i represents the time of observation i and for all positive differences of time between two observations $(t_j - t_i)$ where $1 \leq i \leq j \leq n$.

An unbiased estimation of the slope is given by the median value of B_{ij} ranking the k elements of B_{ij} in ascending order:

$$\hat{\beta}_1 = \begin{cases} B_{\frac{(k-1)}{2+1}} & \text{if } k \text{ is odd} \\ \frac{(B_{\frac{k}{2}} + B_{\frac{k}{2+1}})}{2} & \text{if } k \text{ is even} \end{cases} \quad (5.10)$$

The lower β_1^L and upper β_1^U confidence intervals of the estimator β_1 are calculated from ranked elements of B_{ij} and given by

$$\hat{\beta}_1^{L,U} = \begin{cases} B_{\frac{(k-K)}{2}} & \text{for lower limit } L \\ B_{\frac{(k+K)}{2+1}} & \text{for upper limit } U \end{cases} \quad (5.11)$$

(5.11)

Where K is the product between the critical value if the standard normal distribution (at the $\frac{\alpha}{2}$ level) and square-root of the variance of S :

$$K = \text{norm}_{\frac{\alpha}{2}} \sqrt{\text{var}S}. \quad (5.12)$$

5.2.2 Seasonal Kendall test (SKT)

Environmental variables are usually subjected to complex characteristics such as seasonality, missing values, and non-normal distributions. This is the case of the metocean parameters in the Arctic region, due to the freeze-thaw cycles of sea ice throughout the year.

Hirsch et al. (1982) proposed a modification of the MKT test that is applicable for time series with strong seasonality, namely the Seasonal Kendall test (SKT). It assumes that the time series X can be subdivided into seasons. When considering monthly statistics once can subdivide the signal into 12 seasons (one for each month) such as

$$X = (X_1, X_2, \dots, X_{12}), \quad (5.13)$$

where

$$X_i = (x_{i1}, x_{i2}, \dots, x_{im}), \quad (5.14)$$

where i represents each season and m represents the values associated with the season i . In other words, each of the subsets contains m values from season i . The MKT test can be performed for each month defined as

$$S_i = \sum_{k=1}^{m_i-1} \sum_{j=k+1}^{m_i} a_{ikj}, \quad (5.15)$$

where

$$a_{ikj} = \text{sgn}(x_{ij} - x_{ik}) = \begin{cases} 1 & x_{ik} < x_{ij} \\ 0 & x_{ik} = x_{ij} \\ -1 & x_{ik} > x_{ij} \end{cases} \quad (5.16)$$

Analogous with the MKT test, the variance for each 12 test statistics S_i can be calculated by

$$\text{var}(S_i) = \frac{1}{18} \left[m_i(m_i - 1)(2m_i + 5) - \sum_{u_i} u_i(u_i - 1)(2u_i + 5) \right], \quad (5.17)$$

where u_i represents the extent of a given tie in season i . The summation statistics $S' = \sum_{i=1}^{12} S_i$ has zero median and variance given by

$$\text{var}(S') = \sum_{i=1}^{12} \text{var}(S_i) + \sum_{i,j,i \neq j}^{12} \text{cov}(S_i, S_j), \quad (5.18)$$

where $\text{cov}(S_i, S_j)$ represents the covariance terms between seasons i and j . Under the assumption of independent observations, the covariance terms equal to zero. A two-sided test for trend can be performed by comparing the following seasonal statistic

$$Z_{SKT} = \frac{S' - \text{sgn}(S')}{\sqrt{\text{var}(S')}}. \quad (5.19)$$

Similarly to MKT test, if the absolute number of the statistic Z_{SKT} exceeds the $\frac{\alpha}{2}$ level, the null hypothesis is rejected if

$$|Z_{SKT}| > \text{norm}_{\frac{\alpha}{2}}. \quad (5.20)$$

This implies a statistically significant trend with a positive value of Z_{SKT} indicating an increasing trend and negative value of Z_{SKT} a decreasing trend. The seasonal Kendall slope estimator is given by

$$B_{ijk} = \frac{x_{ij} - x_{ik}}{t_{ij} - t_{ik}}, \quad (5.21)$$

where $1 \leq k \leq j \leq n$.

In a similar fashion to MKT test, the median value of the superset B_{ijk} yields an unbiased estimate of the slope by ranking all elements of B_{ijk} in ascending order. The median value B_{ijk} is obtained the same way as in equation (5.10) and estimates for the lower $\hat{\beta}_1^L$ and upper $\hat{\beta}_1^U$ confidence intervals can be calculated as in equation (5.11).

5.3 Trends in sea ice concentration

In order to evaluate the monthly changes in sea ice coverage, the Mann Kendall test was applied to identify the trends in the 10th and 50th (median) percentiles of the ERA5 sea ice concentration dataset for the period between January 1991 to December 2018. The 10th percentile of sea ice concentration was selected in the analysis considering that the strongest waves occur under conditions of minimum sea ice coverage. The monthly Sen's slope estimations for the 10th and 50th percentiles are shown in Figure 5.1 and Figure 5.2, respectively. In both figures, the dots represent statistically significant trends at the 95% level. Note, however, that due to the high resolution of the grid domain, it was necessary to plot the dots in a coarser resolution, so the colours that represent the trends on each point of the domain are also visible on the map.

The trends for the 10th percentile and median sea ice concentrations demonstrate a similar pattern. The results show that the Arctic is experiencing sea ice reductions every month but at different intensities. What stands out in these figures is the high monthly variability of the trends. In the summer months, it can be seen as a general decreasing trend across the regions that are covered by sea ice almost all year round. In October, the trends of the 10th percentile of sea ice concentration are limited to deepwater in most part of the domain (Figure 5.1), whereas the trends of the median sea ice concentration (Figure 5.2) expand over the coastal areas. Similarly, in November, a difference between the trends in the 10th and 50th percentiles can be noticed in the Chukchi Sea. In this region, the minimum sea ice concentrations are statistically changing only close to the ice edge (Figure 5.1), whereas the median sea ice concentrations are changing across the entire Chukchi Sea (Figure 5.2). In winter, as most part of the Arctic Ocean is covered by sea ice, it is expected that the trends will be limited to the ice-free regions. In winter months (December, January, and February), the sea ice is retreating in the Denmark Strait, Baffin Bay, Barents, and Kara seas, with the highest trends close to the ice edge in the Barents Sea.

The Chukchi Sea has experienced a sea ice reduction in June, November, and December of approximately 1-2 % per year (Figure 5.2). In the Beaufort, East Siberian, Laptev, and Kara seas the sea ice is reducing significantly in all summer months (July-October), with the strongest downward rates in September and October reaching values of approximately -4 % per year. In the Barents Sea, the sea ice is shrinking dramatically in all months of the year (especially in November and December) in the region close to the ice edge – between Svalbard and Novaya Zemlya islands.

The results obtained by applying the SKT to the data sets for the median and 10th percentile of sea ice concentration are shown in Figure 5.3. For the SKT test, each dot marks statistically significant trends in regards to the normal distribution test and also to the homogeneity over monthly MKT tests as described before (section 5.2.2). The SKT results for 10th percentile of sea ice concentration were very similar to the trends for median sea ice concentration. These maps show how the sea ice is melting across the Arctic Ocean considering the changes throughout the entire year and the results demonstrate changes across most part of the Arctic Ocean with the highest rates in the Barents Sea.

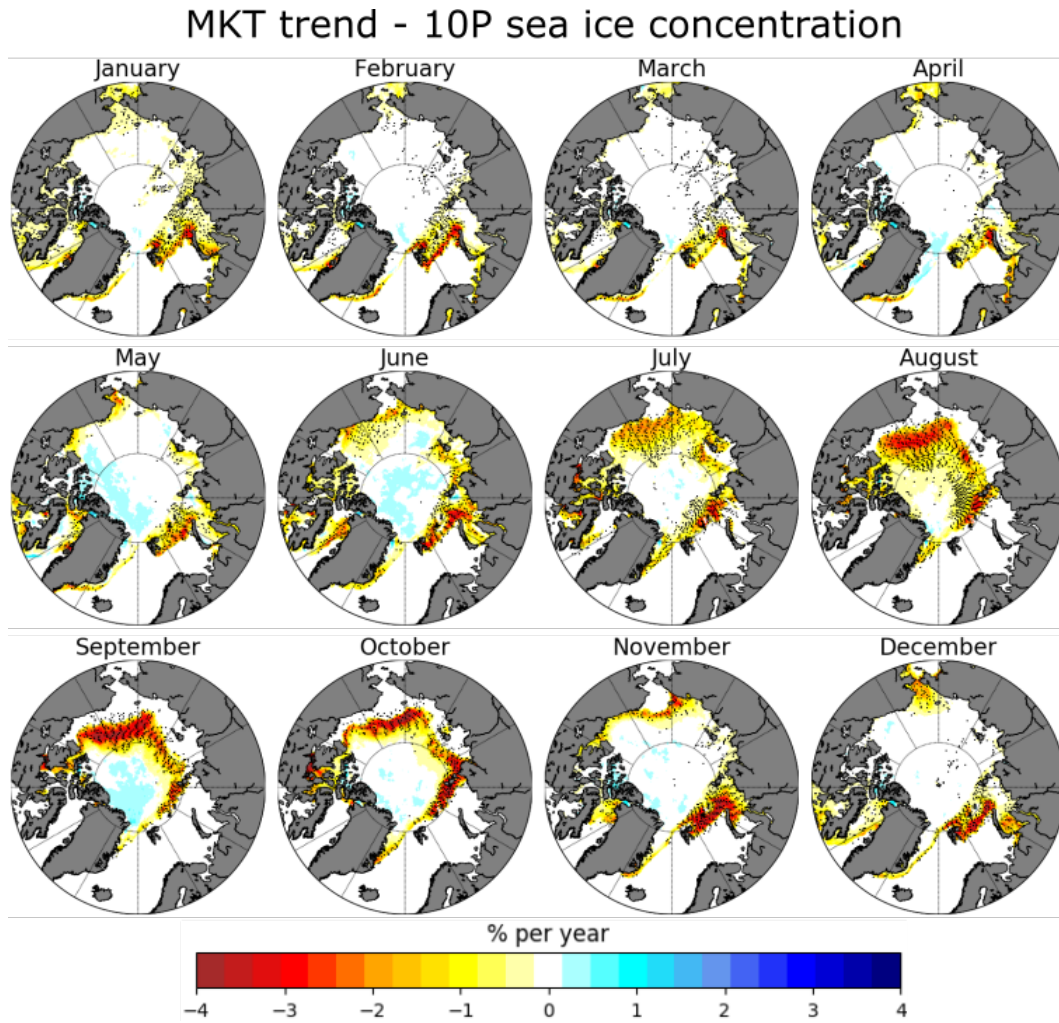


Figure 5.1: Monthly trend estimates (Sen's slope) of 10th percentile of sea ice concentration for the period between 1991-2018 based on ERA5 dataset. Dots indicate statistically significant trends at the 95% level.

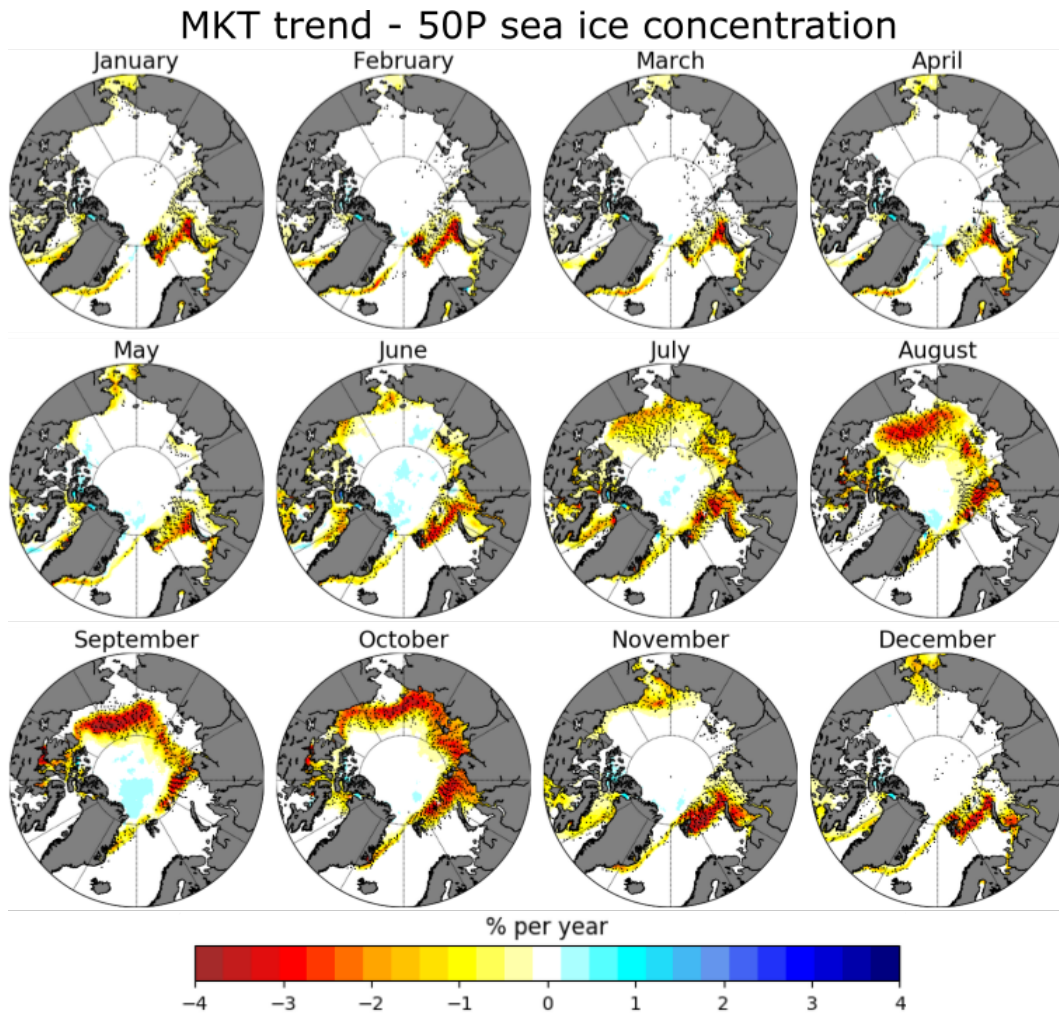


Figure 5.2: Same as Figure 5.1, but for monthly median of sea ice concentration.

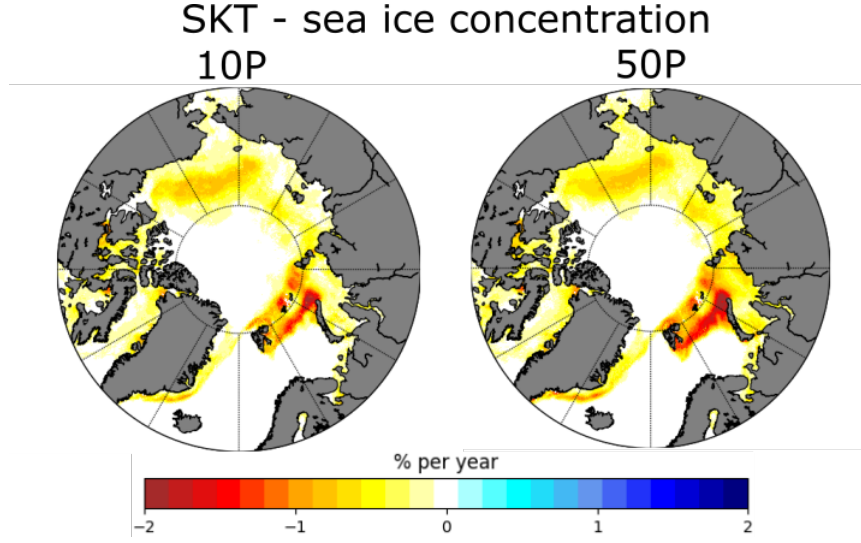


Figure 5.3: Trend estimates (Sen's slope) for 10th percentile (left panel) and median sea ice concentration (right panel) with SKT test applied for 1991-2018 based on ERA5 dataset. All of the points plotted are statistically significant trends at the 95% level.

5.4 Trends in wind speeds

In order to evaluate the changes of average and extreme conditions, the MKT and SKT tests were applied to 50th, 90th, 99th percentiles of ERA5 wind speed (10 m above median sea level - U_{10}) data sets. Previous studies have suggested no significant trends in the wind forcing over the last two decades. For instance, Stopa et al. (2016) and Liu et al. (2016) estimated a slight downward trend on the Atlantic side of the Arctic Ocean, but their trend estimations were not in agreement on the Pacific side. Such differences can be explained as Stopa et al. (2016) estimated the trends for all months together, whereas Liu et al. (2016) considered only two months with the minimum sea ice coverage (August and September). In this study, the MKT test was applied for each month of the year based on the 28-year dataset (1991-2018). Ultimately, the estimations performed in this study might allow a better understanding of the differences found in these previous studies.

Figure 5.4 presents the trends in median wind speed for each month. The dots mark statistically significant trends at the 95% level. What is interesting in this figure is the geographical and seasonal differences of the changes in wind speed across the Arctic. The statistically significant trends include upward trends of approximately 0.06

$$m/s$$

$year^{-1}$ in East Siberia, Laptev, and Kara seas in February.

The central part of the Arctic Basin has been experiencing statistically upward trends in some months (February and December) and downward trends in others (July, August, and November). In April, part of the basin (closer to Greenland) presented downward trends (~ -0.06

$$m/s$$

$year^{-1}$) in average wind speeds, whereas the other part showed a slight increasing trend (~ 0.05

$$m/s$$

$year^{-1}$).

On the Atlantic side of the Arctic Ocean, the Norwegian Sea has experienced statistically significant downward trends in median wind speeds in January and February and in October and December in the northern part (Figure 5.4) and no significant increasing trends. The Denmark Strait is experiencing strong increasing trends (~ 0.1

$$m/s$$

$year^{-1}$ in median U_{10} in some months of the year (January, April, May, and December). The Greenland Sea presented statistically significant increasing trends in May and September, but also decreasing trends (rates lower than -0.09

$$m/s$$

$year^{-1}$) in January and March. It's worth mentioning that those seasonal differences cannot be noticed in the SKT test that considers the changes throughout the entire year (Figure 5.7). The Baffin Bay also demonstrated significant increasing trends reaching rates of ~ 0.07

$$m/s$$

$year^{-1}$ in February, September, November, and December. This region has not experienced any significant downward trends in any month.

The Barents Sea experienced both increasing (in March, May, June, August, and November) and decreasing trends (in January, October, and December). The strongest rates of approximately 0.1

$$m/s$$

$year^{-1}$ occurred in February close to the Novaya Zemlya islands. In July, the northern part of this sea presented an upward trend of 0.05

$$m/s$$

$year^{-1}$ and the coastal areas experienced a downward trend of -0.04

$$m/s$$

$year^{-1}$.

On the Pacific side, the Beaufort and Chukchi seas presented increasing trends in July, September, October of about 0.05

$$m/s$$

$year^{-1}$ and reaching approximately 0.07

$$m/s$$

$year^{-1}$ in median U_{10} in October. The East Siberian Sea has shown statistically significant increasing trends in most part of the year with the highest trends happening in February. The only month that presented a downward trend in this region was May.

Finally, the Kara Sea showed increasing trends just in February, August, November, and December with rates of roughly 0.05

$$m/s$$

$year^{-1}$. The Laptev Sea had the highest upward trends of around 0.07

$$m/s$$

$year^{-1}$ in February but also demonstrated statistically significant increasing trends in January, March, August, September, and November. This sea experienced a slight downward trend in April and May.

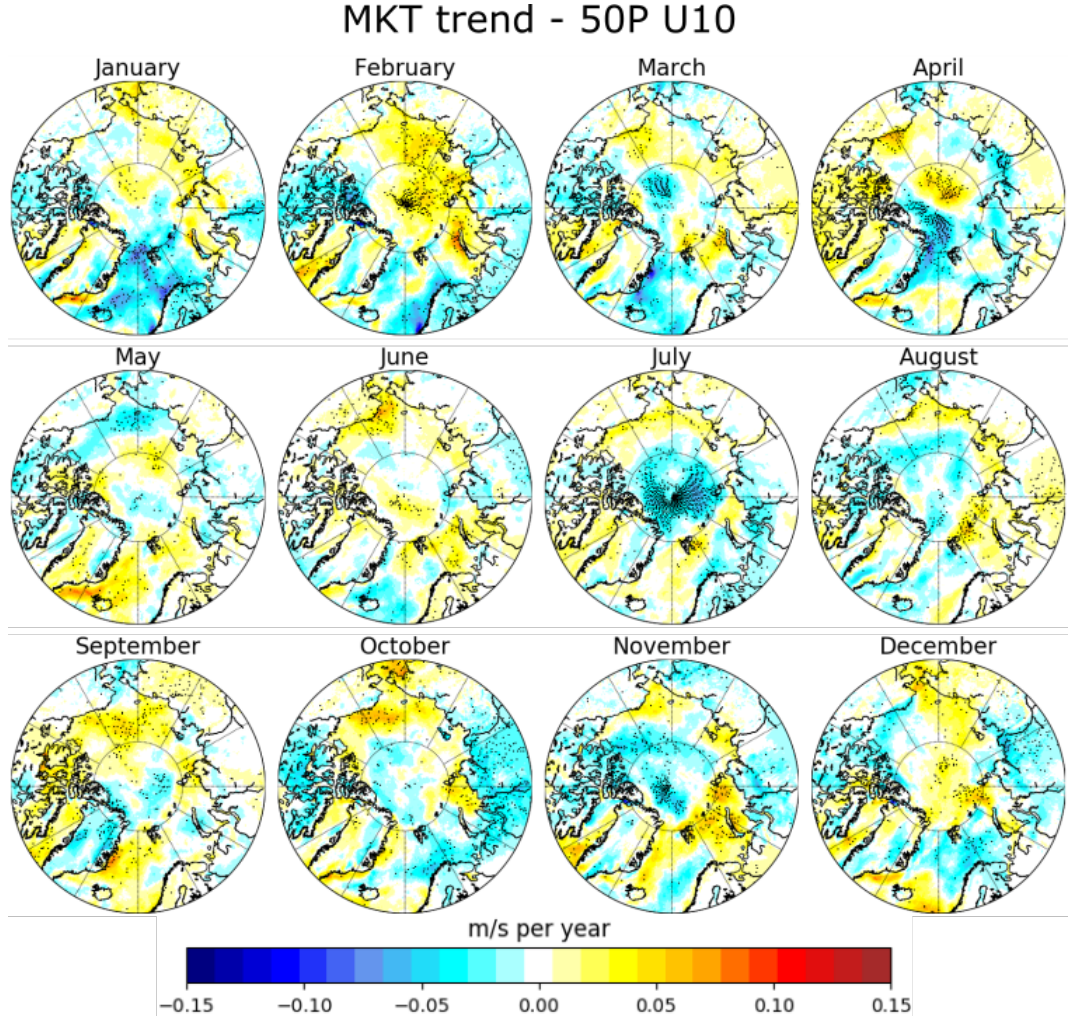


Figure 5.4: Monthly trend estimates (Sen's slope) of median wind speed (m/s) for the period between 1991-2018 based on ERA5 dataset. Dots indicate statistically significant trends at the 95% level.

