THE INFLUENCE OF ATMOSPHERE-OCEAN TELECONNECTIONS ON WESTERN ARCTIC SEA ICE AND SURFACE AIR TEMPERATURE

A Thesis
Presented in Partial Fulfillment of the Requirements for the Degree Master of Arts in the Graduate School of The Ohio State University

By
Thomas Justin Ballinger
Graduate Program in Geography

The Ohio State University
2011

Master's Examination Committee:
Dr. Jeffrey C. Rogers, Advisor
Dr. David H. Bromwich
Dr. Jialin Lin
ABSTRACT

Over the last several decades western Arctic sea ice has declined in thickness and extent while surface air temperatures (SATs) have increased. Numerous studies have analyzed both anthropogenic greenhouse gas (GHG) emissions and the modes of natural variability, known as teleconnections, amongst other contributors. Separating anthropogenically-forced from natural signals is computationally difficult and far from perfected. While it is largely accepted that GHGs play a role in Arctic warming, previous papers have largely neglected to find a consistent multidecadal sea surface temperature (SST) or atmospheric teleconnection capable of explaining a significant amount of sea ice and land SAT variability in the region.

As a result, statistical analysis of ten global teleconnections against sea ice and SATs in the western Arctic is carried out from 1951-2007 over multi-seasonal, summer and annual scales. Rotated principle component analysis (RPCA) is employed to reduce, simplify and negate the potential for multicollinearity amongst the teleconnections while maximizing each component’s explained variance. Those components are then regressed against the eleven separate sea ice retreat longitudes and coastal SAT locales at Barrow, Alaska and Mys Uelen, Russia using the stepwise multiple linear regression (SMLR) technique in order to yield corresponding cumulative predictors of the variability.
Contrary to previous studies, a multidecadal teleconnection presence, in the form of the seasonally-composed (winter, spring and summer) Atlantic Multidecadal Oscillation (AMO), is found to be the initial predictor for ten of the longitudes. The AMO generally explains an increasing amount of the variance across the study ($r^2 = 0.41$) of the poleward ice retreats to a longitude of approximately 146.05ºW (L146) before it decays. In fact, the AMO combined with other multi-seasonal teleconnection predictors, most notably AO/NAO in spring, accounts for approximately half of the explained variance for L151, L146 and L141 sea ice longitudes. A similar pattern with weaker $r^2$ values persists for the summer-only teleconnection and sea ice analysis. Barrow annual SATs are more robust than Uelen in summer and annually, but not during the seasonal analysis. The most robust temperature returns occur in the annual analysis where the AMO explains only a slight portion of the explained variance ($r^2 = 0.19$) in conjunction with the PDO ($r^2 = 0.11$), though these connections pale in comparison to the aforementioned sea ice studies.

Time series of observed and residual values are generally better correlated than observed and predicted values. This indicates rather consistent under prediction by the SMLR statistical model. Nevertheless, the respective t-value and F-ratio regression tests show the slopes significantly differ from zero. The residuals are mostly insignificant and therefore random and normally distributed. Final comparisons of the principal components and raw-averaged teleconnections indices are examined with the sea ice retreats where the largest variances were explained (L151-L141) and Barrow annual temperatures. Notable correlations ($≈ r ≥ 0.50$) further indicate a good fit between the
AMO and ice retreats over the entire study period. These statistical outputs can be physically substantiated thereby supporting the presence of this multidecadal teleconnection in the western Arctic.
DEDICATION

I would like to dedicate this thesis to my family, who has encouraged me through this three-year process. My successes in this world are largely attributable to their unwavering support.
ACKNOWLEDGEMENTS

I would like to thank my advisor Dr. Jeffrey Rogers for his guidance and patience through the duration of my thesis work. His ideas and statistical direction largely form the framework for this paper. I would also like to thank my committee members Dr. David Bromwich and Dr. Jialin Lin for their suggestions and willingness to offer their advice in order to improve this thesis.

I would also like to thank a number of fellow graduate students who were very helpful through this process. Meng-Pai Hung donated his time and talents to structure the IDL programs that were used to generate the schematic and time series for this paper. Mike Davis spent countless hours in the basement of Derby Hall helping me better understand IDL fundamentals. Rachel Mauk, Scott Melaragno, Dan Steinhoff, Aaron Wilson, Meng-Pai and Mike were all willing to offer sound advice and guidance as I completed this paper and prepared for my master’s examinations. I am tremendously thankful to these individuals for both their time and friendship.
VITA

December 1, 1985 ........................................... Born in Mansfield, Ohio

May 2008 ........................................................... B.A. History, Kent State University

FIELD OF STUDY

Major Field: Geography
# TABLE OF CONTENTS

Abstract.................................................................................................................. ii

Dedication................................................................................................................ v

Acknowledgements.................................................................................................. vi

Vita............................................................................................................................. vii

List of Tables............................................................................................................ x

List of Figures.......................................................................................................... xii

Chapters:

1. Introduction......................................................................................................... 1

2. Literature Review................................................................................................ 5
   2.1 Teleconnections and Other Causes of Arctic Sea Ice Variability.............. 5
   2.1.1 Extreme Arctic Sea Ice Event of 2007............................................... 9
   2.2 Teleconnections and Surface Air Temperatures................................. 11
   2.2.1 Arctic Amplification................................................................. 13

3. Data and Methodology....................................................................................... 17
   3.1 Data........................................................................................................... 17
   3.2 Methodology............................................................................................ 25

4. Results............................................................................................................... 29
LIST OF TABLES

Table 1. HadISST sea ice coordinates

Table 2. List of teleconnection indices used in analysis with sea ice and surface air temperature data. The PNA winter and spring indices date back to 1948, while the summer and autumn indices date to 1950

Table 3. Summary statistics for sea ice extents and summer surface air temperatures at Uelen and Barrow. Sea ice extents are in latitudes (ºN) as are standard deviations. Surface air temperatures at Uelen and Barrow are in ºC. Asterisks (*) indicate multiple years with similar values

Table 4. Eigenvectors loadings of the individual multi-seasonal teleconnection indices on the nine rotated principle components chosen as best fit for the analysis. Loadings greater than absolute 0.7 are used to identify the teleconnections by which the component is named in Table 5

Table 5. The descriptive names of the rotated principal components from Table 4 and the individual indices that comprise them. Eigenvalues (λ) and the total dataset variance explained (r²) of the components are also included

Table 6. Same as Table 4 but for the summer-only teleconnection index analysis. Principal component names are in Table 7

Table 7. Same as Table 5 but for summer-only principal components

Table 8. Same as Table 4 but for the annual averaged teleconnection indices. Principal components are named in Table 9

Table 9. Same as Table 5 but for annual principal components
Table 10. Summary of the multi-seasonal orthogonal teleconnection predictors in the SMLR that best explain the variance of the sea ice retreat latitude at the 11 longitudes. The numbered PCs refer to the teleconnection groups identified in Table 5. Results include the explained variance ($r^2$) and regression coefficient ($\pm b$) for each predictor as well as the regression equation constant ($a$).

Table 11. Test statistics (t-value and F-ratio) for the multi-seasonal sea ice regression model. Significance at 95% is italicized, significance at 99% is bold and significance at 99.9% is italicized and bold.

Table 12. Multi-seasonal observed, predicted and residual decadal trends and correlations ($r$) between observed and predicted (ob and pred) and observed and residual (ob and res) time series.

Table 13. Test statistics for the multi-seasonal model residuals. Standard deviation of the residuals ($\sigma_e$) and lag-1 autocorrelation ($r_1$) with corresponding Ljung-Box (L-B) statistic indicated with percent significance.

Table 14. Same as Table 10 but for summer-only.

Table 15. Same as Table 11 but for summer-only.

Table 16. Same as Table 12 but for summer-only.

Table 17. Same as Table 13 but for summer-only.

Table 18. Same as Table 10 but for multi-seasonal (wss), summer-only (su) and annual (ann) temperature results.

Table 19. Same as Table 11 but for multi-seasonal (wss), summer-only (su) and annual (ann) temperature results.

Table 20. Same as Table 12 but for multi-seasonal (wss), summer (su) and annual (ann) temperature results.

Table 21. Same as Table 13 but for multi-seasonal (wss), summer-only (su) and annual (ann) temperature results.