The figures 5.5 and 5.6 display the monthly trends for the 90th and 99th percentiles for wind speed (U_{10} , respectively). It is interesting to note a similar pattern among the monthly trends for all three percentiles analyzed (50th, 90th, and 99th). The differences are essentially in intensity. As expected, the trends in median U_{10} are weaker than the for 90th percentile, which is, in turn, weaker than the trends for 99th. The rates for average winds reach values around 0.09

$$m/s$$

$year^{-1}$. The trends in 90th percentile of wind speed reach values of 0.12

$$m/s$$

year^{-1} at some points (Figure 5.5) and 0.15

m/s

year^{-1} for the most extreme waves (99th percentile in Figure 5.6).

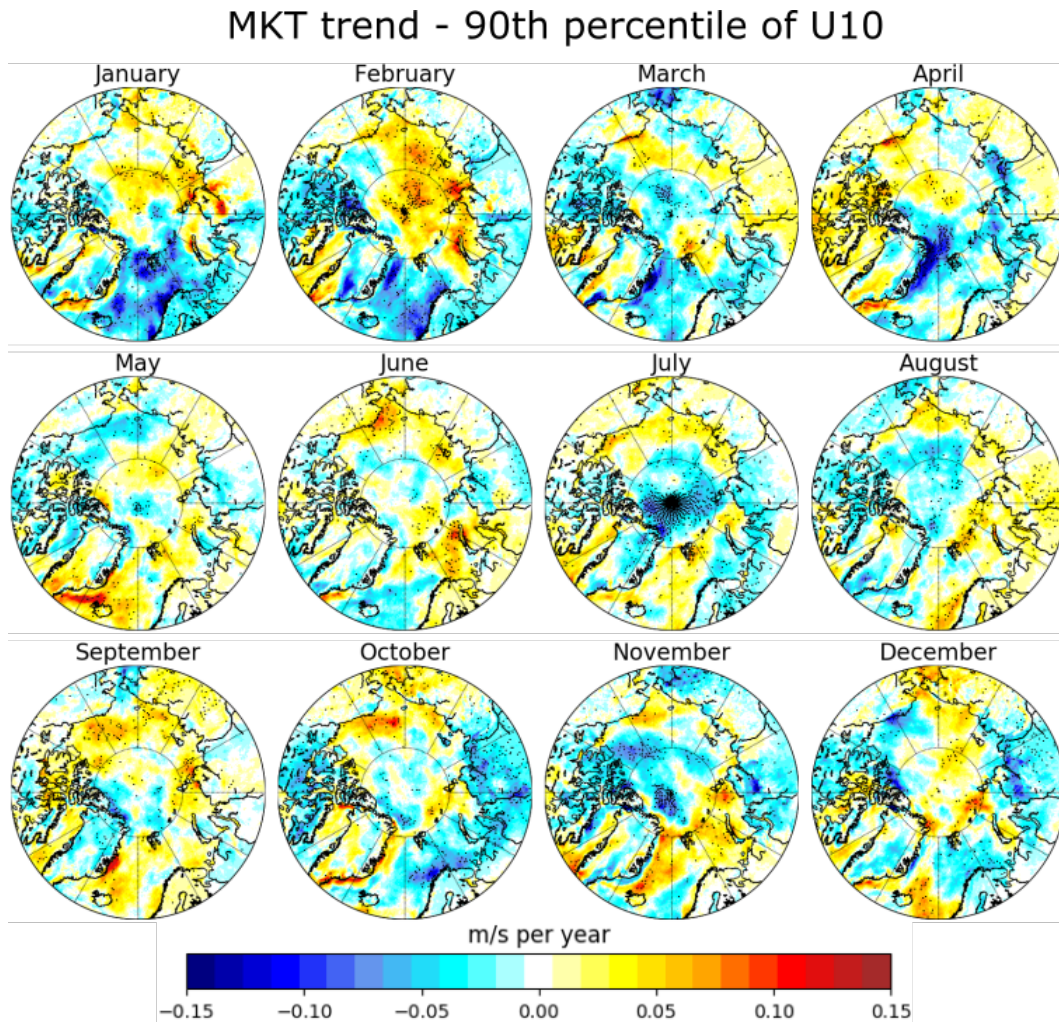


Figure 5.5: Same as Figure 5.4, but trend estimates for 90th percentile of U_{10} (m/s)..

Figure 5.6 demonstrate strong increasing trends on the Pacific side of the Arctic Ocean with values reaching approximately 0.15

m/s

year^{-1} in some points of the Beaufort Sea and, on the other hand, dramatic downward trends on the Atlantic side of this ocean, with rates reaching -0.15

m/s

year^{-1} .

Another interesting aspect to note is that, even though very similar patterns with the results of other percentiles (50^{th} and 90^{th}), the trends in 99^{th} percentile (Figure 5.6) presented some differences in some months such as statistically significant downward trends in November in the region encompassing the Chukchi and the East Siberian seas.

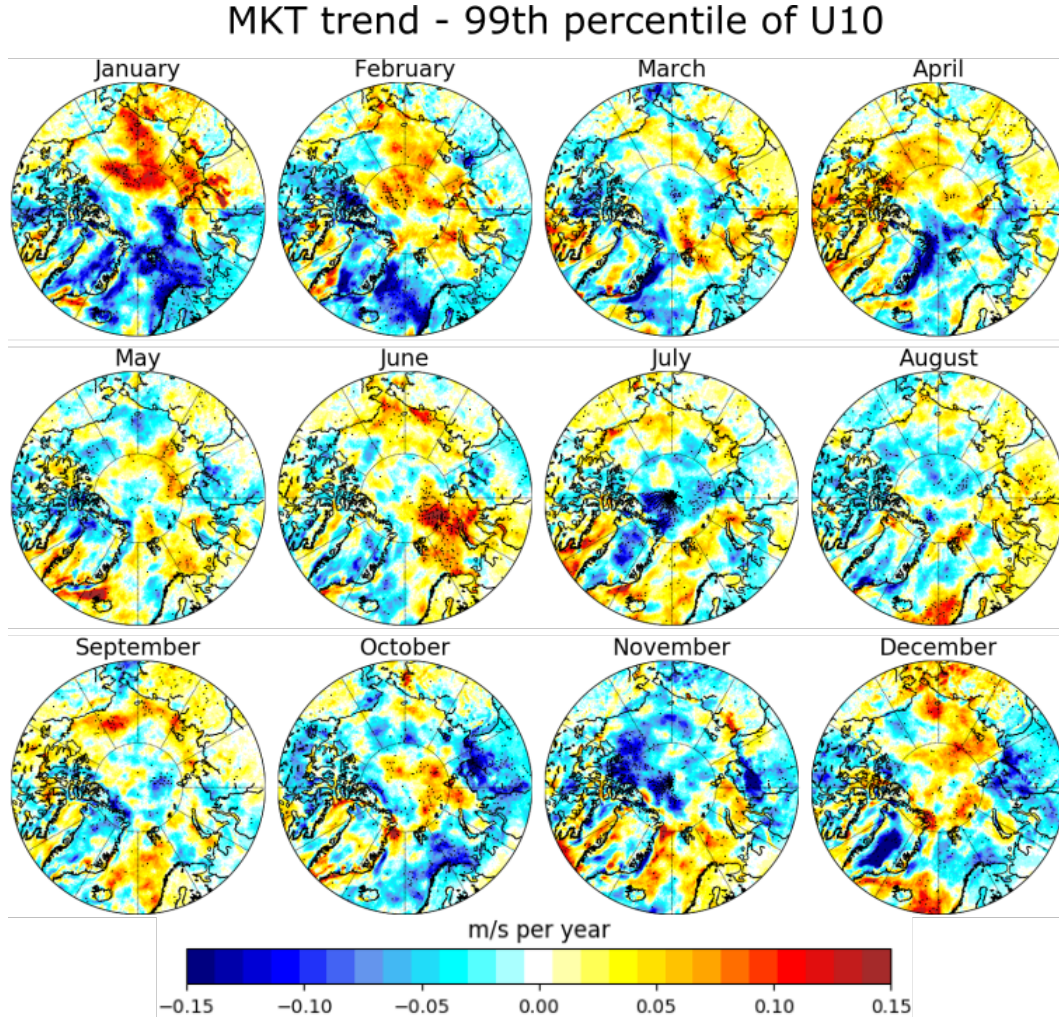


Figure 5.6: Same as Figure 5.4, but trend estimates for 99^{th} percentile of U_{10} (m/s).

Figure 5.7 shows the trend estimations derived from the SKT test for the three percentiles evaluated here. In these maps, all of the points plotted are statistically significant trends at the 95% level. One can note the similar patterns in the trends shown on these three maps. One striking difference is in the Northern Greenland Sea, where it has experienced significant downward trends for the 90^{th} and 99^{th} percentiles, whereas increasing trends for the median U_{10} . The changes in winds are usually

correlated to interannual oscillations such as the North Atlantic Oscillation (NAO) and the Arctic Dipole (AD) as previous studies have demonstrated (e.g. Stopa et al., 2016; Semedo et al., 2015). The results for the trends in median wind speed computed in this study are in agreement with the ones found by Stopa et al. (2016, figure 8), with very similar patterns in trends. According to their study, the negative trends presented in the Nordic, Greenland, and Barents seas are due to the negative NAO observed in this period. In these seas, a positive NAO phase means increasing winds and sea state, whereas negative NAO equates to downward trends in these metocean parameters. This is a natural component that may lead to opposite trends in the future.

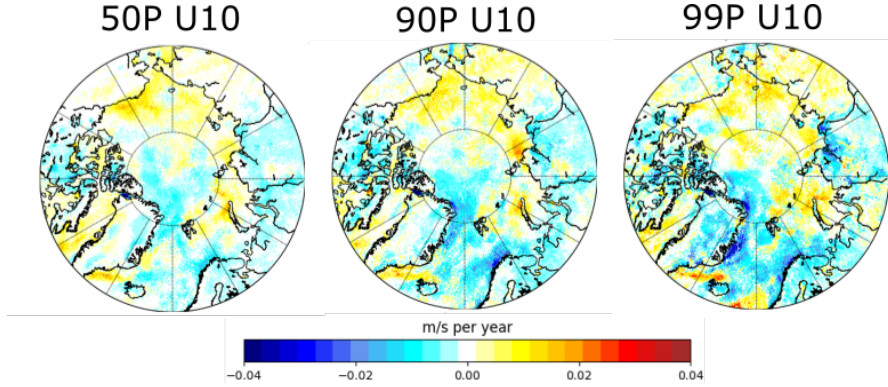


Figure 5.7: Trend estimates (Sen's slope) for median (left panel), 90th (middle panel), 99th percentiles (right panel) of wind speeds (U_{10}) with SKT test applied for 1991-2018 based on ERA5 dataset. All of the points plotted are statistically significant trends at the 95% level.

5.5 Trends in waves

In order to evaluate the trends in waves over the last decades, the MKT test was applied to the 28-year wave hindcast performed in this study, as described in Chapter 3. The Sen's slope was computed after the MKT test was applied. The figures 5.8 and 5.9 show the results of the monthly trend estimations for median H_s in $cm/year$ and median T_p in $s/year$, respectively. Similarly to the results for the other metocean parameters (sea ice concentration and wind speed), the dots on these maps mark statistically significant trends at the 95% level. It is easy to note large seasonal differences in the trends.

With the reduction of sea ice, the waves are expected to increase. It can be noticed a consistent upward trend in the regions that are covered by ice in most part of the year. The increasing rates in average H_s vary between 2 to 7 $cm/year$ and in median

T_p between 0.1 to 0.3 $s/year$ from July to October in the Beaufort Sea (Figure 5.8 and Figure 5.9), with highest rates occurring in October. In the Chukchi Sea, the rates are higher in November with upward trends of approximately 4 $cm/year$ in H_s and 0.2 $s/year$ in T_p . In the East Siberian Sea, the largest trends were found in September and October of roughly 6 $cm/year$ in median H_s and 0.3 $s/year$ in T_p . In the Laptev Sea the increasing trends for average H_s were around 3-4 $cm/year$ for the whole summer (0.1-0.2 $s/year$ in T_p). The largest overall trends were encountered closer to the ice edge in the Barents and Kara seas with rates reaching values up to 12 $cm/year$ for H_s (0.5 $s/year$ for T_p) in December in the region close to the ice edge – between Svalbard and Novaya Zemlya islands. As demonstrated in section 5.3, the decreasing trends in sea ice concentration are the largest in the same region. That explains the high increasing rates in H_s and T_p found in this study. In November, besides sea ice reduction, the wind speeds also increased in this region as demonstrated in Figure 5.4. However, in December, the month that experienced the highest trends in median H_s , the winds did not present significant changes in this region. This makes evident that the contribution of the sea ice reduction in the increasing trends in H_s is more significant than the changes in wind speeds.

The region encompassing the Norwegian and southern Barents seas experienced statistically significant decreasing trends in median H_s in winter (January-March) with rates around -3 $cm/year$. The same region presented increasing trends of ~ 3 $cm/year$ in May and September (Figure 5.8). As shown in Figure 5.9 the downward trends in winter are not so significant for the peak period with values of only 0.05 $s/year$ around the southern Barents Sea and in some points close to Iceland.

In the Denmark strait, large upward rates of H_s of approximately 10 $cm/year$ were found in January, February, and March. It is interesting to note these large upward trends in this region in this season in contrast to the downward trends found in the adjacent areas. This can be explained by the reduced ice coverage in this region that allowed waves to reach regions that were covered by ice before (see Figure 5.2). Even though the downward trends of wind speeds in this region during the same months (January – March), the wave heights have significantly increased. This can bring some attention to this region, where the upward rates can get even larger if the wind speed patterns change.

In the Baffin Bay, the months with statistically significant increasing rates include the summer months with rates of approximately 3 $cm/year$. The Labrador Sea also presented increasing trends reaching values of 6 $cm/year$ in February, and 3 $cm/year$ in September, November, and December. In this region including the Baffin Bay and

the Labrador Sea, the increasing trends in H_s can be explained by sea ice reduction (Figure 5.2) and also by the increasing wind speeds in the same months (Figure 5.4).

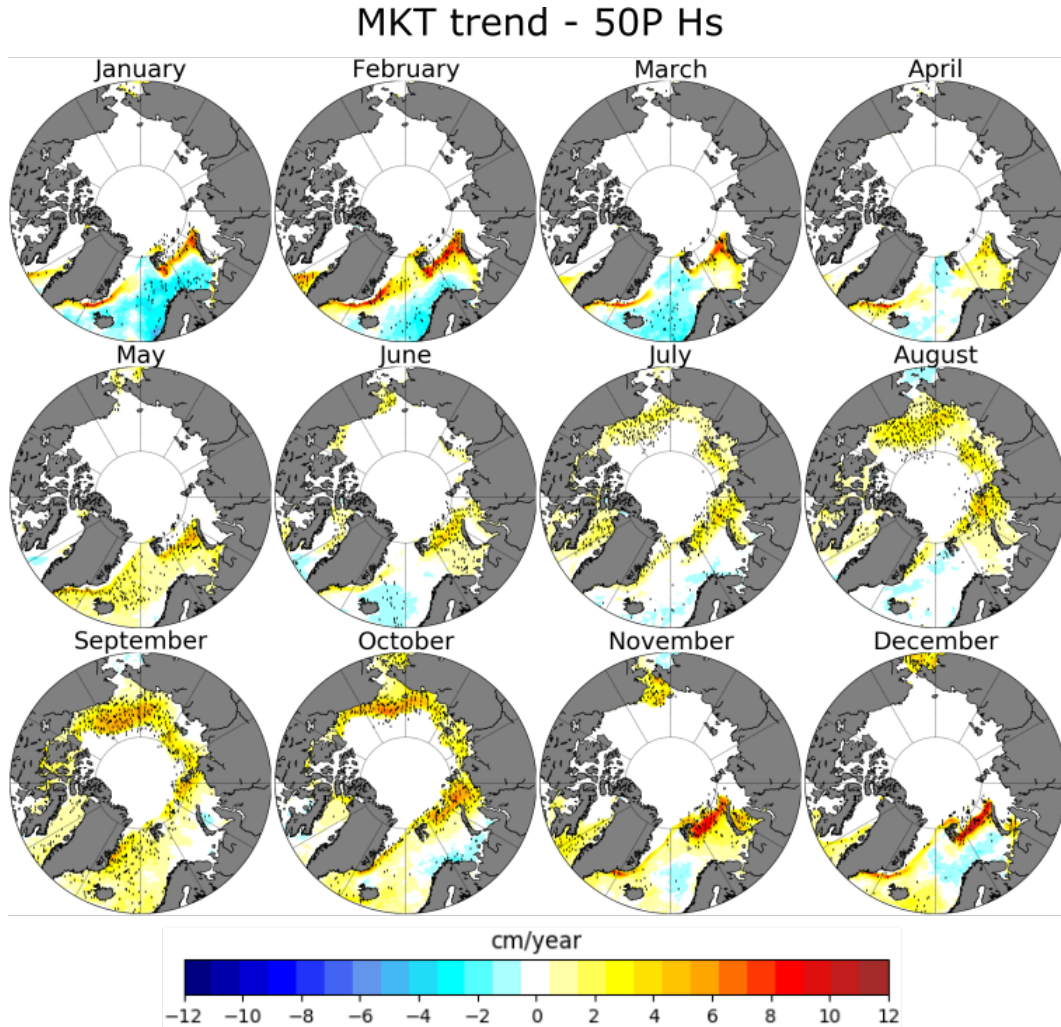


Figure 5.8: Monthly trend estimates (Sen's slope) of median significant wave heights ($cm/year$) in the Arctic Ocean. Dots indicate statistically significant trends at the 95% level.

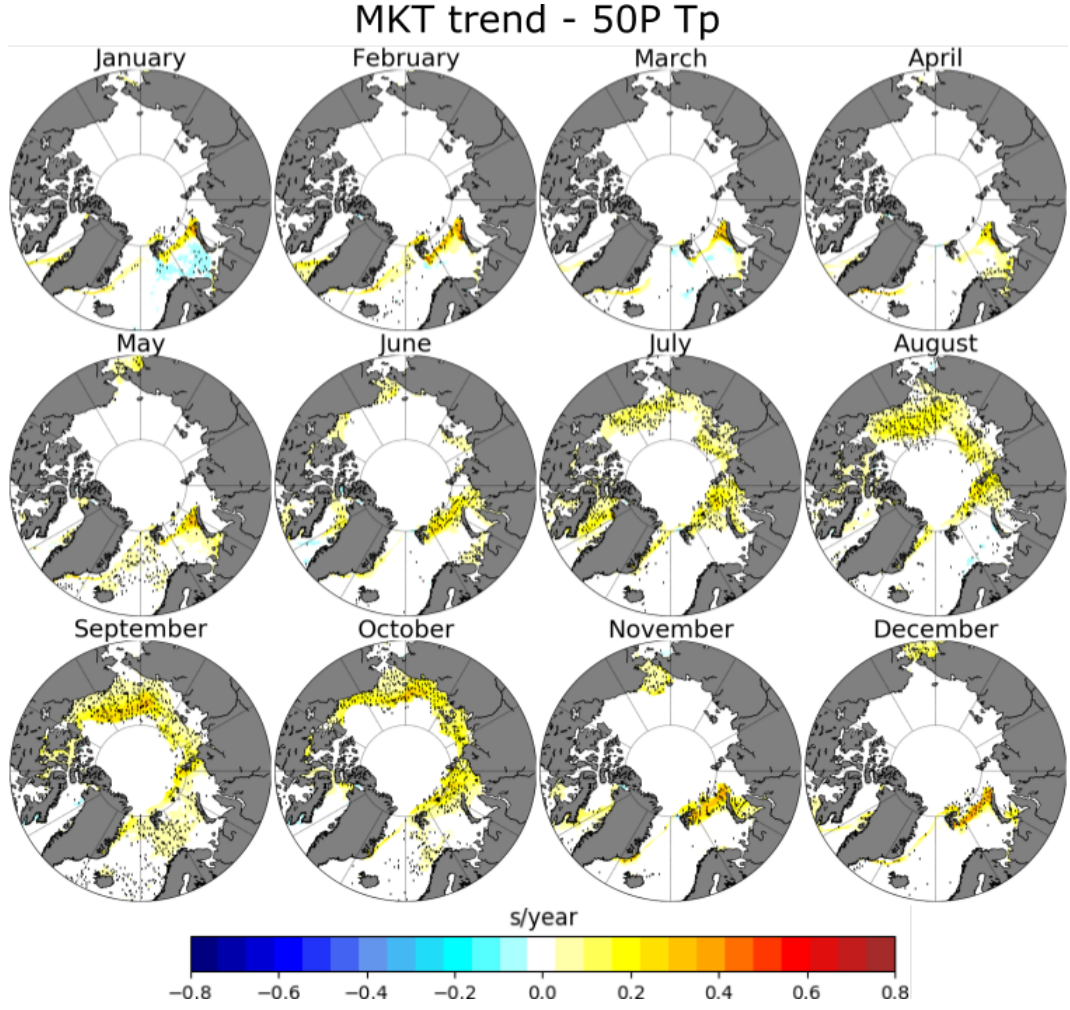


Figure 5.9: Same as Figure 5.8, but trends for median peak periods ($s/year$).