Table 22. Correlations based on most significantly explained variances ($r^2$) of the dataset. The AMO and AO/NAO principle components ($r_{pc}$) from Table 5 and their raw-averaged equivalent values are correlated with the ice longitudes at L151-L141 and separated by the slash marks. Significance at 95% is italicized; significance at 99% is bold.
LIST OF FIGURES

Figure 1. Map of western Arctic sea ice and temperature coordinates. The blue arrow represents the Uelen temperature station and the green arrow represents the Barrow sea ice and temperature location……………………………………………………….24

Figure 2. Scree plot for multi-seasonal teleconnection indices…………………………….41

Figure 3. Same as Figure 2 but for summer-only teleconnection indices………………..42

Figure 4. Same as Figure 2 but for annual teleconnections indices……………………..43

Figure 5. Time series of L176 sea ice extents for (a) observed (solid) and predicted (dashed) values, based on multi-seasonal teleconnections, and corresponding (b) residuals………………………………………………………………….57

Figure 6. Same as Figure 5 but for L171…………………………………………………..58

Figure 7. Same as Figure 5 but for L166………………………………………………….59

Figure 8. Same as Figure 5 but for L161………………………………………………..60

Figure 9. Same as Figure 5 but for L156………………………………………………..61

Figure 10. Same as Figure 5 but for L151………………………………………………62

Figure 11. Same as Figure 5 but for L146………………………………………………63

Figure 12. Same as Figure 5 but for L141………………………………………………64

Figure 13. Same as Figure 5 but for L136………………………………………………65

Figure 14. Same as Figure 5 but for L131………………………………………………66
Figure 15. Time series of L176 sea ice extents for (a) observed (solid) and predicted (dashed) values, based on summer-only teleconnections, and corresponding (b) residuals………………………………………………………………………………………….79

Figure 16. Same as Figure 15 but for L171…………………………………………………………80

Figure 17. Same as Figure 15 but for L166…………………………………………………………81

Figure 18. Same as Figure 15 but for L161…………………………………………………………82

Figure 19. Same as Figure 15 but for L156…………………………………………………………83

Figure 20. Same as Figure 15 but for L151…………………………………………………………84

Figure 21. Same as Figure 15 but for L146…………………………………………………………85

Figure 22. Same as Figure 15 but for L141…………………………………………………………86

Figure 23. Same as Figure 15 but for L136…………………………………………………………87

Figure 24. Same as Figure 15 but for L131…………………………………………………………88

Figure 25. Same as Figure 15 but for L126…………………………………………………………89

Figure 26. Time series of Uelen summer SATs for (a) observed (solid) and predicted (dashed) values, based on multi-seasonal teleconnections, and corresponding (b) residuals………………………………………………………………………………96

Figure 27. Same as Figure 26 but for Barrow…………………………………………………………….97

Figure 28. Time series of Uelen summer SATs for (a) observed (solid) and predicted (dashed) values, based on summer-only teleconnections, and corresponding (b) residuals………………………………………………………………………………100

Figure 29. Same as Figure 28 but for Barrow…………………………………………………………101

Figure 30. Time series of Uelen annual SATs for (a) observed (solid) and predicted (dashed) values, based on annual teleconnections, and corresponding (b) residuals…..104

Figure 31. Same as Figure 30 but for Barrow…………………………………………………………105

Figure 32. Time series of L151 sea ice (solid) compared to the AMO multi-seasonal component (dashed). The AMO index data have been adjusted to the same mean and standard deviation as the sea ice latitude data………………………………………………110
Figure 33. Time series of L151 sea ice (solid) compared to the AO/NAO multi-seasonal component (dashed). The AO/NAO index data have been adjusted to the same mean and standard deviation as the sea ice latitude data.............................................111

Figure 34. Same as Figure 32 except for L146.........................................................112

Figure 35. Same as Figure 33 except for L146.........................................................113

Figure 36. Same as Figure 32 except for L141.........................................................114

Figure 37. Same as Figure 33 except for L141.........................................................115

Figure 38. Time series of Barrow annual temperatures compared to the AMO annual component (dashed). The AMO index data have been adjusted to the same mean and standard deviation as the temperature data.........................................................116

Figure 39. Time series of Barrow annual temperatures compared to the PDO annual component (dashed). The PDO index data have been adjusted to the same mean and standard deviation as the temperature data.........................................................117

Figure 40. Overplot of the L151 (green), L146 (purple) and L141 (teal) sea ice extents and raw-averaged (winter, spring and summer) AMO (red, dashed). The AMO index data have been adjusted to the same mean and standard deviation as the sea ice latitude data. ............................................................................................................118

Figure 41. Atlantic Multidecadal Oscillation index from 1850 to 2005 represented by annual anomalies of SST in the extratropical North Atlantic (30–65°N; top), and in a more muted fashion in the tropical Atlantic (10°N–20°N) SST anomalies (bottom). Both time series come from HadSST2 and are relative to the 1961 to 1990 mean (°C). The smooth blue curves show decadal variations (image from IPCC, 2007).........................126
CHAPTER 1

INTRODUCTION

Arctic air temperature and sea ice variability, gathered from the sparse array of terrestrial and oceanic observation stations throughout the region, has been documented and studied with vigor by the scientific community over the last several decades. Recently, climate scientists came to the consensus that surface air temperatures in the Arctic rose roughly by up to 5°C during the last one hundred years while sea ice thinned and declined in extent (IPCC, 2007). More specifically, Chylek et al. (2009) concluded that Arctic air temperatures warmed two to three times faster than global mean temperatures from 1970-2008, especially in the Arctic north of 70° N where Arctic amplification, the ratio of Arctic to global temperature trends, was most pronounced. Observational and modeling studies have shown that the Arctic amplification phenomenon is largely attributable to increased sea ice losses in recent years which have prompted strong latent heat transfers from the ocean to the atmosphere (Kumar et al., 2010, Serreze et al., 2009). Accurately monitoring sea ice trends and understanding the complex ocean-atmosphere interactions that cause them is essential to projecting future temperature and climate change scenarios in the Arctic.
Since the inception of the satellite era in the late 1970s, annual mean sea ice extent has declined by about 3% per decade with the most notable losses transpiring in September (Stroeve et al., 2008; Serreze and Francis, 2006). The brief recorded history of sea ice loss in the Arctic culminated with the summer of 2007 during which the September extent was 23% less than the previous record minimum extent set in 2005 (Stroeve et al., 2008). Kumar et al. (2010) found the largest land surface warming anomalies in 2007 were focused over northern Alaska and Siberia with the adjacent western Arctic Ocean sea ice decline most substantial. Recent significant losses of perennial sea ice seem to indicate that the Arctic is nearing a time when ice-free summers could be a reality should warming trends persist. In fact, some climate models project this scenario within the next 15-50 years (Wang and Overland, 2009; Holland et al., 2006).

Nevertheless, the climate research community is in the process of defining the causes for polar climate change. The variability is largely attributed to natural (El Niño, the Arctic Oscillation, etc) and anthropogenic sources (greenhouse gas (GHG) emissions, etc). However, separating the contribution of these signals to the observed climate change trends is computationally demanding and requires the use of techniques such as climate model ensemble averaging to differentiate the GHG forcing from the temporally-varying natural signals (Neelin, 2011).

This thesis seeks to statistically evaluate the relationships between several modes of natural variability, referred to as teleconnections, and western Arctic sea ice and land surface air temperature (SAT) trends over the course of several decades. In this region of
the Arctic, these relationships have previously been found to be largely non-existent on multidecadal scales (Polyakov et al., 2003a). Specifically, the main purpose of this analysis is to explore whether the five atmospheric and sea surface temperature (SST) global teleconnections selected for this analysis can reasonably explain a large portion of the variance, and thereby yield predictions, regarding western Arctic sea ice and temperature behavior. These ten teleconnections indices will be analyzed against Chukchi and Beaufort Sea ice and terrestrial SAT observations at Mys Uelen, Russia and Barrow, Alaska over a temporal scale spanning 1951-2007. This research is designed to satisfy these objectives and others including:

1. Which multi-seasonal, summer and annual teleconnection patterns best explain multidecadal sea ice and SAT observations over much of the last half century?
2. Are these findings significant and how well can they be explained statistically and physically over the region?
3. What implications do these results hold for predicting future multidecadal sea ice and SAT trends?