The figures 5.10 and 5.11 present the monthly trend of the 90th percentile of significant wave heights and peak periods, respectively. The patterns were very similar to the ones found by the trends of the average estimates in figures 5.8 and 5.9, but the rates are significantly higher for this percentile. The seas that are covered by ice during most part of the year, like Beaufort, Chukchi, Laptev, and Kara Seas show consistent upward trends with rates around 10 to 12 $cm/year$ ($\sim 0.2-0.4$ $s/year$ for 90th T_p). The largest trends were also found close to the sea ice edge in the Barents Sea with values reaching 20 $cm/year$ in November (~ 0.6 $s/year$ for 90th T_p). Even though very similar patterns compared to the trends in median H_s , one can not some differences between them. For instance, there was a statistically significant downward trend in 90th percentile of T_p on the Atlantic side of the Arctic Ocean in October, whereas one can note an increasing trend for the same region for median H_s .

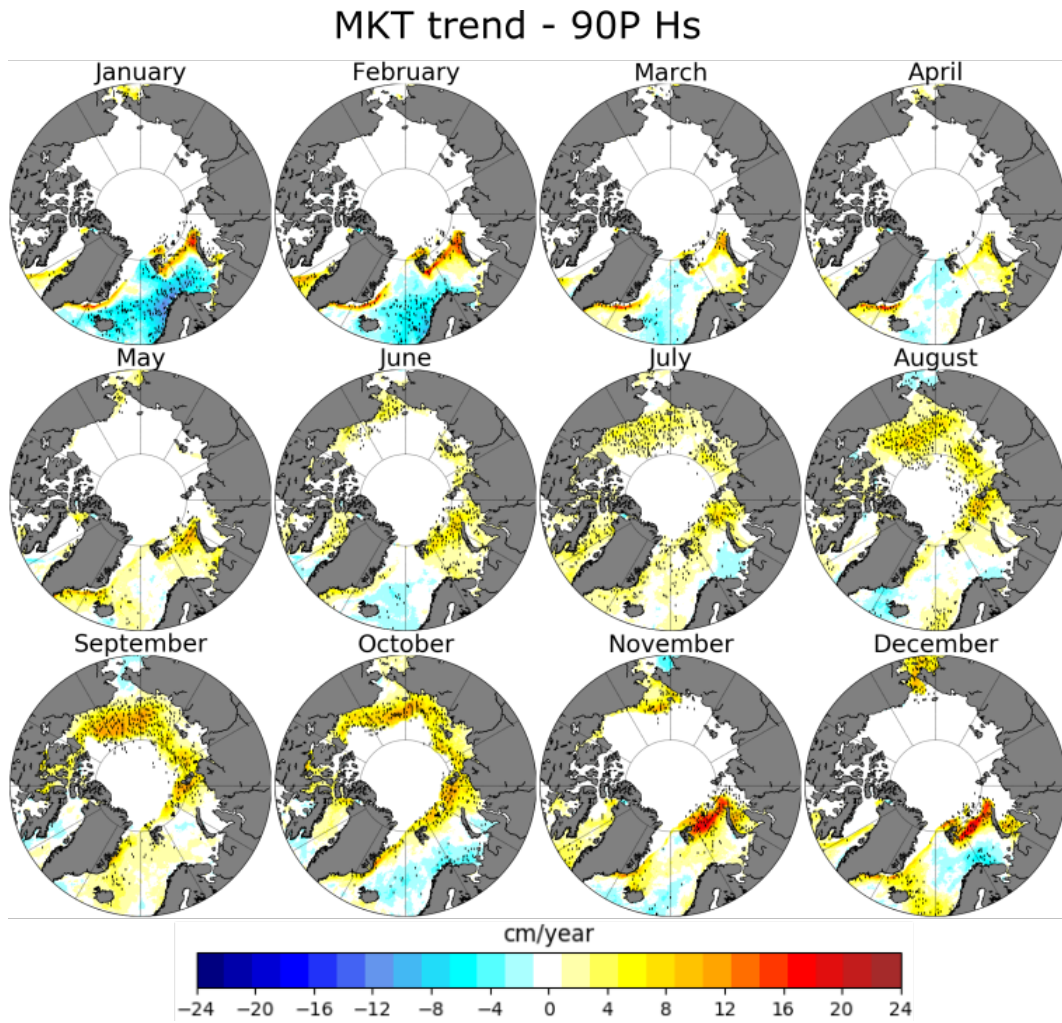


Figure 5.10: Same as Figure 5.8, but trend estimates for 90th percentile of H_s ($cm/year$) .

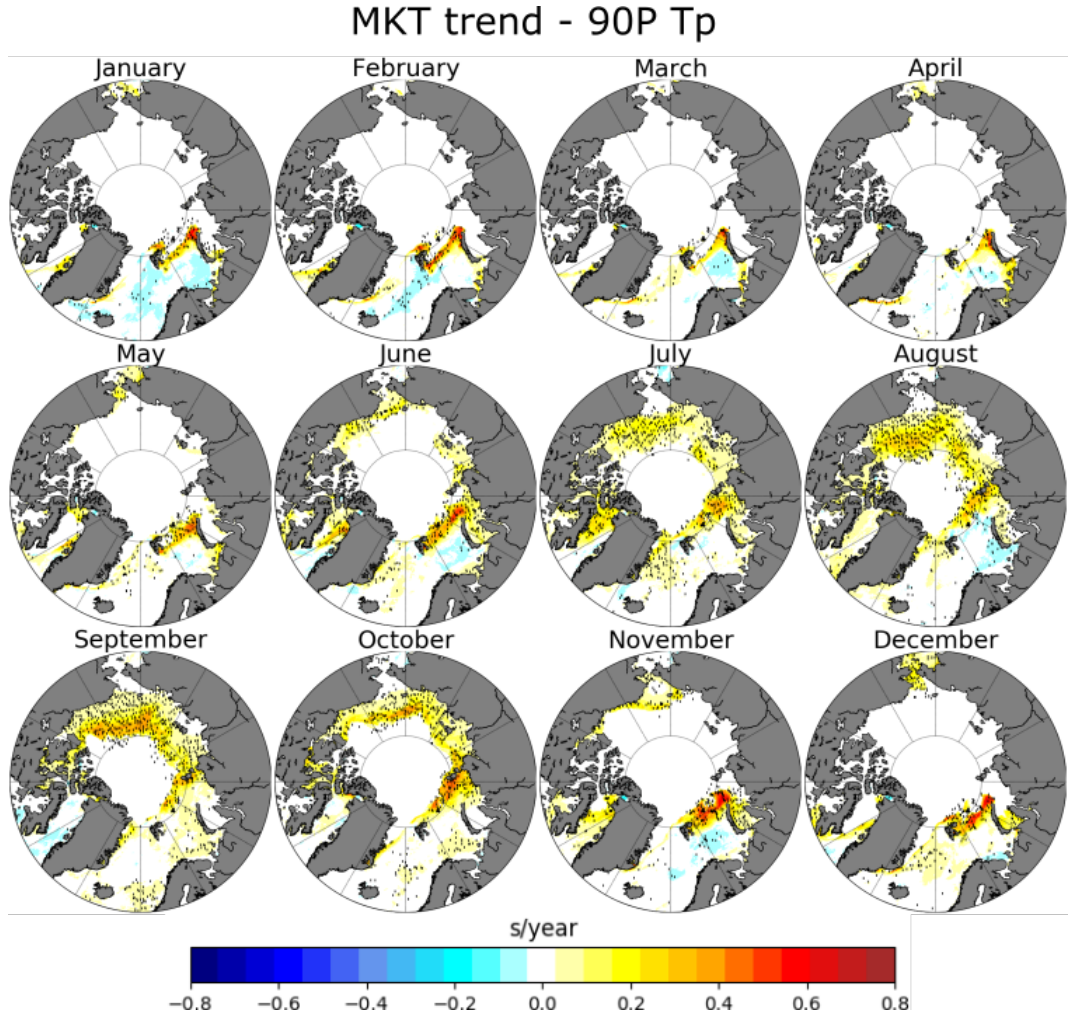


Figure 5.11: Same as Figure 5.8, but estimations for 90th percentile of T_p (s/year).

The monthly MKT trends for the 99th percentile for H_s and T_p are presented in figures 5.12 and 5.13. It is easy to see that the trend patterns for the most extreme waves are similar to the trends in median waves. The rates for 99th percentile trends, however, are roughly twice as higher than for the average wave heights with increasing trends reaching values of 16 *cm/year* in the Beaufort Sea and around 24 *cm/year* in the Barents Sea.

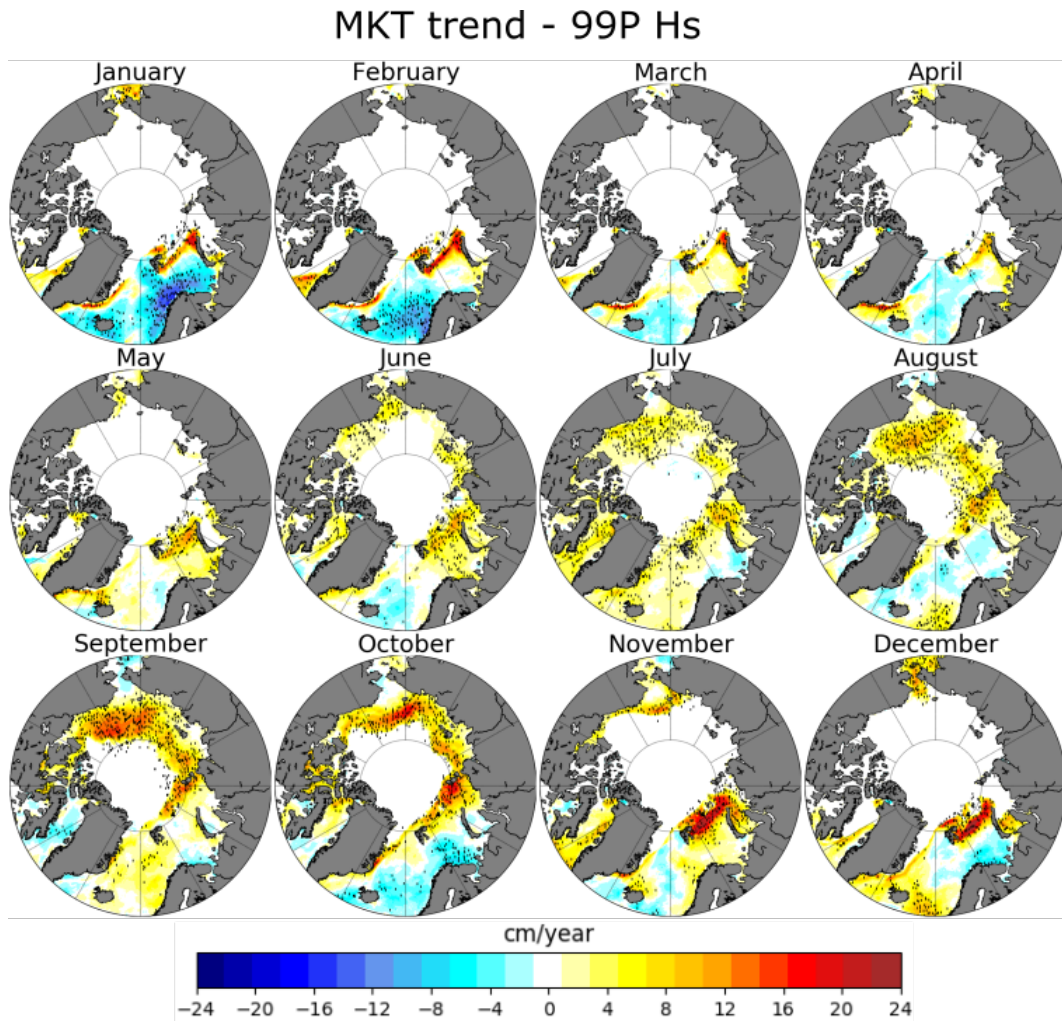


Figure 5.12: Same as Figure 5.8, but estimations for 99th percentile of H_s (cm/year)

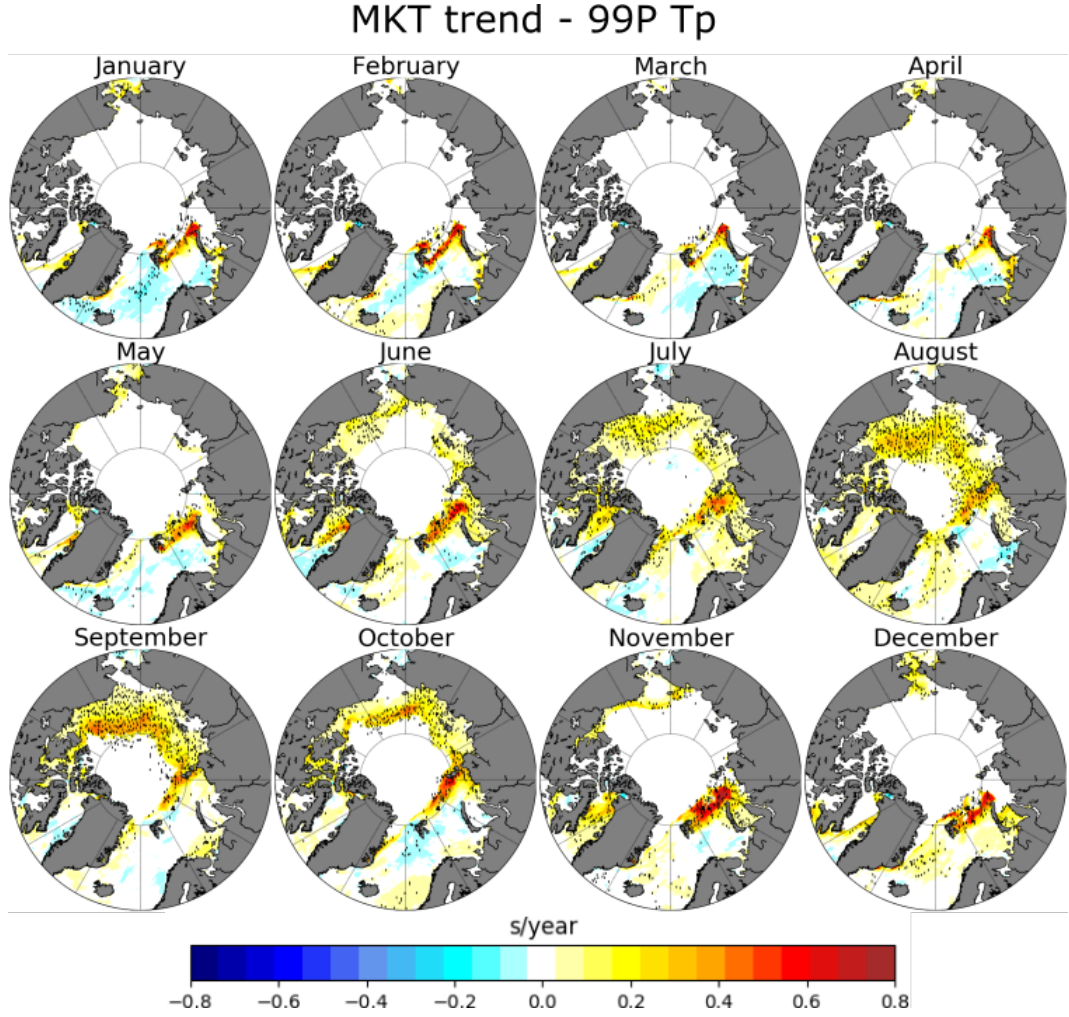


Figure 5.13: Same as Figure 5.8, but trends for 99th percentile of T_p (s/year).

The Figure 5.14 shows the Sen's slope estimates for the Seasonal Kendall test (SKT) for median, 90th and 99th percentiles of H_s and T_p , considering the trends throughout the whole year together. Both H_s and T_p have very similar trend patterns. Most of the basin experiences a consistent upward trend with rates in median H_s of approximately 1 cm/year and in median T_p of ~ 0.05 s/year. The strongest trends in median H_s and T_p (~ 4 -5 cm/year and 0.2 s/year, respectively) occur close to the sea ice edge in the Barents Sea and in the Denmark Strait. The trends delivered by the SKT test for the 90th and 99th percentiles show very similar trend patterns to the ones estimated by the monthly averaged H_s , but with upward rates reaching 7 cm/year for 90th percentile of H_s (0.3 s/year for T_p) and 9 cm/year (0.4 s/year for T_p) for 99th percentile of H_s . The overall rates were approximately 2-3 cm/year in most part of the Arctic Ocean and a downward trend of approximately 1-2 cm/year

close to the Norwegian Sea. The downward trends were not statistically significant for the median H_s .

The trends found here are consistent with the ones found by Stopa et al. (2016). They computed the Sen's Slope with the MKT test for monthly averaged H_s for 23 years (1992-2014) based on altimeter observations and wave hindcast performed with CFSR wind forcing. According to their results, the trends in wave heights for the whole period were negative for the region closer to the North Atlantic Ocean, with the exception of the Denmark Strait. The downward trends in this region were about 1 cm/year. They also found consistent upward trends across the regions where are covered by ice during most part of the year with rates of approximately 1-2 cm/year with values reaching 4 cm/year in the areas close to the ice edge in Beaufort, Kara, Barents and Laptev seas (Stopa et al., 2016, Figure 8).

Liu et al. (2016) also computed the trends based on 20-year altimeter data for the months with minimum ice coverage (August and September) for the period between 1996-2015. They found increasing trends in regions including Chukchi, Laptev, and Kara Seas and the Baffin Bay with rates of approximately 2 cm/yr with the strongest rates of 4 cm/year (Liu et al., 2016, Figure 7). Their results were consistent to the trends found by the pioneering altimeter-based work of Francis et al. (2011) that showed upward trends of 2 cm/yr in the Chukchi Sea and 34 cm/yr along the Beaufort Sea for the period between 1993-2010 (Francis et al., 2011, Figs. 3 and 4).

Stopa et al. (2016) also presented trends of the annual number of ice-free days per year and the strongest trends were located in the Barents and Kara seas with 8 more ice-free days per year. Regions including the Denmark Strait, Beaufort and Laptev seas had approximately 4 or 5 more ice-free days per year in that period. These results explain the upward trends in wave heights that occur in those regions.

In this study, the SKT results for median H_s did not show decreasing trends in the region closer to the North Atlantic Ocean, as demonstrated by Stopa et al. (2016), but we could note downward trends for median H_s in the winter months in this region (Figure 5.8) and also for the SKT trends in 90th and 99th percentiles of H_s (Figure 5.14). As demonstrated in previous studies (e.g Semedo et al., 2015; Stopa et al., 2016), the negative North Atlantic Oscillation observed in this period was responsible for the downward trends in wind speeds and consequently in wave heights. Semedo et al. (2015) demonstrated an important agreement between H_s and the NAO in the Nordic seas, supporting the fact that the trends in waves are related to the large scale atmospheric circulation.

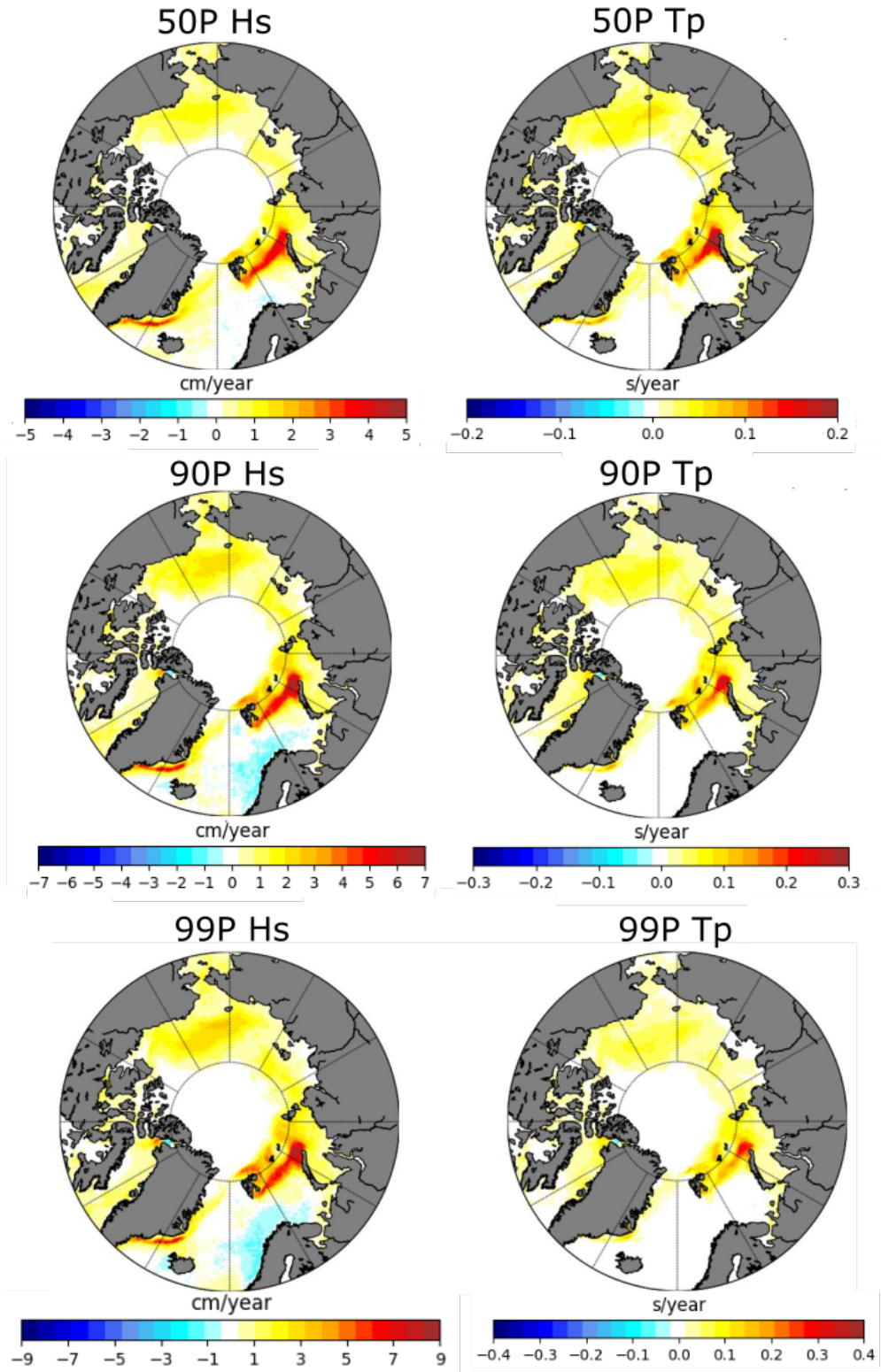


Figure 5.14: Sen's slope estimates with Seasonal Kendall trends for 50th (upper panels), 90th (middle panels), and 99th (bottom panels) percentiles of significant wave heights (*cm/year*) (left panels) and peak periods (*s/year*) (right panels) in the Arctic Ocean. All of the points plotted are statistically significant trends at the 95% level.