This thesis continues with Chapter 2 which will provide a brief overview of past research and provide additional motivation for studying atmospheric and oceanic mechanisms in conjunction with sea ice and surface air temperature variability. Chapter 3 will describe the data and methodology employed in this research. Chapter 4 will cover the statistical results of this thesis by examining the multi-seasonal, summer and annual teleconnections relationships to the sea ice and SAT. The conclusion of the Chapter 4 will attempt to physically explain statistical relationships where appropriate. Chapter 5
will summarize the key findings and conclusions of this thesis and briefly discuss important implications for future research.
CHAPTER 2
LITERATURE REVIEW

2.1 Teleconnections and Other Causes of Arctic Sea Ice Variability

Arctic sea ice declines have been traced to a number of physical factors on a number of temporal scales. Teleconnections relationships to Arctic sea ice variability on decadal scales have been well documented in recent years. Maslanik et al. (2007b) show that sea ice decline in the late 1980s and early 1990s was strongly tied to a positive Arctic Oscillation (AO) signature. This AO feature is comprised of a main pressure center in the Arctic (the Icelandic Low) and two less pronounced climatological pressure features over the North Atlantic (Azores High) and the North Pacific (Aleutian Low). When the AO is positive, the Icelandic Low deepens in conjunction with a weakening of Azores High and Aleutian Low. As a result, anomalous westerly wind fields produced by enhanced cyclonic flow and surface heat flux into the Arctic promote ice advection from the eastern to the western Arctic (Nghiem et al., 2006, Liu et al., 2004). Synoptic mechanisms, discussed later in this section, act to both promote sea ice advection away from Siberian and Alaskan coasts and feed the ice into the Beaufort Gyre and Trans-polar Drift Stream (Maslanik et al, 2007a, Nghiem et al., 2006). This series of behaviors have been observed in conjunction with a positive AO, most notably during the winter season.
In recent years multi-year sea ice (MYI) has largely been replaced by younger, thinner ice that is more susceptible to retreat given the appropriate summertime conditions (Maslanik et al., 2007a). Generally, this decline in sea ice thickness and extent has transpired in the face of the AO returning to a more neutral state. Similarly, Deser and Teng (2008) found that the weak amplitude of spring and summer SLP trends suggests that the AO and North Atlantic Oscillation (NAO) signals, collectively termed the Northern Annular Mode (NAM), are not dominant factors motivating summer sea ice concentration declines in the recent past.

While the AO/NAO has been a factor in past but not recent sea ice retreat, another less known teleconnection has been suggested in connection to these observed losses. Maslanik et al. (2007b) concluded that the frequency of Arctic low pressure and positive dipole patterns increased from 2000-2004 as Arctic sea ice extent declined. Sometimes referred to as the Dipole Anomaly (DA) because of its two pressure centers, this pattern is recognized as the second EOF of SLP north of 70º N during the winter season (October – March) and is connected to a strong meridional wind anomaly (Watanabe et al., 2006; Wu et al., 2006). More recently, (Wang et al., 2009) argues that the DA also shows up as the second EOF in summer. During the positive DA, there is a positive SLP anomaly in the Canadian Archipelago and a negative one Barents Sea while the negative DA presents the opposite scenario (Wang et al., 2009). Physically, Wang et al. (2009) and Overland et al. (2008) found that during the positive summer DA phase strong southerly geostrophic meridional wind anomalies from eastern Siberia act to bring warm Pacific water into the region through the Bering Strait and force sea ice eastward from the western Arctic and
into the North Atlantic via the Trans-polar Drift Stream. Wang et al. (2009) contends that with the AO return to a more neutral phase around 1995 that the DA is a major contributor to sea ice declines in recent summers.

Although less publicized than the AO/NAO, the El Niño-Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO) have also been connected to declining Arctic sea ice trends. El Niño events (positive ENSO) have been connected to less ice in the Chukchi/Beaufort seas by changing the Ferrel Cell, which allows an anomalous meridional heat flux to penetrate into the region (Liu et al., 2004). Similarly, the PDO has been found to modulate the effect of ENSO at high latitudes and western Arctic warming over the last several decades (Serreze and Francis, 2006; Papineau, 2001). Bering Sea ice anomalies are found to be governed by the strength of the Aleutian Low and commonly tied to the recent positive PDO (Francis and Hunter, 2007).

While the previous teleconnections largely vary on decadal or shorter temporal scales, the Atlantic Multidecadal Oscillation (AMO) has a periodicity of roughly 50-80 years (Kerr, 2000). The AMO, also referred to as the Low-Frequency Oscillation (LFO), has been largely identified in conjunction with Arctic sea ice and temperature change during its positive phase (Polyakov and Johnson, 2000). During this phase, SSTs in the North Atlantic are anomalously warm for several decades and these warm waters percolate into the Arctic through the Fram Strait and Barents Sea and cause sea ice variability in some of the marginal Arctic seas. The AMO signal was found to be strongest in the Kara Sea, but it weakens eastward and has largely not been observed in the western Arctic (Francombe et al., 2010; Polyakov et al., 2003b).
Synoptic oceanic and atmospheric factors are also important interannual causes of ice variability across the western Arctic. While the decadal and multidecadal teleconnections may or may not force some of the sea ice variability, synoptic variability is ever-present to some degree in the region. Annual pack ice drift patterns across the region are primarily dictated by the Beaufort Gyre, which is an ocean surface current fueled by the Coriolis force that perpetuates anticyclonic motion of ice in the Canadian Basin, and the Trans-polar Drift Stream, which is the large scale transporter of ice from the Siberian coast through the Fram Strait. Winter and summer have contrasting pressure fields over the Arctic Ocean. During winter, there is a trough of low pressure over the Atlantic portion of the Arctic and high pressure and stable conditions persist over the pole as a result of large scale sea ice cover. In contrast, during summer the Atlantic pressure trough is replaced by a ridge over the Barents and Kara Seas. As a result, there is weak low pressure over the pole and anticyclonic conditions persist in the Beaufort Sea (i.e. the Beaufort High). It is the combination of the oceanic mechanisms and the mean synoptically driven surface winds that largely force the resultant ice motion in the region (Serreze and Barry, 2005).

Research has shown that during light ice summers the Beaufort High is strongly defined over the Canadian Arctic Archipelago (Drobot and Maslanik, 2003). The persistent anticyclonic flow produces northerly and easterly winds that promote advection of sea ice out of the Beaufort Sea and toward the Fram Strait along the Trans-polar Drift Stream (Ogi et al., 2010; Drobot and Maslanik, 2003; Rogers, 1978). Deser and Teng (2008) also found a connection between easterly geostrophic wind anomalies and
negative summer sea ice trends in the East Siberian and Beaufort Seas (1993-2006). Ogi et al. (2008) observed large retreat of first-year ice (FYI) during the summer of 2007 that were fueled by Ekman drift patterns and enhanced by anomalously high SLP over the Beaufort Sea throughout most of the summer. Further, Ogi et al. (2008) found that the highest summer SLP observations (i.e. from a strengthened Beaufort High) from this region during 1979-2008 (1995, 1998, 1999, 2005, 2007 and 2008) quite often corresponded to sea ice record minima through that period (1995, 2005 and 2007).

2.1.1 Extreme Arctic Sea Ice Event of 2007

The summer record minimum of 2007 was the nexus of several oceanic and atmospheric anomalies. It is important to mention both because it was an anomaly that transpired at the tail end of the time series used in this study and because it still stands as the Arctic minima to this day. During the summer of 2007, positive Arctic Ocean SST anomalies were up to 5° C, most notably in parts of the Chukchi, Bering and Beaufort Seas (Steele et al., 2008). Further, Woodgate et al. (2010) found that not only was the heat flux into the Arctic in 2007 double what it was in 2001, but that this increase of heat into the region, from the Pacific through the Bering Strait, was enough to be responsible for approximately 1/3rd of the Arctic sea ice loss in 2007. This meridional heat transport was propelled by the DA amongst other factors, as previously mentioned (Wang et al., 2009).

While an influx of warm water penetrated the western Arctic and produced upper-ocean warming in 2007, other mechanisms promoted the anomalous event. Zhang et al. (2008) projected that 70% of the loss was due to amplified melting from warming
conditions and the remaining 30% was due to ice advection. The warm tropospheric conditions prompting the anomalous retreat were also fueled by an atmospheric forcing that strengthened the Trans-polar Drift of ice out of the Pacific sector and central Arctic Ocean through the Fram Strait and to Baffin Bay (Nghiem et al., 2007; Zhang et al., 2008). L'Heureux et al. (2008) found that the Pacific-North American pattern (PNA) was greater than three standard deviations above the 1950-2007 mean during the boreal summer (JAS) of 2007. The primary atmospheric signal affiliated with the enhanced pattern was a strong, anomalous anticyclone collocated with the greatest Arctic sea ice decline. Moreover, Stroeve et al. (2008) contend that the strong anticyclone formed in early June and persisted for three months in conjunction with low pressure over central and western Siberia. The low pressure patterns produced southerly winds that aided the transport of sea ice away from the Siberian coast and into the western Arctic. This ice was then met with warm waters and predominantly clear skies resulting from the strong surface high. This created an environment conducive to melt as largely unimpeded solar (shortwave) radiation increased the surface heat content of the upper ocean, which further accelerated the ice-albedo feedback (Perovich et al., 2008; Stroeve et al., 2008; Maslanik et al., 2007a).