5.6 Conclusions

The Mann-Kendall test (MKT) was applied to identify trends in different metocean parameters such as sea ice concentration, wind speeds, significant wave heights, and wave periods. The results demonstrated that these metocean parameters are changing in a significant way across the Arctic and the changes vary significantly in different seasons of the year. In the summer period, the trends show a sharp rise in the significant wave height due to the sea ice melting that is occurring in the last decades. This is evident in the regions that are covered by ice in most part of the year such as in Beaufort-Chukchi, East Siberian and Laptev seas. On the Atlantic side of the Arctic Ocean, the trends vary spatially and also temporally. In seven months of the year, the trends in wave height in the Norwegian Sea were downward and it followed the trends on winds. It is explained by the negative NAO observed in the period. The Seasonal Kendall test (SKT) that considers the trends along the entire year by summing up the trends in each month demonstrated an overall increasing trend across the Arctic, except for the Atlantic side where the trends for H_s were 1-2 *cm/year* downward for the higher percentiles. The trends in wind speeds were less dramatic, comparing to the trends experienced by sea ice concentration and wave parameters. Essentially, we could notice a slight downward trend on the Atlantic side of the Arctic Ocean and an upward trend on the Pacific side.

The SKT trends for the most extreme conditions for each parameter make evident that the sea ice melting has major responsibility for increasing trends in the wave heights across the Arctic Ocean. Whereas, the downward trends in H_s in the Atlantic sector are caused by a downward trend in wind speeds (Figure 5.15).

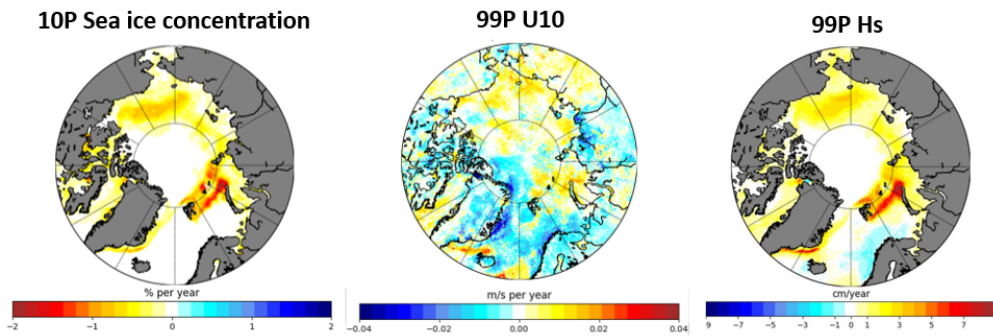


Figure 5.15: Sen's slope estimates with Seasonal Kendall trends in 10th percentile of sea ice concentration (left panel), and 99th percentiles of wind speeds (middle panel) and significant wave heights (right panel) in the Arctic Ocean. All of the points plotted are statistically significant trends at the 95% level.

Chapter 6

Extreme value analysis of winds and waves

6.1 Introduction

Extreme value analyses (EVA) are used in estimating the magnitude and frequency of extremes of different environmental variables. The determination of extreme value estimates of wave heights is crucial in coastal and offshore applications. Extreme events in oceans are often associated with destructive accidents with high environmental, economic, and social costs. Considering the high rates of coastal erosion and changes happening in the Arctic coastlines, a correct estimation of extreme waves in this region has significant importance in evaluating risks affecting human life, coastal habitats, and infrastructures.

Observations and model data are seldom continuous and long enough to allow estimates of extreme values with a return period of 100 years that are normally required in oceanography activities. Hence, a common practice is to extrapolate the available time series for a return period longer than the duration of the observations after fitting a parametric distribution to lower probabilities of exceedance (Breivik et al., 2013). In other words, extreme value analysis is based on fitting a theoretical probability distribution function (PDF) to the observed extreme values, in order to extrapolate the tail and estimate the extreme values for a given return period (e.g. 50 or 100 years).

Notable efforts have been made in order to accurately estimate return period values of different metocean variables, such as significant wave height. There is a number of different studies around extreme estimates of environmental variables based on a wide variety of data sets, such as altimeter data (Alves and Young, 2003; Vinoth and Young, 2011; Young et al., 2012), long-term reanalyses (e.g. Muis et al., 2016),

model hindcasts (Aarnes et al., 2012), and ensemble data (Breivik et al., 2013; Meucci et al., 2018). Ideally, a long-duration time series of observations should be used on extreme value analyses. For instance, in order to evaluate significant wave heights, the easiest way to obtain long measured time series is to use buoys, offshore platforms data, or satellite data. However, the records are usually not long enough or not consistent in time and space. Hence, a validated numerical model has the advantage of temporal and spatial consistency.

Normally, those extreme estimations are based on two extreme value distributions: the generalized Pareto (GP) and the generalized extreme value (GEV). The nature of the historical dataset will determine the best distribution to fit the PDF of a given environmental variable. There are three different approaches to extreme value analysis that have been extensively used in the estimation of the wave extremes: the initial distribution method (IDM), the annual maximum method (AMM), and peaks-over-threshold method (POT) (Coles et al., 2001; Goda, 2010; Ochi, 1993).

The IDM method is normally used when the size of the observed time series is relatively small (Goda, 2010; Coles et al., 2001). This method consists in fitting a PDF to the entire dataset and extrapolate it to the desired return period. This method allows stable estimates. However, there is a number of drawbacks, such as dubious accuracy of the tail as it is extrapolated by fitting a distribution with the entire body of the PDF. Besides that, there is no guidance in the literature on the choice of the PDF to be used in fitting the data.

The independent maxima approach, as opposed to IDM, consists of two categories: asymptotic and threshold models (Coles et al., 2001). In this approach, in order to achieve valid estimates of the extremes, the data should be independent and identically distributed (IID). In order to be independent, the data selected must be statistically uncorrelated. For instance, the data points should not be derived from the same storm. A practical solution is defining a time window of 48 hours when selecting the peaks of a time series, in order to avoid selecting data from the same storm (e.g. Vinoth and Young, 2011; Takbash et al., 2019; Meucci et al., 2018).

For asymptotic models, the extreme value theorem indicates that a generalized extreme value (GEV) distribution can be applied:

$$F(x) = \exp\left\{-\left[1 + k\left(\frac{x-a}{B}\right)\right]^{\frac{-1}{k}}\right\} \quad (6.1)$$

where $F(x)$ is the cumulative distribution function, and k , A , and B are shape, location, and scale parameters, respectively. The GEV can assume three forms depending on the value of the shape parameter k :

- Gumbel (type 1) distribution when $k = 0$
- Fréchet (type 2) distribution when $k > 0$
- Weibull (type 3) distribution when $k < 0$

For Weibull distribution, when $k < 0$, there is an upper bound to the distribution. For the other two distributions (Gumbel and Fréchet), there is no upper bound to the magnitude of x , and it can assume very large values tending to infinity, even though at very low probability levels.

In the case of asymptotic models, the time series usually consists of extraction of the annual maxima (AM). One advantage of the AM approach is a comprehensive theoretical basis and the warranty of IID data. However, in this method, the time series are usually short as only one value is taken per year. Hence, this method rarely allows robust estimates of the desired return values (e.g. Meucci et al., 2018; Takbash et al., 2019). One way to solve this issue is by applying the so-called peaks-over-threshold (POT) approach (Pickands, 1975) that considers only the exceedance of a certain threshold. In such a case, the data follows a generalized Pareto distribution (Coles et al., 2001):

$$F(x) = 1 - \left[1 + k \left(\frac{x - A}{B} \right) \right]^{-\frac{1}{k}} \quad (6.2)$$

where A is the value of the threshold, which is usually based on high percentiles (e.g. 90th percentile; Takbash et al., 2019; Meucci et al., 2018). Nonetheless, there is no theoretically robust approach to the threshold selection. One should consider the stability and bias of the distributions for a given time series. In other words, the threshold should be low enough to ensure sufficient data to fit a stable PDF and large enough to avoid bias on fitting the extreme value distribution.

These established EVA methods assume that observations are a stationary process. However, trends and low-frequency oscillations such as seasonality have a significant influence in return value estimates (Coles et al., 2001). Considering the seasonality and the dramatic changes in metocean parameters occurring in the Arctic, such as large increasing trends in significant wave heights, the standard stationary approach is not suitable for the estimation of extreme values in the Arctic. Therefore, in order to evaluate the extremes in this region, an alternative method that takes into account the time-varying time series should be selected. In the present analysis, a non-stationary method developed by Mentaschi et al. (2016) was applied for wind speeds and significant wave heights.

6.2 Stationary method

To date, extreme winds and waves have not yet been investigated across the entire Arctic Ocean. In order to have an initial benchmark of extreme winds and waves across the Arctic Ocean, a standard stationary EVA was applied before assessing the extreme values with a non-stationary method.

6.2.1 Peaks-over-threshold (POT) approach

As mentioned previously, the POT approach is suitable for estimating extremes of different environmental variables as it can ensure enough extreme data to obtain stable and not biased probability density functions. Hence, the methodology adopted here is based on this approach with the GPD distribution to fit the extreme value series. The resulting extreme values are often strongly dependent on the selection of the threshold. Considering that significant part of the Arctic Ocean is covered by sea ice in a great part of the year, 28-years of data at some points correspond to fewer data compared to other regions of the planet that have waves all year round. In some cases, it is common to set a threshold of around 98th percentile in the POT method. However, such a high threshold provides fewer peaks for fitting a theoretical distribution. In particular, points located close to the sea ice edge will not have enough data to fit a PDF. Therefore, we consider a threshold of 90th percentile in the analyses performed in this study.

6.2.2 Wind extremes

Firstly, the POT approach was applied to winds that are the driving forces of surface waves. Figure 6.1 shows the 100-year return period values, their corresponding 95% confidence intervals (CI95) for U_{10} (m/s), and its upper limits obtained with a POT approach and a GPD distribution in a stationary approach with a threshold set for the 90th percentile of the ERA5 dataset. The CI95 is estimated, assuming that the uncertainty distribution around the return levels is log-normal with standard deviation. The highest values of U_{10}^{100} occur in Greenland (approximately 40 m/s). There were some points in Northern Greenland that reached values of 50 m/s, however, the results for this region have wide confidence intervals as shown on the right panel of Figure 6.1. Overall, the U_{10}^{100} were approximately 20-25 m/s across the Arctic Ocean and the CI95 was lower than 0.5 m/s with low spatial variability. These results are in good agreement with the ones estimated by Breivik et al. (2014) who estimated U_{10}^{100} based on global ensembled with stationary POT (threshold 99.7th percentile) and

exponential distribution (e.g. Fig.1; Breivik et al., 2014). However, one should note that even though with high confidence levels, the stationary approach does not consider the seasonality and the long-term trends in the analysis.

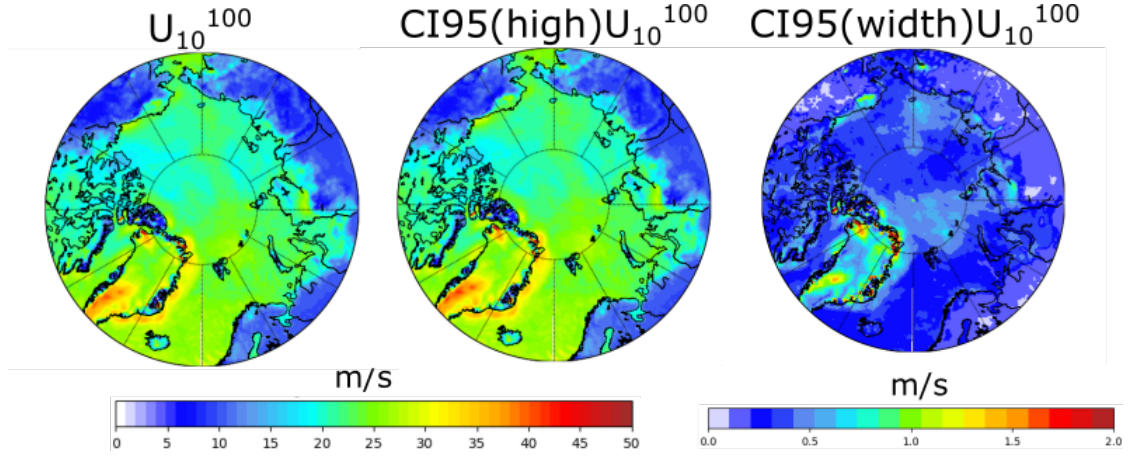


Figure 6.1: 100-year return period values for U_{10} (m/s) obtained with a POT analysis (90^{th} percentile) and a GPD distribution in the stationary approach (left panel); upper limit of 95% confidence interval for U_{10}^{100} (middle panel); and width of 95% confidence interval for U_{10}^{100} (right panel).

6.2.3 Wave extremes

The wave extreme estimates and corresponding confidence intervals based on the stationary approach of the POT method (threshold of 90^{th} percentile) and GPD distribution applied to the 28-year hindcast performed in this study are shown in Figure 6.2. The results show more energetic waves on the Atlantic side of the Arctic Ocean ($H_s^{100} \sim 14$ m), whereas, the values of H_s^{100} are much lower on the Pacific side ($\sim 6-7$ m). The less energetic waves occur due to geographical features of this region with limited fetches in this region that limit the development of the waves. In contrast to the enclosure seas of the Pacific side, the seas located on the other side of the Arctic Ocean are affected by energetic swells coming from the North Atlantic. The results estimated for the Norwegian Sea here are lower compared to Breivik et al. (2013). These differences can be explained by the inconsistency of not incorporating the long-term variability and seasonality in the estimations using this conventional stationary approach of EVA.

The left panel of Figure 6.2 reveals higher uncertainties close to the ice edge. These results are expected as there are fewer data in those regions, as the sea is covered by ice in most part of the year. Overall, the confidence levels were quite narrow with values lower than 0.5 m across the Arctic and lower than 1 m close to the ice edge.

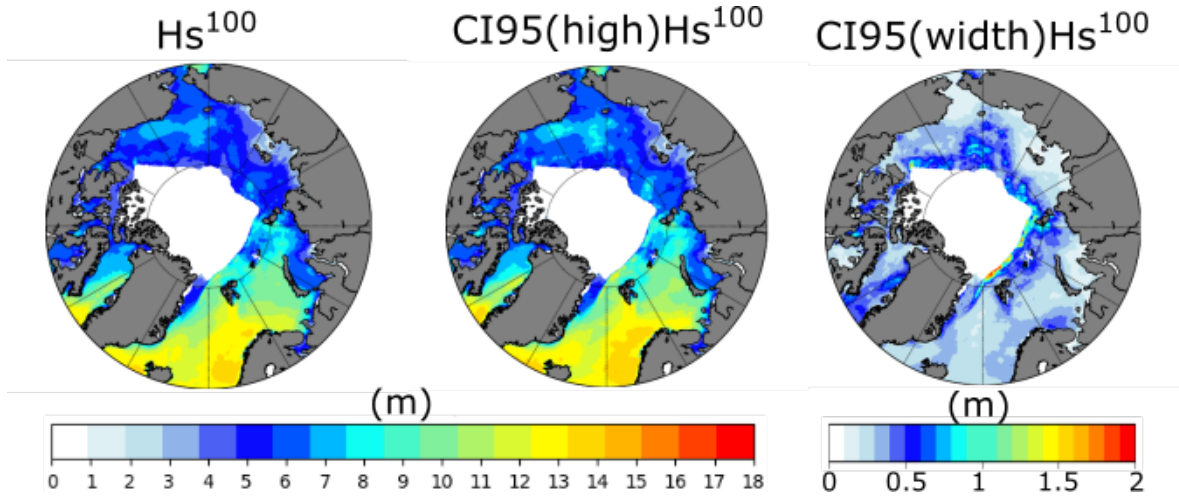


Figure 6.2: As in Figure 6.1, but for H_s (m).

6.3 Methodology for non-stationary EVA

Trends and seasonality can affect the accuracy in extreme estimates from different environmental variables considerably (Coles et al., 2001). This problem can be overcome by selecting non-stationary techniques that take into account non-stationary features of time series in the estimations of extreme values (Coles et al., 2001; Mentaschi et al., 2016). Estimating trends from historical data sets with long-term variability becomes crucial with climate change. In particular, the dramatic changes that are occurring in the Arctic Ocean, such as large increasing rates in wave heights, should be incorporated into the extreme estimations.

Previous studies have evaluated the impact of climate change in extreme value analysis for different environmental variables. For instance, Kharin and Zwiers (2005) assessed changes in extremes of near-surface air temperature and precipitation by applying GEV distribution on annual extremes with time-dependent parameters and fitted by the method of maximum likelihood (Coles et al., 2001). Wang and Swail (2006) examined the impact of changes in waves using combined climate models' projections for different forcing scenarios and non-stationary GEV analysis described by Wang et al. (2004).

A general theory for non-stationary extreme value analysis has not yet been formulated (Coles et al., 2001). However, there is a number of studies introducing different methodologies for non-stationary EVA that use standard extreme value theories enhanced with statistical techniques that take into account changes in time such as

long-term trends and seasonality (e.g. Coles et al., 2001; Husler, 1986; Davison and Smith, 1990; Mendez et al., 2006; Mentaschi et al., 2016).

A well-know non-stationary approach consists in expressing time-varying parametric functions in order to obtain the parameters of an EVA. The maximum likelihood estimator (MLE) is usually used in the process of the distribution as its versatility on estimating the changes of a model structure (Coles et al., 2001). However, this established method does not indicate a formulation of the time-varying parametric functions. Coles et al. (2001) suggest that the model should be simple and at the same time should be able to explain as much of data variability as possible. Therefore, several models should be tested in order to assess the maximum likelihood and low degrees of freedom, making the process quite complex.

Another option is to slice the data sets into quasi-stationary different parts and apply a stationary EVA (Vousdoukas et al., 2016). Nevertheless, this approach leads to shorter time series that increase the uncertainties in the estimation of long-term periods.

Other non-stationary EVA methods were recently developed in order to account the climate change in extreme estimations (e.g. Cheng et al., 2014; Vanem, 2015; Mentaschi et al., 2016). Cheng et al. (2014) introduced an EVA method based on Bayesian inference and Differential Evolution Markov Chain (DE-MC) for global optimization over the real parameter space and it assesses trends in the observations and if needed, performs a non-stationary analysis. Vanem (2015) developed various non-stationary GEV models for significant wave height that are fitted to block maxima in a particular set of wave data obtained for a historical control period and future projections based on different emission scenarios.

Mentaschi et al. (2016) proposed the so-called Transformed Stationary (TS) method that overcomes the complexity of estimating the time-varying parameters comprising the entire time series available. This methodology consists of transforming a non-stationary time series into a stationary one, performing an established stationary EVA into this resulting time series, and finally back-transforming the obtained extreme value distribution into a time-dependent one based on the trends of the original time-series. This method was chosen in the analysis undertaken in this study.

The transformation of the time series is based on the following equation:

$$x(t) = \frac{y(t) - T_y(t)}{S_y(t)}, \quad (6.3)$$

where $x(t)$ is the stationary time-series, $y(t)$ is the non-stationary time-series, $T_y(t)$ is the long-term trend of the series and the $S_y(t)$ is the long-term varying standard

deviation. The computation of $T_y(t)$ and $S_y(t)$ are based on a running mean acting as a low-pass filter removing the variability within a given time window W . In this study, we chose the long-term time window of 5 years which provided an adequate estimation of the long-term trends.

In order to ensure a stationary time series $x(t)$, the equation 6.3 should guarantee uniform average and standard deviation of $x(t)$ in time. Therefore, it is recommended checking if the time series is stationary before applying the EVA to the transformed signal. The simplest option is checking if its higher-order statistics such as kurtosis and skewness are roughly constants (Mentaschi et al., 2016).

After the verification of the stationarity of $x(t)$, one should select the distribution that best fits its extremes. In this study, the POT method was applied. As discussed in section 6.1, the POT method consists in fitting the GPD to a certain threshold defined as a higher percentile of a time series that should guarantee a stable and unbiased PDF. In this study, the 90th higher percentile was chosen as the threshold for the EVA in order to obtain sufficient data to fit a reliable PDF. In particular, in the estimation of extreme waves, a condition of at least 1000 highest peaks was set to compute the wave extremes, in order to ensure a stable PDF. It means that at some locations where the sea is covered by ice almost all year round, the TS EVA method was not applied.

According to Mentaschi et al. (2016), the POT/GPD parameters for this non-stationary approach are given by

$$A_y(t) = S_y(t) \cdot A_x + T_y(t) \quad (6.4)$$

$$k_y = k_x = \text{const.} \quad (6.5)$$

$$B_y(t) = S_y(t) \cdot B_x, \quad (6.6)$$

where $A_x(t)$ and $A_y(t)$ are the thresholds of the x and y time series, k_x and k_y are the shape parameters, B_x and B_y are the scale parameters of x and y . The estimation of the trend T_y is based on a running mean of the time series $y(t)$ on a multi-year time window W . This time window is used to estimate the intra-annual variability of the standard deviation

The time-dependent PDF is obtained by incorporating the long-term variability from the original time series into the resulting distribution derived from the EVA applied to the transformed time series. This time-dependent PDF allows getting

partial return period values for a given year and therefore assess the changes of the return period values throughout the period within the time series.

In addition to the long-term variability, the seasonality can also be incorporated on the statistical analysis by adding the seasonal components of the trend and the standard deviation and selecting a seasonal time window (for example 1 or 2 months) for the estimation of the seasonality. In this case, the GPD parameters are given by

$$A_y(t) = S_{0y} \cdot s_S(t) \cdot A_x + T_{0y}(t) + s_T(t) \quad (6.7)$$

$$k_y = k_x = \text{const.} \quad (6.8)$$

$$B_y(t) = S_{0y}(t) \cdot s_S(t) \cdot B_x, \quad (6.9)$$

where $T_{0y}(t)$ and $s_T(t)$ are respectively, the long-term varying and seasonal components of the trend, $S_{0y}(t)$ is the long-term varying standard deviation and $s_S(t)$ is the seasonality factor of the standard deviation. In the notation, the subscript 0 denotes the long-term varying components. In this approach, besides the estimation of the return values for each year of the time series, it is possible to compare the return values for each month.

It is recommended to estimate the associated errors of trends, standard deviation, and seasonality, in order to propagate them to the statistical errors of the non-stationary parameters of the EVA. According to Mentaschi et al. (2016), the errors on the time-varying GPD parameters are as follow:

$$Err[A_y] = \sqrt{\left(S_{0y} \cdot s_S \cdot Err[A_x]\right)^2 + \left(S_{0y} \cdot Err[s_S] \cdot A_x\right)^2 + \left(Err[S_{0y}] \cdot s_S \cdot A_x\right)^2 + Err_T^2} \quad (6.10)$$

$$Err[k_y] = Err[k_x] \quad (6.11)$$

$$Err[B_y] = \sqrt{\left(S_{0y} \cdot s_S \cdot Err[B_x]\right)^2 + \left(S_{0y} \cdot Err[s_S] \cdot B_x\right)^2 + \left(Err[S_{0y}] \cdot s_S \cdot B_x\right)^2}, \quad (6.12)$$

where

$$Err_T^2 = Err^2[T_{0y}] + Err^2[S_T] \quad (6.13)$$

$$Err[s_{0y}] = S_{0y} \cdot \sqrt[4]{\frac{2}{N_t}} \quad (6.14)$$

$$Err[s_T] = S_{0y} \sqrt{\frac{12}{N_{tot}} + \frac{1}{N_t}} \quad (6.15)$$

$$Err[s_S] = s_S \sqrt[4]{\frac{288}{N_{tot}^2 N_{sn}}}, \quad (6.16)$$

where N_t represents the number of observations available during the time period $[t - \frac{W}{2}, t + \frac{W}{2}]$, N_{tot} is the total number of elements of the series $y(t)$, and N_{sn} is the average number of observations within the time window W_{sn} and assuming $N_t \gg N_{sn}$.

6.4 Non-seasonal approach

First, the non-seasonal approach was applied to the ERA5 wind data sets and the wave hindcast performed in this study for 1991-2018. In this approach, just the long-term variations in the estimation of the extremes are considered. The analyses were undertaken using long-term time window (W) of 5 years, which resulted in a satisfactory estimation of the long-term trends. Figure 6.3 shows an example of the long-term estimations based on the running mean with this selected time window for a point located in the Kara Sea for 1993-2017. It can be noticed a good estimation of the long-term trend and its consequences in the time-dependent PDF generated by the non-seasonal TS EVA method using a POT method with a 90th percentile applied to wind and wave extremes over the world oceans from very large ensembles (GPD). It shows a slight downward trend between 1993 to 1999 when this point was covered by ice in most of the year, and an upward trend between 1999 to 2017.

As mentioned before, the advantage of the TS method in climate change studies is the possibility of getting partial return period values for each year within the time series. Therefore, the 100-year return levels for significant wave height (H_s^{100}) were assessed every five years (the same length as W) for the period between 1993 to 2018.

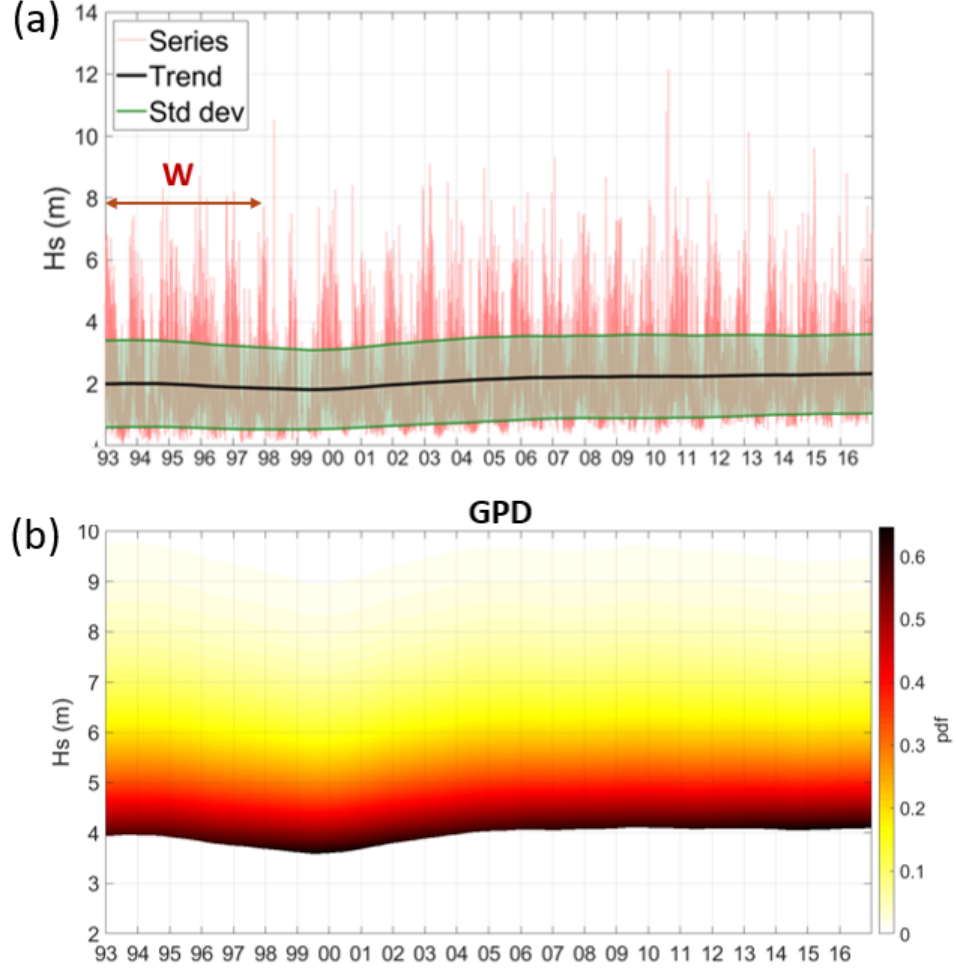


Figure 6.3: Non-seasonal analysis of the projections of significant wave height for a point located in the Kara Sea: (a) series, its trend and standard deviation computed with a time window of 5 years; (b) non-stationary time-dependent GPD of POT (90th percentile).

6.4.1 Wind extremes

Figure 6.4 displays the results for the non-seasonal approach applying the TS EVA method with a POT approach (threshold of 90th percentile) and GPD distribution comparing the 100-year return values for 1993 and 2018. The results for both years are very similar. This is expected, as the long-term trends for wind speeds in the past decades were not significant, as demonstrated in Chapter 5. The 100-year return values estimated for U_{10} were approximately 25 m/s across the Arctic Ocean, reaching values of 40 m/s in Greenland. The discrepancy between these years shows a difference in U_{10}^{100} on the Atlantic side of the Arctic Ocean of roughly $-1-3$ m/s with

strongest differences reaching -6 m/s in the northern Greenland Sea. On the other side of the ocean, close to the Pacific, there was an increase in U_{10}^{100} of $\sim 1\text{-}3 \text{ m/s}$. It corresponds to a decrease of approximately 5-10% in extreme waves on the Atlantic side and an increase of 5-10% on the Pacific side. The Kara Sea also experienced a slight increase of approximately 1 m/s in U_{10}^{100} in this period. It is interesting to see that the slight increase trend in extreme winds occur precisely in the region where a significant sea ice melting is occurring, as shown in Chapter 5.

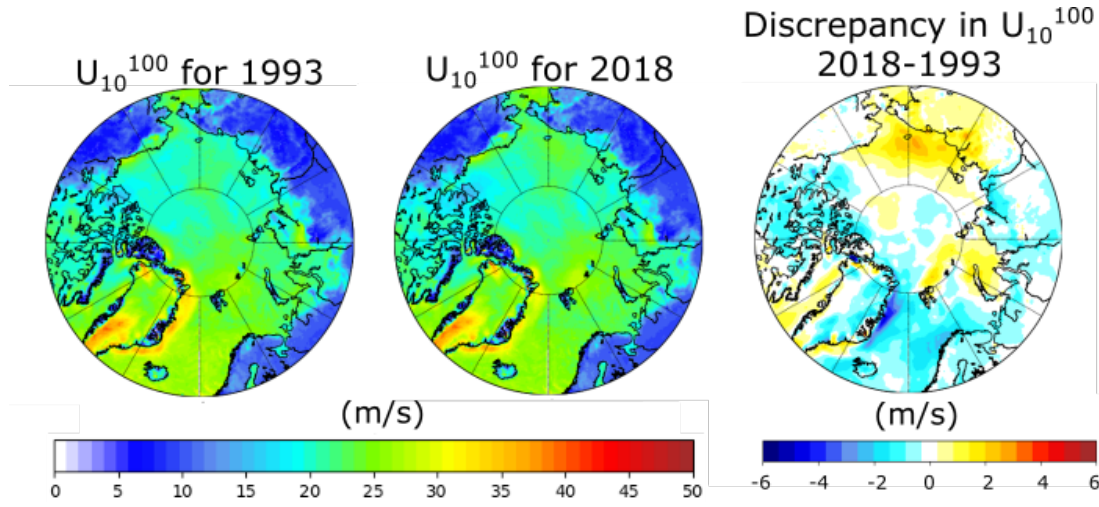


Figure 6.4: 100-year return period values for U_{10} (m/s) obtained with a POT analysis (90^{th} percentile) and a GPD distribution in the TS EVA non-seasonal approach. Results for 1993 (left panel), 2018 (middle panel), and their difference (right panel). Data obtained from ERA5 reanalysis.

Figure 6.5 shows the 95% confidence intervals for the estimations for 2018 in the non-seasonal approach of the TS EVA. The results for this approach were very similar to the ones computed with the stationary approach in section 6.2. The mild long-term trends in winds shown in Chapter 5 explain the similarities between these approaches. Overall, the CI95 widths were lower than 0.5 m/s , and the highest values were found in Greenland, where the most extreme winds occur.

In order to quantify better the changes in extreme winds in each sea, the average of the 100-year return levels over the area of each sea (i.e. areal-average) was computed for each sea every five years from 1993 to 2018 (Figure 6.6). There are no significant trends in the Beaufort, Kara, and Laptev seas, and the Baffin Bay. In these seas, it can be noticed only a small and expected variability in extreme winds in these 25 years. The only seas that are experiencing increasing trends in wind speeds include the East Siberian and Chukchi seas. However, the increases are not significant: in

the Chukchi Sea the increase was only 0.6 m/s and in the East Siberian Sea was 0.8 m/s between 1993 and 2018. On the other side of the Arctic Ocean, there was a slight decrease in extreme winds. The seas that experienced mild decreases were the Barents, Norwegian and Greenland seas. Figure 6.7 displays the values of U_{10}^{100} for each year normalized by the values for 1993 so one can have a qualitative idea of the changes in each sea. The results do not indicate significant trends. The East Siberian Sea has experienced the strongest increase in extreme wind speeds of 4% over these 25 years (an increase of 0.8 m/s , as shown in Figure 6.6). The Chukchi Sea had a slight increase of only 3%. On the other hand, the Norwegian and Greenland seas have experienced decreases of -4.5% and -4% (~ -1.2 m/s and -1 m/s), respectively.

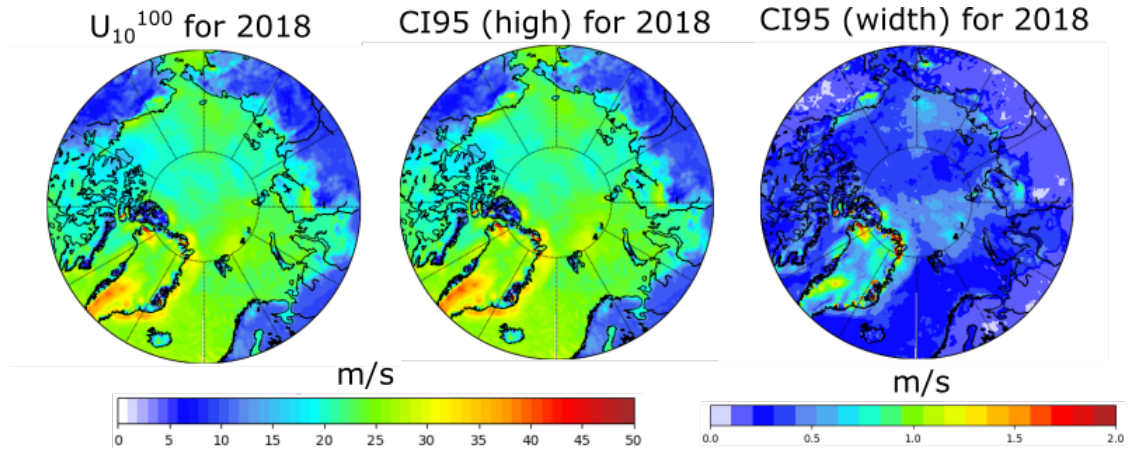


Figure 6.5: U_{10}^{100} (m/s) obtained with a POT analysis (90th percentile) and a GPD distribution in the TS EVA non-seasonal approach for 2018 (left panel); upper limit of 95% confidence interval for U_{10}^{100} for 2018 (middle panel); and width of 95% confidence interval for U_{10}^{100} for 2018 (right panel).

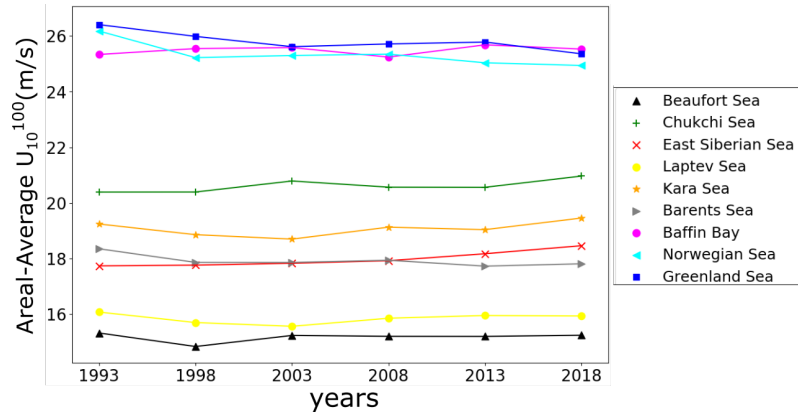


Figure 6.6: Areal-averages of 100-year return period values for U_{10} (m/s) estimated by non-seasonal TS-EVA approach for each sea in the Arctic Ocean.

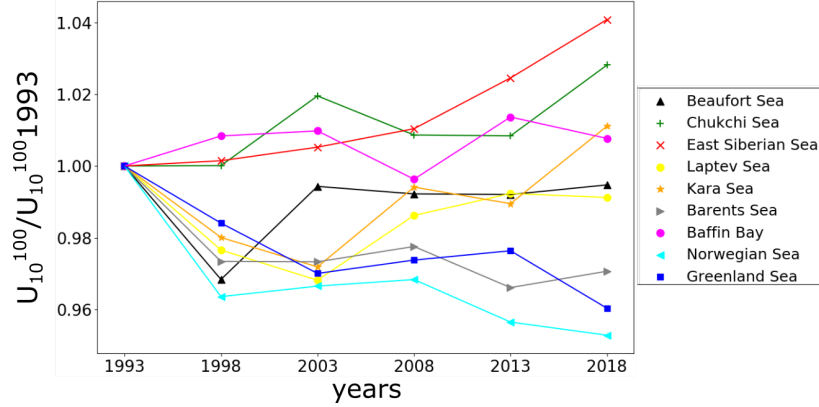


Figure 6.7: Normalized areal averages of U_{10}^{100} for each sea.

6.4.2 Wave extremes

Figure 6.8 shows the 100-year return period values for significant wave height (H_s^{100}) for 1993 and 2018 estimated with the non-seasonal approach of the TS EVA. The largest differences between them were found in the East Siberian and Chukchi seas, and close to the sea ice edge in the Barents Sea.

As expected, the largest 100-year return levels for H_s were found on the North Atlantic side with values higher than 14 m. The values of H_s^{100} estimated for the Norwegian Sea with this non-seasonal TS EVA method are lower than the ones estimated by Breivik et al. (2013, Figure 6). This was the only region that experienced a decrease in extreme waves. It is possible to note that the H_s^{100} for 1993 are slightly higher than the ones estimated for 2018 for this region. These results are consistent with the trends in the 90th percentile between 1991 and 2018 demonstrated in Chapter 5. The Sen's slope computed for this region was approximately -2 cm/year, which corresponds to a decrease of roughly 0.5 m for the 90th percentile of H_s between 1993 and 2018. The right panel of Figure 6.8 shows that the discrepancy in H_s^{100} between these years was around 1-2 m, which is equivalent to a decrease of around 7-15% in H_s^{100} in this region over the last 25 years.

In the rest of the ocean, the differences between return values for 1993 and 2018 show a consistent increase in wave extremes. In the Chukchi Sea, the 100-year return period values for H_s in 2018 were higher than 9 m, and in the Beaufort Sea, they were approximately 8 m. The estimations of H_s^{100} were significantly lower in these areas, especially closer to the ice edge with differences of H_s^{100} for 1993 and 2018 of approximately 4-5 m (an increase of $\sim 60\%$ in H_s^{100}).

For 1993, the values were lower than 4 m in most of the East Siberian and Laptev seas, as shown in Figure 6.8. For 2018 estimations, the values of H_s^{100} experienced significant increases with values reaching up to 9 m in some regions.

Another region of the Arctic Ocean that has experienced significant changes in extreme waves over these 25 years is the region in the north and the eastern side of Svalbard. The discrepancies in extreme waves in these areas reach values higher than 9 m. That happens because energetic waves are recently allowed to propagate in regions where it was covered by ice before as discussed in Chapter 5.

As mentioned before, it was not possible to compute the extreme waves in regions close to the ice edge due to the lack of enough data to fit the distribution, so the apparent minimum sea ice coverage is the area where it was not possible to apply the EVA. Hence, the white regions on the maps correspond to the areas where there was not enough data to fit the PDF. It is important to mention that it does not mean that the H_s^{100} are zero in these regions. In reality, waves can usually propagate through these areas.

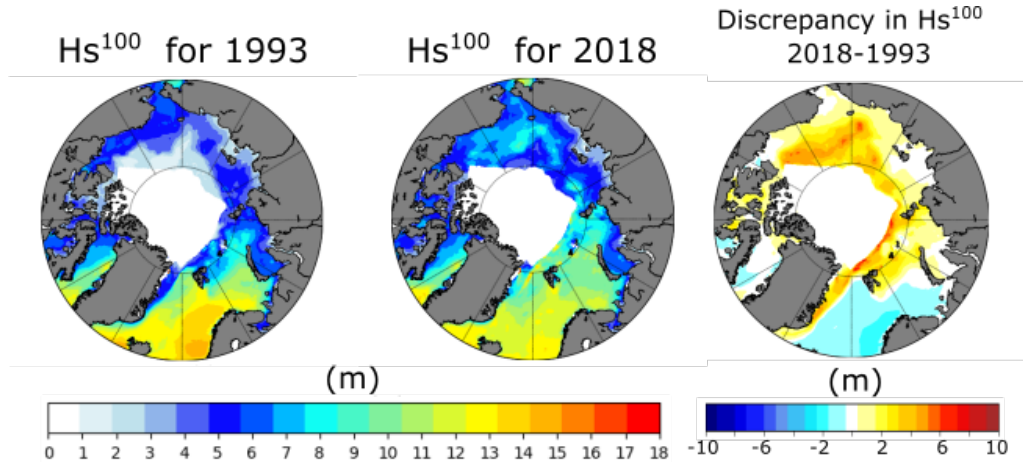


Figure 6.8: 100-year return period values for H_s (m) obtained with a POT analysis (90th percentile) and a GPD distribution in the TS EVA non-seasonal approach. Results for 1993 (left panel), 2018 (middle panel), and their difference (right panel). Data obtained from the 28-year wave hindcast.