It is important to note that the evolution and transition of sea ice in the western Arctic in recent years before labeling the 2007 event strictly as a result of oceanic and/or atmospheric anomalies. As previously noted, the pack has undergone several record minima in the last couple of decades. During that time the extent and thickness of the perennial (multi-year) ice has generally declined in favor of thinner perennial and even
seasonal (first-year) cover (Maslanik et al., 2007a; Nghiem et al., 2007). With a preponderance of thin, seasonal ice in the region, Nghiem et al. (2006) correctly predicted that a strong melt could cause a record minimum in ice cover to transpire in the western Arctic. Therefore, the fragile condition of the marginal ice combined with the anomalously warm ocean waters and high pressure converged to produce a record minimum for the region in 2007. However, the stage has been set for future minima to occur given the direction that Arctic climate appears to be heading.

2.2 Teleconnections and Surface Air Temperatures

Similar to sea ice as previously mentioned, teleconnections and Arctic SAT variability have been extensively evaluated on interdecadal scales. Perhaps the most historically documented atmospheric teleconnection is the North Atlantic Oscillation (NAO). Observed “seesaws” in winter SATs, created by the phases of the NAO, between western Greenland (Jakobshavn) and northern Europe (Oslo) date back to the 18th century (van Loon and Rogers, 1978). Thompson and Wallace (1998) have argued the NAO is actually part of a larger mode of sea level pressure variability called the Arctic Oscillation (AO), or NAM as previously defined in Section 2.1, but also referred to as the surface signature of the polar vortex. Sections 4.5 and 4.6 will refer to the NAO and AO separately and collectively as the Northern Annular Mode (NAM) because the modes are seasonally well correlated with each other. Rogers and McHugh (2002) argue the two are inseparable only during winter when they share a similar North Atlantic storm track. Both of these teleconnections have been separately tied to Arctic SAT variability during the latter part of the twentieth century. Until the mid-1990s a warming trend in surface
temperatures was thought to be connected to positive phases of both the AO and NAO (Comiso, 2003). From 1996-2004 and largely through the present, the AO returned to a nearly neutral phase, but Arctic SATs continued to rise (Overland and Wang, 2005). The recent increase in Arctic temperatures will be more critically examined in Section 2.2.1.

The PDO has also been tied to western Arctic temperature change in recent years. Hartman and Wendler (2005), in agreement with Papineau (2001), found that an abrupt shift in the PDO from a negative phase (1951-1976) to a positive phase (1977-2001) occurred in conjunction with substantial warming of Continental and Arctic Alaska, especially during winter and spring. Wendler et al. (2010) found Barrow mean annual SATs to have increased 2.9 °C from 1972-2007. The intensified Aleutian Low of the recent period was thought to be somewhat responsible for advecting warm air into the interior and higher latitude areas of Alaska during the aforementioned seasons. Nevertheless, quantifying the PDO’s contribution, versus that of other natural modes, to the observed temperature changes not only to the North Slope of Arctic Alaska, but also throughout the Arctic has been a challenge to the researchers (Serreze and Francis, 2006; Hartman and Wendler, 2005).

Also similar to sea ice, the SST-based AMO index has been statistically connected to Arctic temperature variability on multidecadal scales. Chylek et al. (2009) found the Parker et al. (2007) version of the AMO index, constructed of eigenvector-based worldwide SSTs and NOAA detrended SSTs of the North Atlantic, to be correlated with annual Arctic temperatures at 0.69 and 0.79 respectively. Polyakov and Johnson (2000) also found an AMO, again they define as LFO, connection to SAT and pressure.
Further, this oscillation was defined by enhanced cyclonic flow and above average temperatures in the central Arctic, much like the AO but on a greater temporal scale.