The upper limits and widths of the 95% confidence intervals (CI95) estimated by the TS methodology for H_s^{100} for 2018 are shown in Figure 6.9. The widths of CI95 are generally lower than 0.7 m and reaching up to 2 m close to the ice edge. Taking into account the absence of waves where the sea is covered by ice during most part of the year, it is expected smaller data sets in the regions closer to the ice edge. This explains the larger confidence intervals found in these regions. The widths of the 95%

confidence intervals found here are tighter comparing to the ones estimated by Breivik et al. (2013) for the EVA applied to the ensemble data for the region closer to the North Atlantic Ocean (~ 1 m). It is important to stress that the confidence intervals displayed in Figure 6.9 do not account for errors associated with the estimation of the trend, standard deviation, and seasonality.

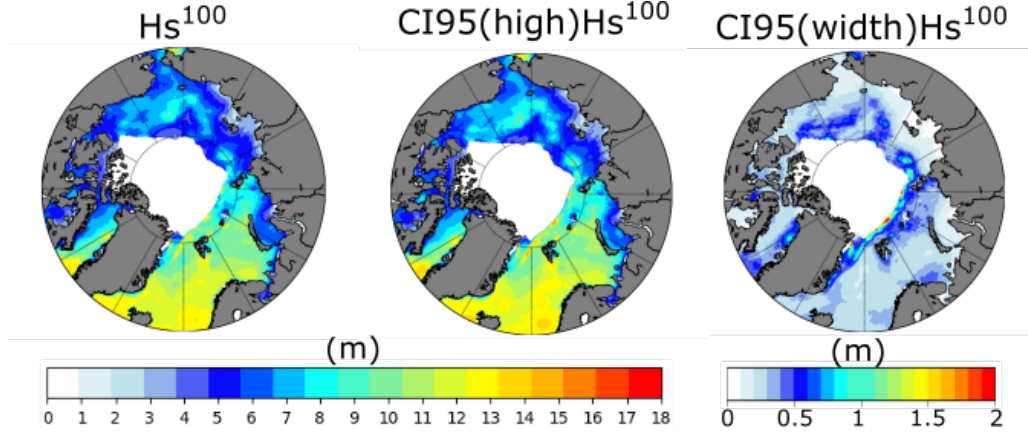


Figure 6.9: H_s^{100} (m) obtained with a POT analysis (90th percentile) and a GPD distribution in the TS EVA non-seasonal approach (left panel); upper limit of 95% confidence interval for H_s^{100} for 2018 (middle panel); and width of 95% confidence interval for H_s^{100} for 2018 (right panel).

The areal-average for each sea of 100-year return levels are shown every five years for 1993-2018 in Figure 6.10. It can be noticed a clear upward trend in the seas that are covered by ice in most part of the year (upper panels in Figure 6.10). In the Beaufort-Chukchi seas, the increase in areal averages was 1.8 m (from 5.1 to 6.9 m). The East Siberian Sea encountered the most significant increase of 2.1 m from 3.5 m to 5.6 m. In the Laptev Sea the increase was slightly lower (~ 1.4 m) and in the Kara Sea was less than 1 m. The changes in extreme waves were not significant in the seas close to the North Atlantic Ocean. In the Baffin Bay, for instance, the areal averages of H_s^{100} vary from 10.4 to 11.1 m with the highest value in 2008.

The Norwegian Sea was the only sea that presented a significant decrease in H_s^{100} of more than 1 m over the 25 years. The extreme waves in this sea are not affected by the reduction on the sea ice in the Arctic, as they are primarily derived from swells generated in the North Atlantic Ocean. The areal averages for H_s^{100} in the Greenland and Barents seas shown in Figure 6.10 demonstrate that these seas have not experienced significant changes in the past decades. However, as shown in Figure 6.8, some regions including the Denmark Strait, the coastal region of the Greenland Sea, and the region closer to the ice edge in the Barents Sea where the sea ice is

melting experienced significant increases in the most extreme waves. Whereas the offshore region of the Greenland Sea and the coastal region of the Barents Sea are experiencing decreasing trends in wave heights due to the downward trends in wind speeds. Therefore, the negative trends in some areas of these seas counterbalance the positive trends in other regions when the areal-average is computed.

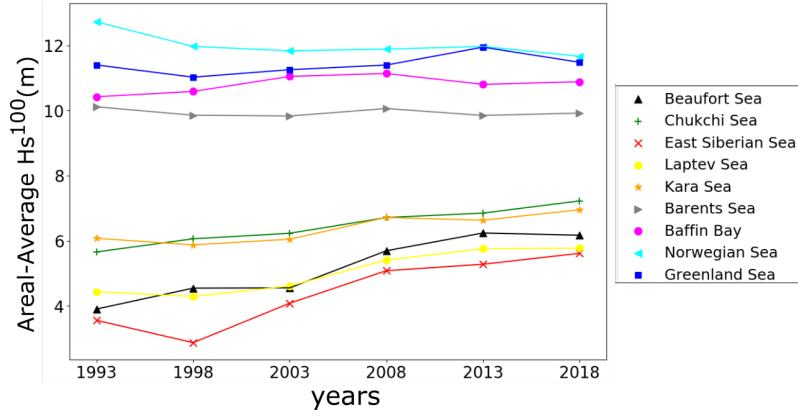


Figure 6.10: Areal averages of 100-year return period values for H_s in meters estimated by non-seasonal TS-EVA approach for each sea in the Arctic Ocean.

Figure 6.11 presents the areal-averages normalized by the values for 1993, in order to compare the changes qualitatively in each sea in the past decades. One can notice a dramatic increase of H_s^{100} in the Beaufort and East Siberian seas of approximately 60% between 1993 and 2018. It can be noted that the decrease in the Norwegian Sea is insignificant (of just 10%) compared to the changes that the rest of the Arctic Ocean is experiencing due to the sea ice melting.

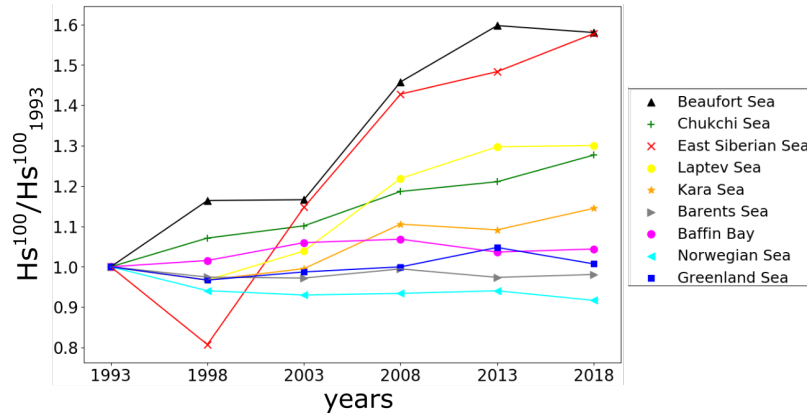


Figure 6.11: Normalized areal averages of H_s^{100} for each sea.

6.5 Seasonal approach

The results of the seasonal approach of TS EVA for H_s for a point located in the Kara Sea obtained with the wave hindcast forced with ERA5 atmospheric data performed with ST6 source term are shown in Figure 6.12. The analyses were undertaken using long-term time window (W) of 5 years, the same used in the non-seasonal approach. The seasonal time window (W_{sn}) of 2 months was selected. Figure 6.12 shows that this seasonal time window provides great estimations of the seasonal cycles.

This section discusses the results for the seasonal TS EVA applied to the wind speeds (U_{10}) of the ERA5 reanalysis and significant wave heights obtained from the 28-year hindcast performed with ST6 source term. This is the first EVA applied to these metocean parameters taking into account the long-term fluctuations together with the dramatic seasonal cycles for the entire Arctic Ocean.

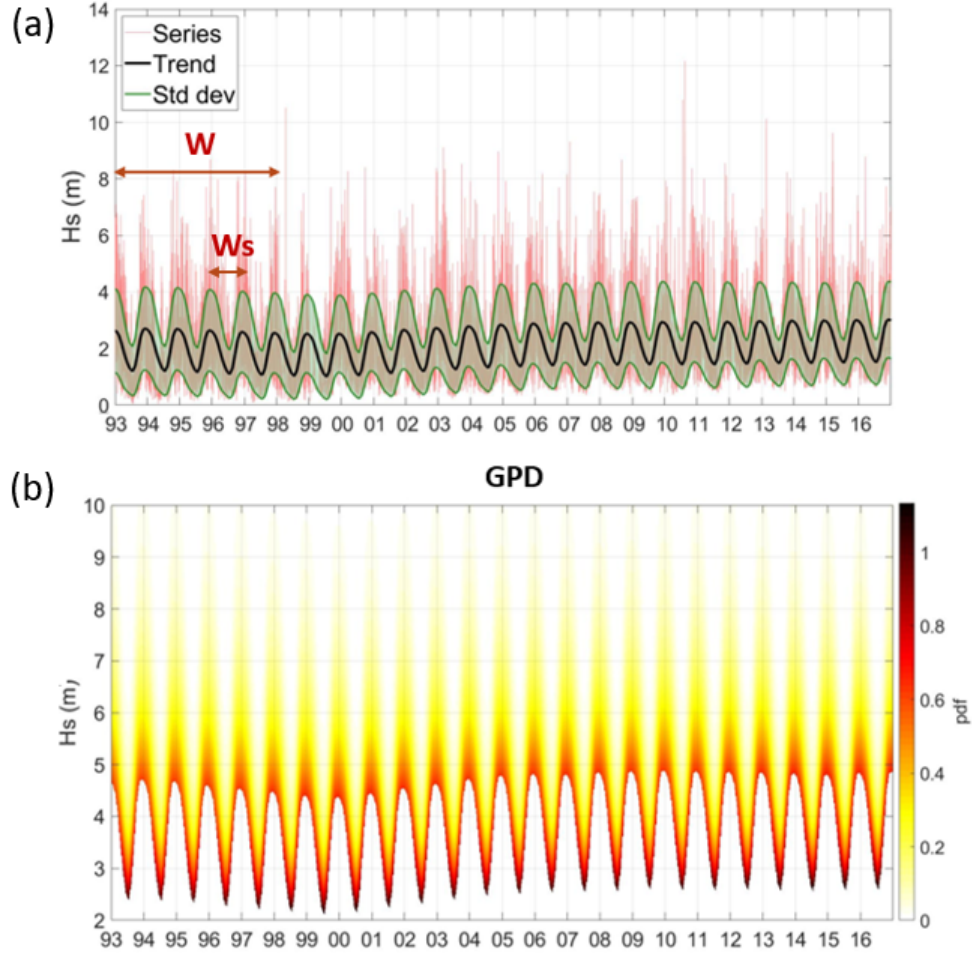


Figure 6.12: Seasonal analysis of the projections of significant wave height for a point located in the Kara Sea: (a) time series, its trend and standard deviation computed with W of 5 years and W_{sn} of 2 months; (b) non-stationary GPD of POT (threshold of 90th percentile).

6.5.1 Wind extremes

Figures 6.13 and 6.14 show the monthly results for 100-year return values for wind speeds (U_{10}^{100}) for the years 1993 and for 2018 obtained with seasonal TS EVA with POT approach (threshold of 90th percentile) and GPD distribution. The estimations for these two years are quite similar. It can be noticed that the strongest winds occur in southern Greenland with U_{10}^{100} reaching values of 50 m/s at some points in February. The patterns are quite similar for all winter months with values of U_{10}^{100} of approximately 25 m/s across the Arctic Ocean, weaker winds of ~ 20 m/s in the Laptev Sea, and stronger winds of ~ 40 m/s in eastern Greenland coast. Similarly, the summer months have similar results for extreme winds with maximum U_{10}^{100} reaching

approximately 30 m/s in Greenland and values lower than 20 m/s in most part of the ocean.

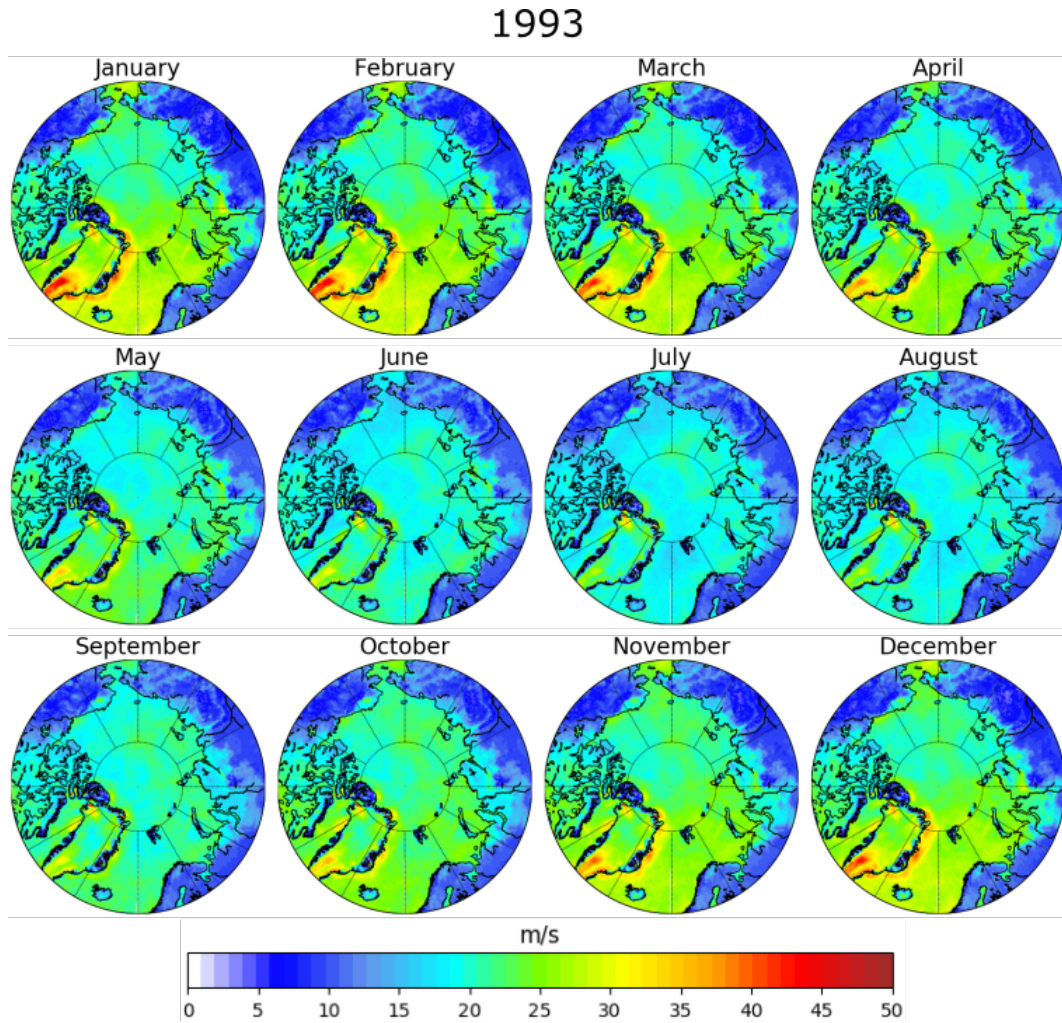


Figure 6.13: 100-year return period values for U_{10} (m/s) for 1993 obtained with a POT analysis and a GPD distribution in the TS EVA seasonal approach. Data obtained from the ERA5 dataset.

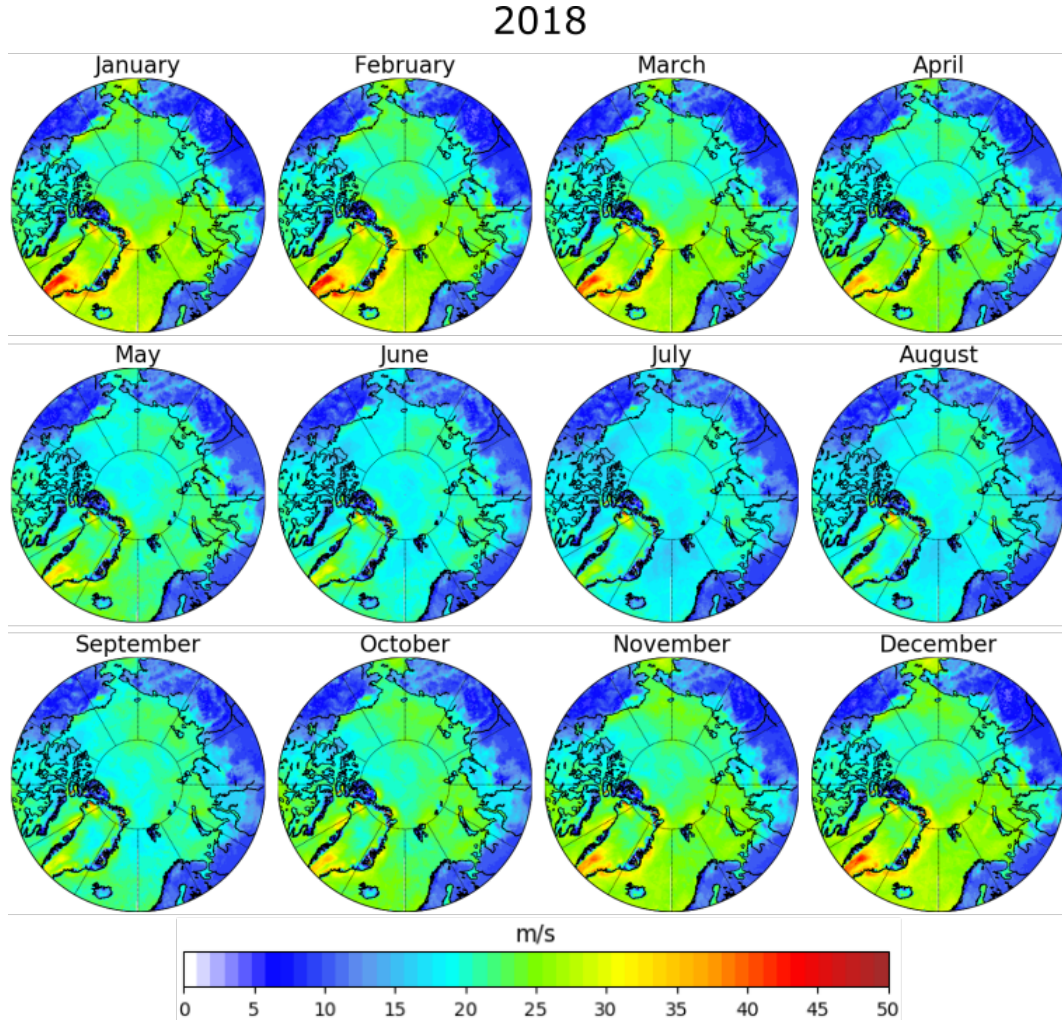


Figure 6.14: Same as Figure 6.13, but estimations for 2018.

Taking into account that the maximum 100-year return levels occur in different months for each region with this seasonal approach, the maximum values estimated for each year were plotted together on the same map. Figure 6.15 shows the maximum values of extreme winds obtained for 1993, 2018 and the differences between the estimations for these years. The discrepancy between them is very similar to the ones estimated by applying the non-seasonal approach of TS EVA as shown in Figure 6.4. The differences are not significant with increase of $1\text{--}3\text{ m/s}$ in U_{10}^{100} in the Pacific side and decrease of $-1\text{--}3\text{ m/s}$ in the Atlantic side of the Arctic Ocean, with the exception of the Norwegian Sea that experienced a slight decrease of $\sim 1\text{ m/s}$ in the maximum seasonal estimations for each month in this period of 25 years. The largest decreases were approximately 6 m/s in the northern Greenland Sea.

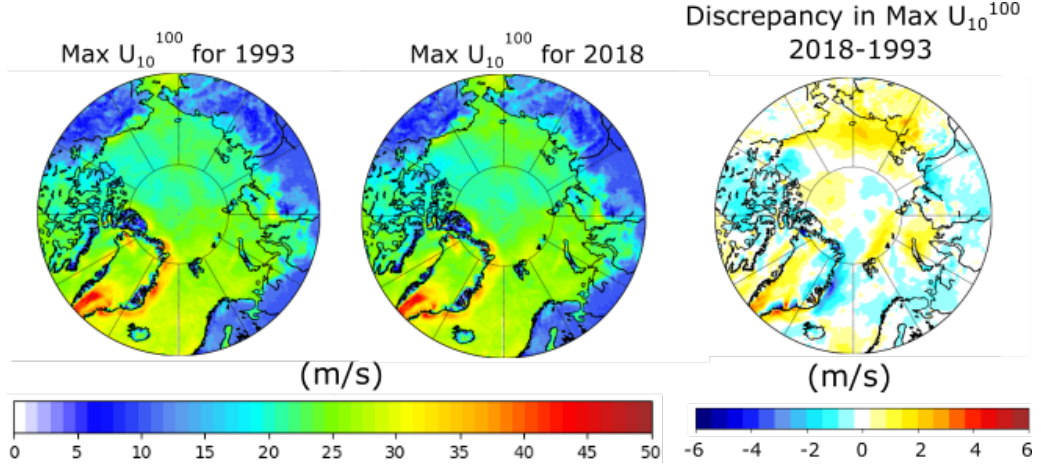


Figure 6.15: Maximum U_{10}^{100} (m/s) obtained with a POT analysis (90th percentile) and a GPD distribution in the TS EVA seasonal approach. Results for 1993 (left panel), 2018 (middle panel), and their difference (right panel).

6.5.2 Wave extremes

This section presents the estimations for 100-year return period of significant wave height (H_s^{100}) obtained with seasonal TS EVA with POT approach and GPD distribution applied to the 90th percentile of the 28-year wave hindcast performed with ERA5 wind forcing and ST6 source term. Figures 6.16 and 6.17 show the results for 1993 and 2018, respectively. The results demonstrate a strong seasonality throughout the year. The highest values are found in the region encompassing Greenland and Norwegian Seas, where energetic swells coming from the North Atlantic Ocean propagate through, as demonstrated by previous studies (e.g. Liu et al., 2016; Stopa et al., 2016). The months where the highest values occur in this region are the winter months when the winds become stronger. In the estimations for 2018, the values of H_s^{100} reached 17 m close to the Norwegian coast in January. In the southern Greenland Sea, the highest values happen in December, and they reach 18 m. In these regions, the 100-year return values estimated for 25 years earlier (in 1993) were very similar to the ones estimated for 2018. This is consistent with the trends found previously in this study. These regions experience a slightly downward trend in significant wave height (Chapter 5).

The maps shown in Figure 6.16 are masked by the minimum sea ice coverage of in the first two years of the data sets (1991-1993). The maps of Figure 6.17 are masked by the minimum sea ice coverage for the period 2013-2018, which corresponds to the long-term time window (5 years) in the long-term trend and standard deviation estimations. The dashed lines represent the minimum ice coverage for 1991-1993. In

winter the minimum ice coverage areas for those years were very similar. It can be noticed that the only area that experienced a significant difference in minimum ice coverage in winter months during these two decades was the region between Svalbard and Novaya Zemlya islands in the Barents Sea. In summer the consequences of the ice melting are evident when looking at the most significant differences between the results for 1993 and 2018, especially in the regions where it is covered by ice during most part of the year including East Siberian, Chukchi and Beaufort seas. As mentioned before, it was not able to fit a stable PDF at points in regions that are covered by ice most part of the year. So the apparent minimum sea ice coverage between July and October actually represents the region where it was not possible to apply the EVA. Similarly to the non-seasonal approach, in order to ensure a stable PDF, a condition of at least 1000 highest peaks was set to compute the extremes.

In the region close to the ice edge in the Barents and Kara seas, the most energetic waves occur in November and December when the sea ice coverage is still retreated from the summer period, and the winds are becoming stronger. Those facts together contribute to higher waves with 100-year return values for 2018 of 17 m close to Svalbard Island and 16 m in the Kara Sea. The estimations for 1993 were similar close to the coast, however relatively smaller closer to the ice edge. In the region close to Svalbard Island, the H_s^{100} used to be 3 m lower (~ 14 m) and in the Kara Sea a significant part used to be covered by sea ice and the values of H_s^{100} were about 11-13 m. Over the other side of the Arctic Ocean, close to the Pacific Ocean, the sea is covered by ice during most part of the year. The most extreme waves happen when the sea ice coverage is minimum. In the Beaufort Sea, the highest H_s^{100} occur in October when the values reach values higher than 15 m for 2018 estimations. Figure 6.16 shows that the extreme waves in 1993 were also around 15 m, however closer to the ice edge, there is a significantly large area where there were usually no waves due to the presence of the sea ice, and recently H_s^{100} are 6 m.

In the Chukchi Sea, the highest values are approximately 16 m in December close to the Bering Strait (Figure 6.17). However, closer to the ice edge, the most extreme waves occur in October with values reaching 14 m for 2018, 4 m higher than the highest ones in December in the same region. The comparison between the estimations of H_s^{100} for 1993 and 2018 are similar to the Beaufort Sea, as the sea ice is shrinking, the extreme waves are becoming more energetic, especially closer to the ice edge.

In the East Siberian Sea, the values of the 100-year return period of significant wave heights vary from 6 to 14 m in October and November. In this sea, the most energetic waves occur in November in the eastern part, in the region closer to the

Chukchi Sea. In the western part of this sea, the highest H_s^{100} occur in October, and they are approximately 9 m. The most dramatic differences between the estimations of 1993 and 2018 of H_s^{100} occur in this sea. This sea had practically no waves before the ice retreat with H_s^{100} reaching values of approximately 6 m in a limited open water area in October. In November, the sea was nearly entirely covered by sea ice in 1993, whereas in 2018, as mentioned before, the extreme waves could grow and develop in a way that H_s^{100} were higher than 6 m.

In the Laptev Sea, the most extreme waves occur in October, and the 100-year return values for H_s vary between 7-13 m for 2018 estimations and around 5-11 m for estimations in 1993. In November of 1993, this sea was entirely covered by sea ice, whereas the estimations of H_s^{100} for 2018 show values of approximately 9 m.

In the Baffin Bay, the most energetic waves occur in October, November, and December. In December part of this bay is already covered by ice. However, it is in this month that the most extreme waves happen in the region with H_s^{100} reaching values of 16 m for 2018 estimations. In the northern part of this bay, the highest values reach 14 m in October. For this region, the estimations for H_s^{100} for 20 years earlier do not show any significant difference. These results are in line with the relatively small upward trends in this bay shown in Chapter 5.

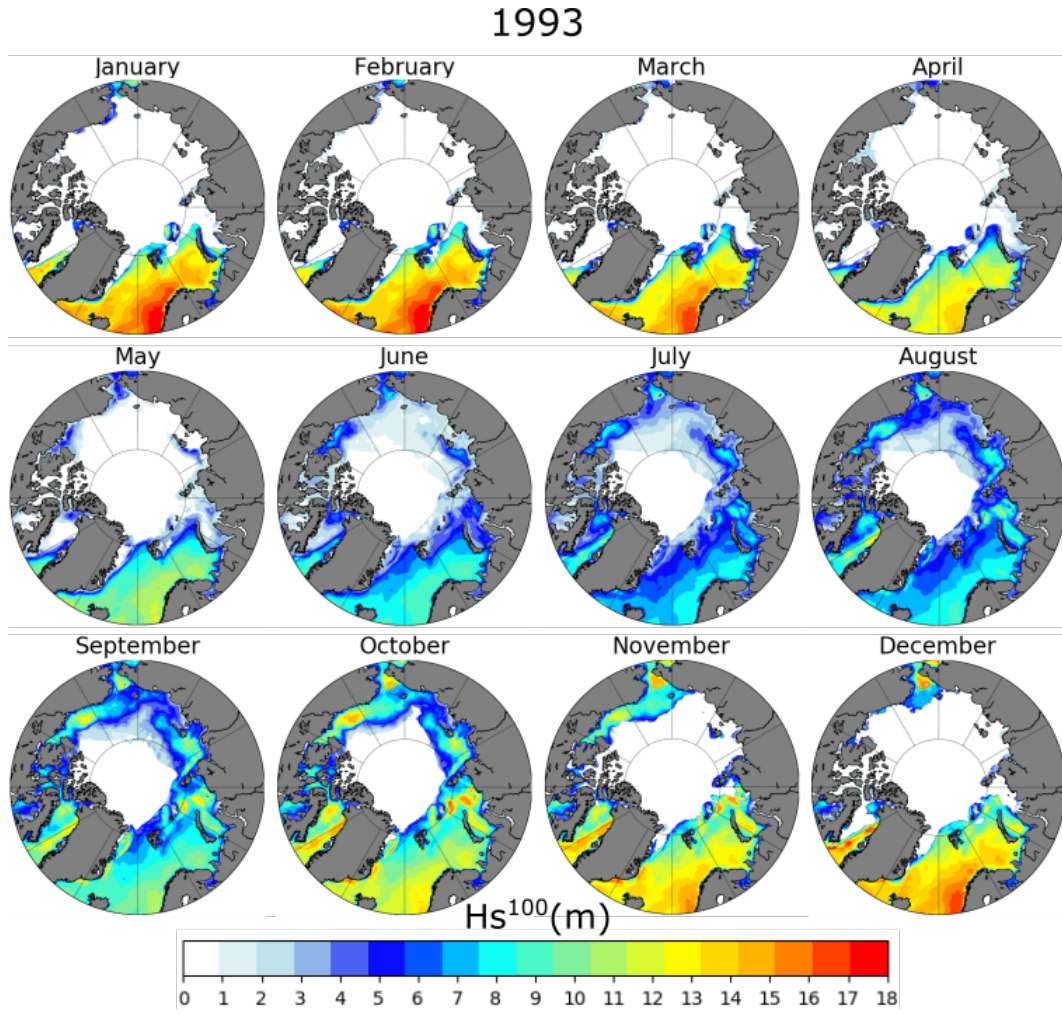


Figure 6.16: 100-year return period values for H_s (m) for 1993 obtained with a POT analysis and a GPD distribution in the TS EVA seasonal approach. Data obtained from the 28-year wave hindcast with ERA5 wind forcing.

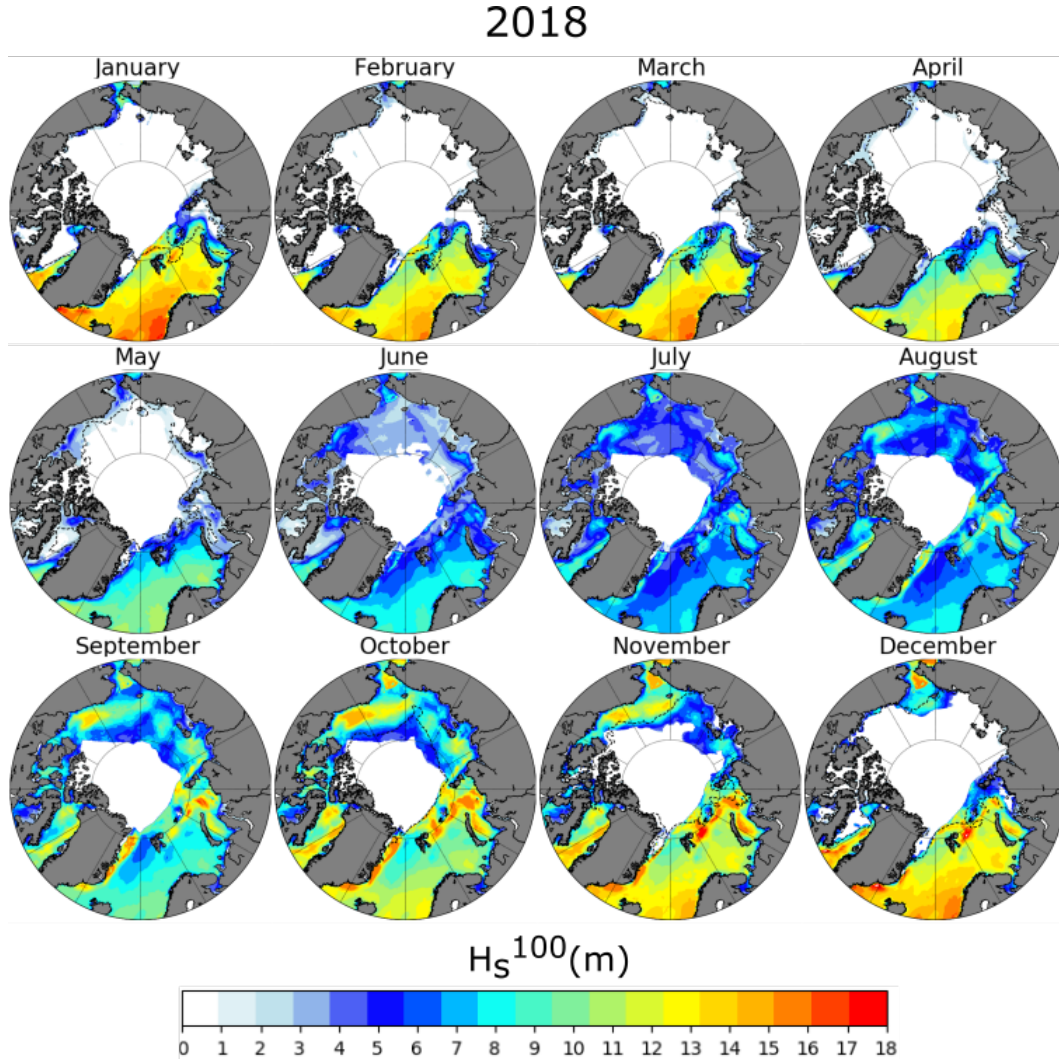


Figure 6.17: Same as Figure 6.16, but estimations for 2018.

In a similar way that was done previously to the 100-year return levels for wind speeds, the maximum H_s^{100} estimated for each year were plotted together on the same map. Figure 6.18 displays the maximum H_s^{100} for 1993, 2018, and the discrepancies between the estimations for these two years. It can be noticed that extreme waves have increased across the Arctic Ocean in the past two decades. The differences vary from 2-6 m in the region encompassing the Beaufort, Chukchi, East Siberian, and Laptev Seas. The highest increases occur close to the ice edge in the Kara and Barents seas and in the northeastern coast of Greenland. On the other hand, in the region close to the Atlantic Ocean, there was a slight decrease in extreme waves over these 25 years.

The maximum values estimated by applying the seasonal approach of TS EVA are significantly higher than the ones estimated by the non-seasonal approach. In

the North Atlantic part, the 100-year return values for H_s for 2018 reach 18 m with the non-seasonal approach and just 13 m with the non-seasonal one. Whereas in the Beaufort Sea the values reach 14 m with the seasonal approach and 8 m with the non-seasonal one. Considering the seasonality in the back-transformation of the stationary EVA shifts the tail of the PDF into higher frequencies, resulting in higher estimated extremes.

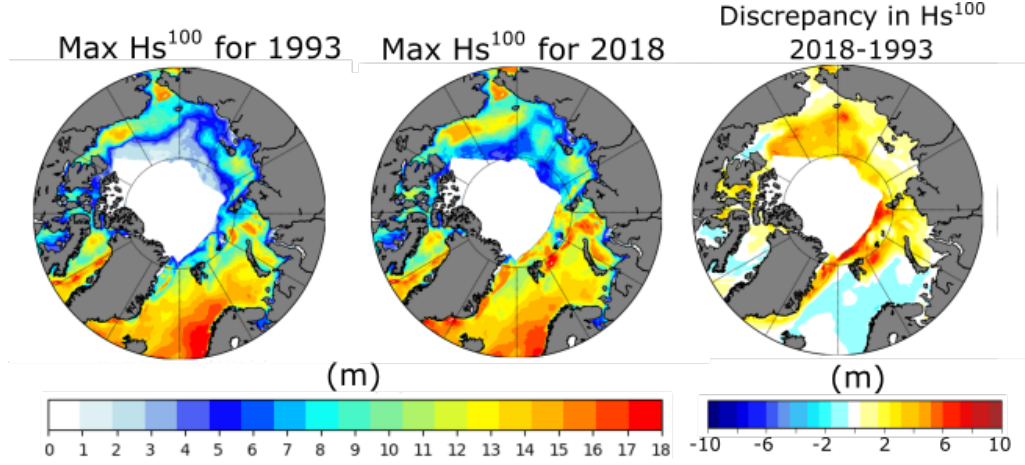


Figure 6.18: Maximum H_s^{100} (m/s) obtained for each month with a POT analysis (90th percentile) and a GPD distribution in the TS EVA seasonal approach. Results for 1993 (left panel), 2018 (middle panel), and their difference (right panel).

6.6 Effects of different wave model source terms in extreme waves

As demonstrated in Chapter 3, the most recent and widely used source terms available in WW3 model (ST4 and ST6) achieved very similar performances compared to altimeter data (see figures (3.12 and 3.14)). This section discusses the effects of selecting these different source terms in the estimation of extreme waves. The seasonal TS EVA approach was applied to the 28-year hindcast performed with ST4 source term, utilizing the same input data and boundary conditions used in the simulations carried out with ST6 source term.

Figure 6.19 show the monthly estimations for H_s^{100} for 2018 applying the POT approach with a GPD distribution to the 90th percentile of the significant wave height dataset produced with ST4 source term, similar to Figure 6.17 that shows the results with ST6 source term. The results are very similar just by looking at these two figures. However, looking at their discrepancy shown in Figure 6.20, it is possible

to note differences of approximately 0.5-1 m in the estimations. In most part of the Arctic Ocean, the estimations with ST6 source term are higher than the ones estimated with ST4 source term products. The only region that ST4 source term provided higher H_s^{100} values was the region close to the Atlantic Ocean. Figure 6.21 displays the discrepancies in maximum seasonal estimations between 2018 and 1993 derived from ST6 (left panel) and ST4 (right panel) source terms hindcast. One can note that even though slight differences in the maximum estimations of 100-year return levels shown previously, the discrepancies computed for each source term were almost the same. That means that the simulations with different source terms preserve the long-term trends in the 90th percentile of the time series.

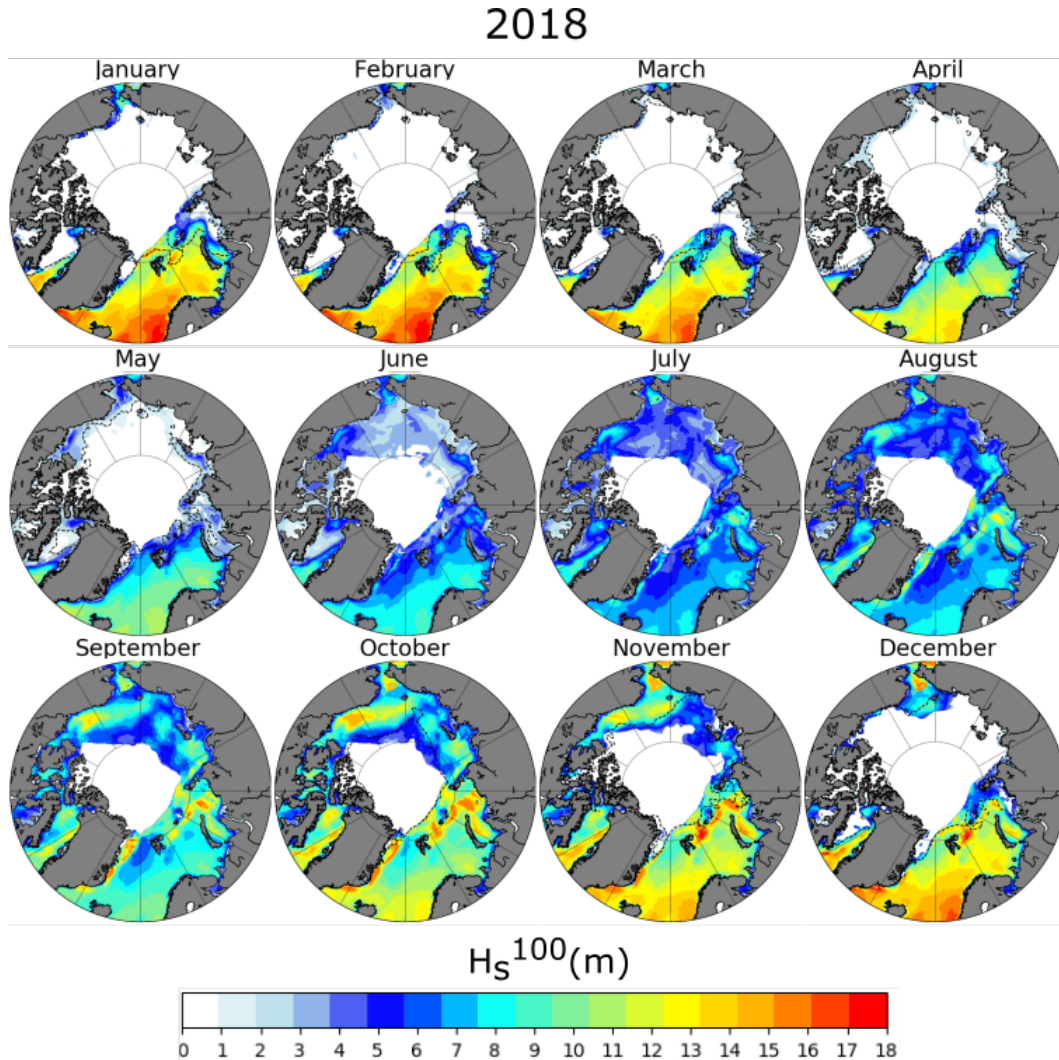


Figure 6.19: Same as Figure 6.17, but for ST4 source term.

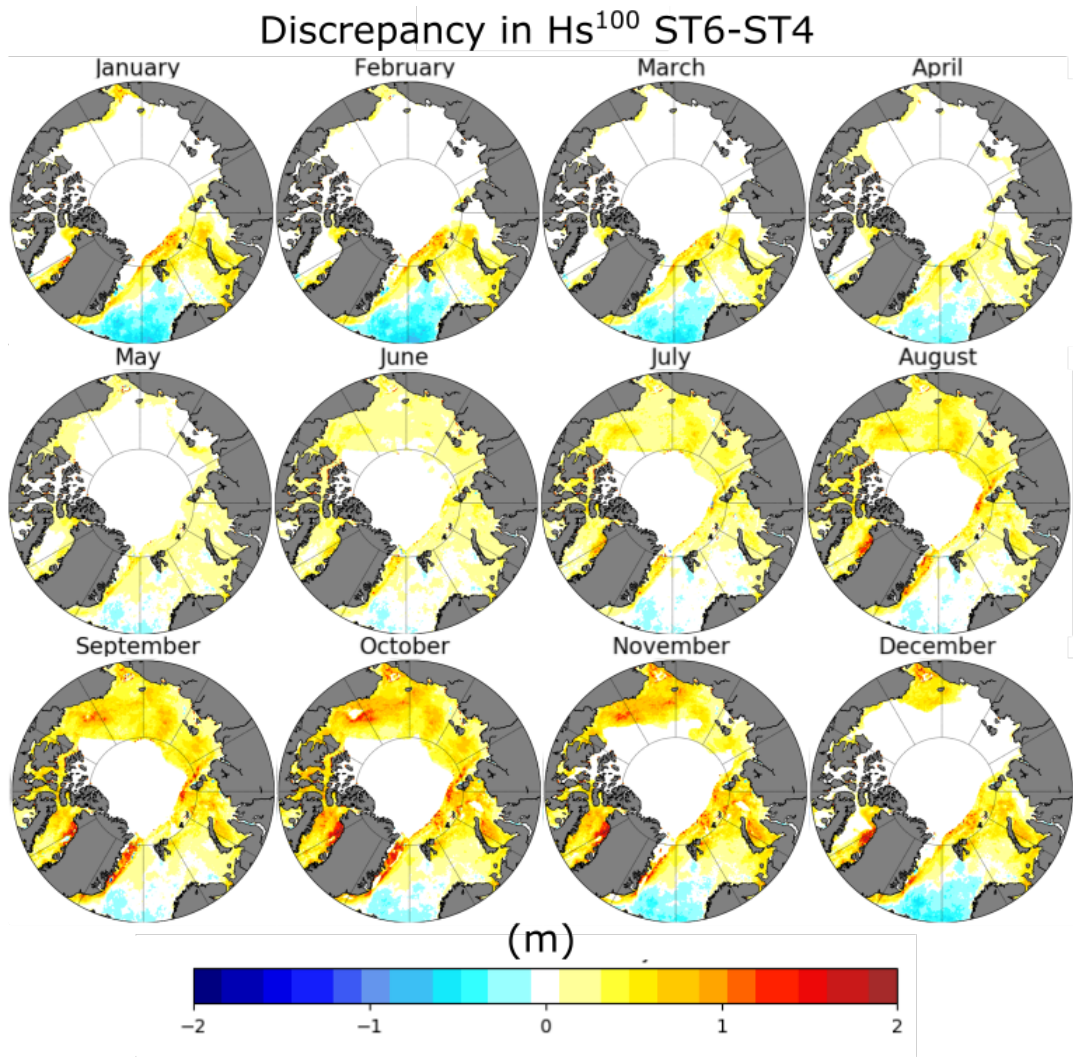


Figure 6.20: Discrepancy in H_s^{100} for the results with ST6 and ST4 source terms.

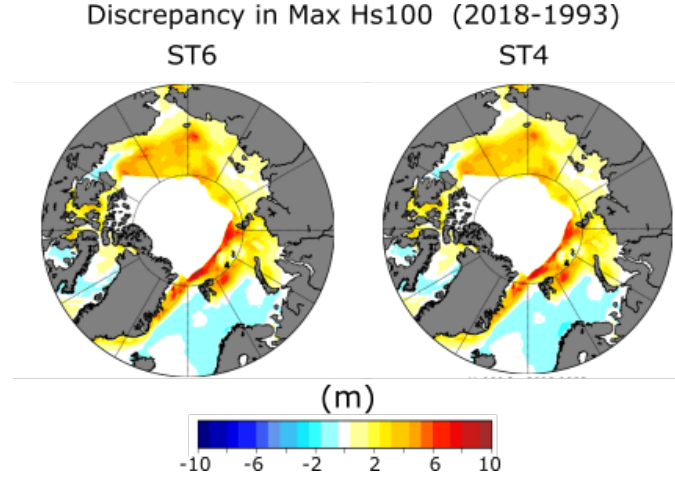


Figure 6.21: Differences in maximum H_s^{100} (m/s) obtained for each month with a POT analysis (90th percentile) and a GPD distribution in the TS EVA seasonal approach for 2018 and 1993 using different source terms: ST6(left panel) and ST4(right panel).

6.7 Conclusions

This chapter outlined the application of a non-stationary EVA method for estimating extreme winds from ERA-5 data sets and extreme waves in the Arctic Ocean derived from 28-year hindcast performed with ST6 source term. The TS EVA was applied to evaluate the extreme, taking into account the long-term trends and seasonality of the time series, as the Arctic has significant seasonal differences, and it is experiencing a dramatic climate change.

First, an EVA was applied using the peaks over threshold (POT) method (threshold of 90th percentile) and GPD distribution as a benchmark of this study, as there are no previous studies among wind and wave extremes across the Arctic Ocean. The results obtained with this method demonstrated thig confidence levels. However, the established EVA methods assume that the time series are stationary and fail to incorporate the seasonality and the dramatic changes occurring in the Arctic that we observed in the monthly MKT trends in Chapter 5.

The non-seasonal TS EVA applied to wave extremes showed an increase of the areal-average of the 100-year return period values of H_s of approximately 2 m across the Arctic Ocean, except for the region closer to the North Atlantic Ocean that has experienced a slight decrease in wave heights in the past decades. The Beaufort and East Siberian experienced the highest increasing rates in areal-averages of wave extremes, reaching values of 60% between 1993 and 2018, whereas the Norwegian Sea presented a decrease of 10%. The estimations for H_s^{100} obtained with this non-seasonal

approach for 2018 were quite similar to the ones obtained with the conventional stationary method, but the results for the Pacific side of the ocean were higher with the non-seasonal TS EVA and smaller in the Atlantic side. These differences were expected, taking into account the strong upward trends in wave heights on the Pacific side and the slight decrease in the region close to the Atlantic Ocean as shown in Chapter 5.

The non-seasonal results for extreme winds did not demonstrate significant long-term changes over the past decades as estimated for extreme waves. There was an increase of approximately 3 m/s from 1991 to 2018 on the Pacific side of the Arctic Ocean and a decrease of roughly 2-3 m/s on the Atlantic side. These results correspond to differences in extreme wind speeds varying from -4% to 4% in this period of 25 years (1993-2018) as demonstrated by the computation of the areal-averages. This way, the dramatic changes in extreme waves can only be explained by the increasing fetches due to reduced sea ice coverage.

The seasonal analysis allowed a deeper understanding of spatial changes in extreme values throughout the year and how much extreme winds and waves have increased over the past decades. The monthly estimations for wind extremes showed two similar patterns in extreme wind speeds: one for summer months when values of U_{10}^{100} are lower than 20 m/s across the Arctic Ocean and another one for winter months when U_{10}^{100} are around 20-25 m/s with maximum values reaching 50 m/s in southern Greenland. The maximum values estimated for each month of 2018 with the seasonal TS EVA and the ones estimated with the non-seasonal approach for the same year are comparable, but the seasonal estimations were slightly higher, especially in Greenland.

The maximum values of H_s^{100} for 2018 obtained with the seasonal approach were significantly higher than those estimated by the non-seasonal EVA approach. For instance, the highest values were found in the North Atlantic part where they reached values of 18 m with the seasonal method and only 13 m with the non-seasonal approach. The estimations for the Norwegian Sea obtained with the seasonal approach agree with the estimations computed by Breivik et al. (2013) in the same region. On the other side of the ocean, in the Beaufort Sea, the values reach 14 m with the seasonal approach and 8 m with the non-seasonal one.

In order to compare the differences in extreme waves using different source terms in WW3, the seasonal TS EVA approach was also performed for a 28-year hindcast using the ST4 source term. The results for both source terms (ST4 and ST6) were very similar. However, the ST6 source term provided higher estimations for H_s^{100} (~ 0.5 -1

m higher) across the Arctic Ocean, with the exception of the region closer to the North Atlantic Ocean, where ST4 source term products achieved higher estimations than ST6 source term results.

Chapter 7

Conclusions

7.1 Summary

Climate change has impacted the Arctic Ocean in such a way that any other region on Earth has experienced yet. The changes are not limited to the temperature rise. The sea ice has been melting consistently over the past decades affecting the ocean dynamics, marine life, and coastlines. This research provides a deeper understanding of changes in the most significant metocean parameters in the region. A detailed evaluation of the climate, seasonality, and trends of sea ice concentration, wind speeds, and wave parameters are discussed in this dissertation. In addition to that, extreme winds and waves across the Arctic Ocean are assessed for the first time.

In order to establish a better-suited wave model set-up for the long-term simulations performed in this research, a calibration of the WW3 model was carried out by comparing the performance of the model with different atmospheric forcing, sea ice concentration data sets, WW3 model source terms, spatial resolutions, and evaluating the effects of including boundary conditions and ocean currents in the simulations. The best-fit was achieved by forcing the model with the atmospheric forcing from the recently released ERA5 reanalysis and also its sea ice concentration. The performance of the model using the most recent source terms (ST4 and ST6) available in the WW3 model demonstrated very similar results. The overall standard error metrics were slightly better with the ST4 source term, whereas for the higher percentile of wave heights (90th percentile), the model was more accurate when applying the ST6 source term.

Two long-term wave hindcasts for the period between 1991 and 2018 were performed by using both source terms evaluated in this research. The validation of both simulations showed excellent agreement with satellite data. The standard metrics,

such as correlation, RMSE, and bias computed for 2012-2016 showed better performance than previous hindcasts undertaken in previous studies (e.g. Stopa et al., 2016). Taking into account the ultimate goal of this study on evaluating changing wave extremes across the Arctic, the long-term hindcast selected on the assessing the sea-state, seasonality, and trends of wave parameters was the one performed with the ST6 source term that achieved a better agreement with observed data for the most energetic waves.

The descriptive analyses of the metocean conditions showed substantial seasonal differences in all parameters evaluated in this study. The seasonal cycles of sea ice were evident in the monthly average and lower percentiles of sea ice concentration and they play an essential role in affecting other parameters such as winds and waves. The differences between the first (1991) and last year (2018) analysed in this study make evident the consequences of climate change in the sea ice coverage and the extension of the marginal ice zone. The average and higher percentiles of wind speeds and wave parameters were also assessed. The results show that the strongest winds (99th percentile) are 50-60% stronger than average winds (50th percentile). Similarly, the higher percentiles of wave parameters are substantially more energetic than average waves (~60-70% higher and ~50% longer). The seasonal component of the wave heights is also quite remarkable, considering that the significant wave heights in winter are approximately 50% higher than in summer on the Atlantic side.

The Mann-Kendall test was used to identify trends in all metocean parameters assessed in this research showing dramatic changes in the past decades and substantial seasonal differences. The results demonstrated a general increase in wave heights, except for Greenland and Norwegian seas due to the negative NAO observed in this period by previous studies. The trends in wind speeds were milder compared to trends in waves and sea ice concentration. It could be noticed a slight downward trend on the Atlantic side and an upward trend on the Pacific side.

The evaluation of the differences in the marginal ice zone between 1991 and 2018 showed that besides the reduction of sea ice extent, the sea ice is becoming more fragmented. The dependency between trends in wave heights and trends in sea ice concentration showed by the results of the trend analyses performed in this study might play an important role in these changes of the marginal ice zone.

Transformed-stationary extreme value analysis developed by Mentaschi et al. (2016) was applied to evaluate the extreme winds and waves across the Arctic, taking into account the long-term trends and seasonality in the estimations, as environmental variables should not be considered as stationary in the Arctic. The non-seasonal

approach showed an increase in the areal-average of the H_s^{100} of approximately 2 m across the Arctic Ocean, except for the region closer to the North Atlantic Ocean. The extreme waves have increased by $\sim 60\%$ in the Barents and East Siberian seas. At the same time, extreme winds have only increased by 4%. Therefore, the changes in extreme winds cannot explain the changes in extreme waves. These results make evident that the sea ice melting has primary responsibility for these dramatic changes in extreme waves.

The seasonal approach of the extreme value analysis allowed a better understanding of regional changes in extremes throughout the year and how much the extreme waves have increased over the past decades. According to the results of this study, the most extreme waves in the Arctic Ocean occur on the North Atlantic side of this ocean and the 100-return levels of H_s^{100} can reach values of 18 m at some points.

7.2 Outlook

The non-stationary extreme value analysis of wave heights performed in this study is a powerful tool to understand how the extreme sea-state over the Arctic Ocean is changing over the last few decades providing a good insight of the quantities. However, there are still many uncertainties about the projections of sea ice concentration, and consequently, of waves, as many physics are still not well known in the processes that occur in the Arctic. The formation of the sea ice floes, the wave-ice interactions, including the wave attenuation due to ice coverage, and the breakup of the sea ice triggered by the waves are not yet well understood.

The wave-ice interactions were not included in the wave simulations of this study, as the focus of this research was open waters where no wave-ice interactions take place and taking into account the lack of robust physics of wave attenuation in the presence of sea ice available in the wave model. However, recent efforts have been made in order to couple the WW3 model into the CICE sea ice model (e.g. Bennetts et al., 2017). Therefore, a further study could investigate the effects of including the wave-ice interactions on the long-term simulations of the sea state in the Arctic Ocean.

An area of future research would be to investigate the long-term variability of ocean currents in the Arctic Ocean. A recent study based on altimeter data between 2003-2014 demonstrated that sea ice melting has been driving an expansion of the Beaufort gyre and it has been increasing its freshwater content. The gyre circulation

increases when winds get stronger (Regan et al., 2019). In this study, an evaluation of long-term trends based on the ocean reanalyses GLORYS2v4 was attempted. However, no trends were found in the results. Hence these results were not shown in this dissertation. The effects of including these ocean currents in the wave simulations also demonstrated inconsistencies in the coastal areas. These uncertainties can be explained with the coarse resolution of these ocean data used and also due to a lack of robust physics of wave-current interactions available in the wave model. It would be interesting to investigate the effects of coupling the wave model into an ocean model with higher spatial resolution, such as the ROMS model by using the COAWST modelling system to couple both models. The results of such an ocean model, together with the results of this study on changes in waves could provide a better understanding of the coastal erosion occurring along the Arctic coasts. They can potentially be used as an input for coastal models to access the morphological changes that are taking place in some parts of the Arctic.

Appendix A

Extra plots of calibration of WW3 model

Figures A.1, A.2 display the comparison of the significant wave height results from the best-fit of each source term and wind input. The results show good agreement with buoy data and it can be noticed that the results with the ST6 source term and ERA-Interim wind matches the variability of the observations better than CFSR atmospheric forcing.

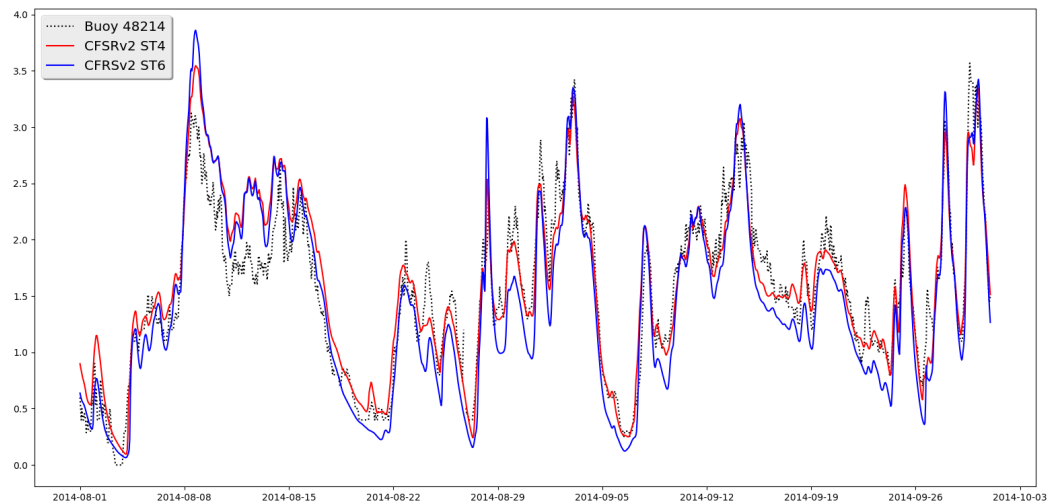


Figure A.1: Significant wave height time series for August and September of 2014. The black dashed line represents the buoy data, and the solid lines represent the WW3 model results with CFSR wind forcing and different source and sink terms (ST4 and ST6).

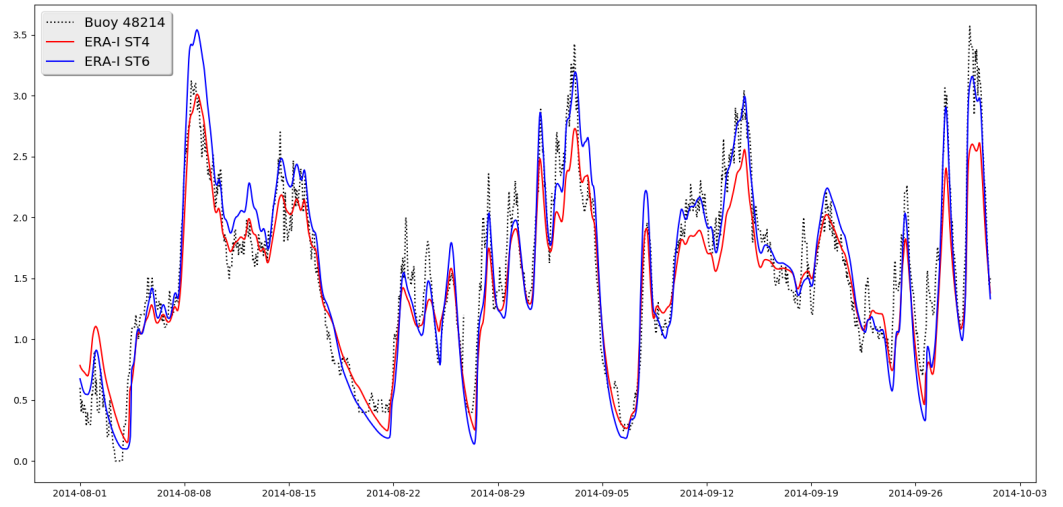


Figure A.2: Same as Figure A.1, but for ERA-Interim atmospheric forcing.

Appendix B

Wave hindcast with ERA-Interim

In the first stage of this study, a long-term hindcast simulated with the WW3 model (version 5.18) and ERA-Interim wind forcing was performed. This simulation was carried out without boundary conditions. Figure B.1 shows the monthly MKT trends for the 95th percentile of Hs based on this hindcast for the period 1993-2017.

The long-term trends obtained with this hindcast have similar patterns to the ones obtained with the hindcast discussed in this dissertation. However, the validation of this hindcast did not present such good agreement as the results for the hindcast performed with ERA-5.

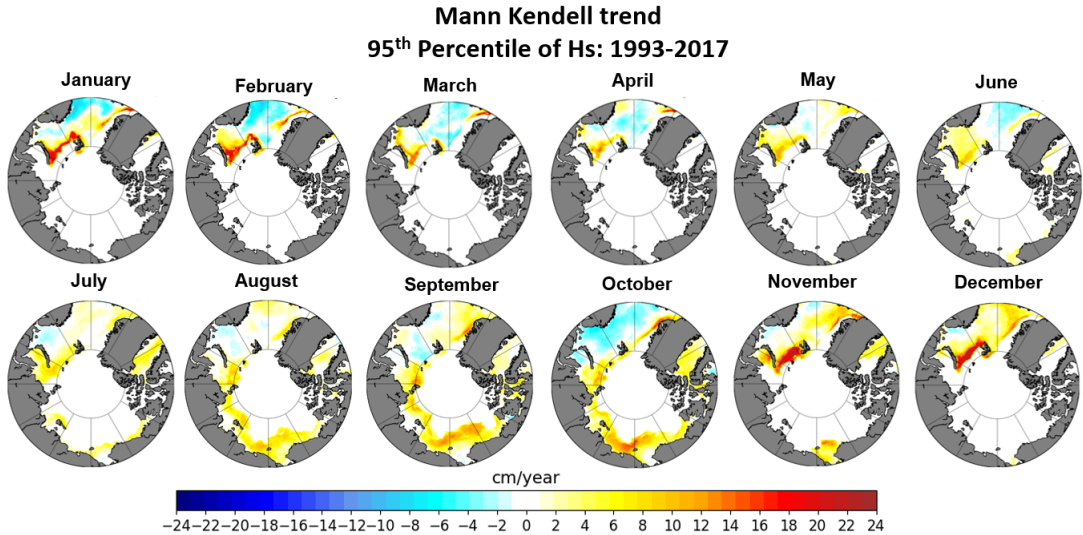


Figure B.1: Monthly trend estimates (Sens slope) of 95th percentile of the significant wave heights (cm/year) in the Arctic Ocean. Data delivered by the hindcast with ERA-Interim wind forcing.

Appendix C

Wave extremes with ERA-Interim

The results for non-seasonal TS EVA obtained with the hindcast forced with ERA-Interim reanalysis are presented here.

In the Barents Sea, for 1993 the Hs100 was 11m and it has increased by almost 1m to 12m. In the Greenland Sea, the increase was a bit smaller from 11.9m to 12.6m with a slight decrease in 2012. In the Beaufort and Chukchi seas, the increase was also of 1m from 6.9m to 7.9m. The East Siberian Sea encountered the largest increase of 3.3m from 3.5m to 6.8m. In the Norwegian Sea the Hs100 was almost the same for these two decades.

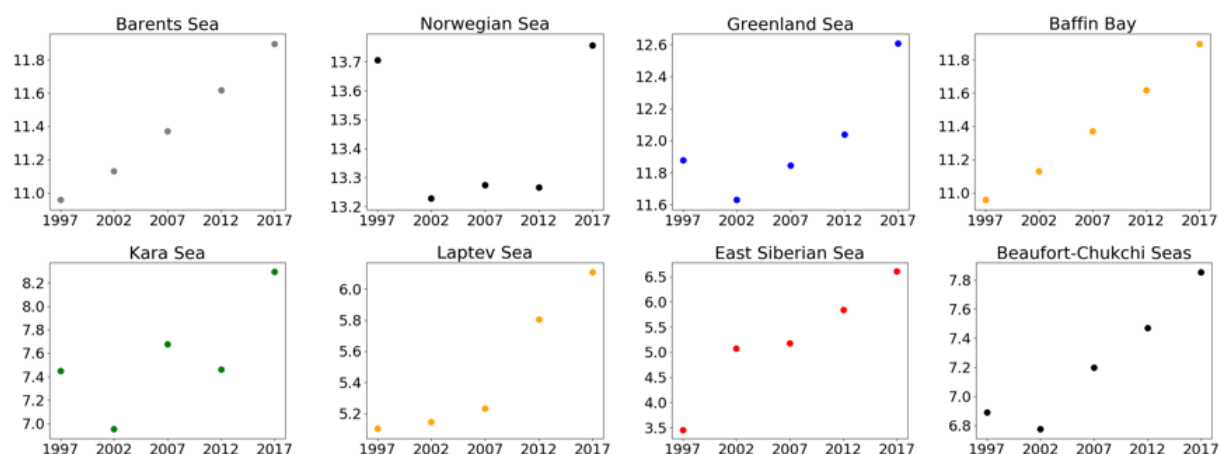


Figure C.1: Areal averages of 100-year return period values for Hs in meters estimated by non-seasonal TS-EVA approach for each sea in the Arctic Ocean.

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