Polyakov et al. (2002, 2003a) evaluated AMO trends through the 20th century and revealed some interesting results. After sampling of 75 of the most homogenous and continuous weather station records poleward of 62° N from 1875-2000, they concluded that Arctic temperatures were higher in the 1930s-40s than the trend through 2000. The Arctic temperature trend from 1875-2000 was approximately 0.09 °C/decade. However, limiting the results to strictly the 20th century actually produced a marginally cooler Arctic decadal trend (0.05 °C/decade) relative to the Northern Hemisphere trend (0.06 °C/decade). More recent studies have also disputed past warming trends. Chylek et al. (2009) found that the Arctic amplification was greater in both the low (64-70° N) and high (70-90° N) Arctic from 1910-1940 versus 1970-2008. Though these comparisons are interesting to point out, they should not be intensely debated. The number of land and ocean observational stations added since the 1910-1940 period combined with near global coverage of SATs afforded with the advent of the satellite era has drastically increased confidence in temperature trend analysis since the former period. While the AMO connection to Arctic temperatures is apparent, considerable care should be taken to avoid definitively labeling any widespread high latitude (or any latitude for that matter) areas of the early 20th century as warmer or cooler than those today.

2.2.1 Arctic Amplification

In recent decades, Arctic SATs have risen at almost twice the global SAT rate (Bekryaev et al., 2010; Serreze and Francis, 2006). The observed ratio increase in Arctic
to global temperatures is known as Arctic amplification. There has been ongoing debate regarding what exactly is fueling this warming. Overall, there is a sense of hesitation in the scientific community to solely anoint either natural variability (teleconnections, etc) or greenhouse gas emission (GHG) as the primary culprit forcing northern high latitude warming is largely because differentiating their contributions to warming is difficult and complex (Hoerling et al., 2011; Bekryaev et al., 2010; Serreze et al., 2009; Serreze and Francis, 2006).

There is evidence that the frequency and amplitude of interannual ocean-atmosphere phenomena such as ENSO may be altered in a warmer climate (Neelin, 2011). Therefore, the modes of natural variability could be enhanced by the warming environment that surrounds them. An attempt to separate the signals requires an ability and understanding of the climate models. For instance, ensemble model runs of naturally and anthropogenically forced scenarios of the twentieth century can be used to compare the contributions of the different signals to warming (Neelin, 2011). The likely combination of natural and anthropogenic causes of the warming provide one reason why studying each phenomenon’s separate contribution to high latitude climate change is important.

Regardless of the underlying sources, ongoing Arctic warming leads to a decrease in snow and ice and this effectively lowers albedo of the ocean and land surface thereby prompting increased absorption of solar radiation in a process known as the ice-albedo feedback (Serreze and Barry, 2005). Particular focus needs to be given to the impacts of the Arctic Ocean in this process. When this feedback persists increased shortwave
radiation penetrates the open ocean surface and increases its sensible heat content (during summer-only). In turn, ice formation, which acts to shield the warm ocean surface from the cold Arctic atmosphere, is delayed in fall and winter. As a result, this promotes strong upward heat fluxes, which act to heat the surface and lower troposphere (Serreze et al., 2009). These processes, which combine to enhance the ice-albedo feedback, indicate that the primary driver of recent warming appears to be declining sea ice (Kumar et al., 2010; Screen and Simmonds, 2010; Serreze et al., 2009).

This recent surface based warming signal from sea ice depletion is largely confined to the lower 1000 meters of the troposphere in the Arctic (north of 60° N) and is quite seasonally pronounced (Deser et al., 2010; Kumar et al., 2010; Screen and Simmonds, 2010). The majority of the warming is focused near the surface because the region is defined by strong low-level stability that inhibits vertical mixing (Screen and Simmonds, 2010; Serreze et al., 2009). This warming also displays an obvious seasonal cycle. During summer, the atmosphere loses heat to the ocean and warms the upper ocean, but the contribution of ocean surface warming to SAT increase is minimal. During late fall and winter, the excess heat stored in the upper ocean is released to the atmosphere as the re-freeze of sea ice is delayed (Screen and Simmonds, 2010; Deser et al., 2010; Serreze et al., 2009).

Explanations for observed Arctic amplification are complex and complicated. Determining exactly what mechanisms have triggered the warming and to what extent they impact current trends is difficult to quantify. Previously mentioned, there is near consensus in the scientific community that GHG emissions are contributing to northern
high latitude warming. However, at the same time there is widespread agreement that the modes of natural variability are also contributing. Separating these signals is an ongoing challenge and regardless of what factors contribute to the warming, the observed effects are undeniable. This thesis will not approach this topic from an anthropogenic standpoint, but will look to examine climate change in the Arctic in terms of potential natural drivers of its variability.
CHAPTER 3
DATA AND METHODOLOGY

3.1 Data

The summer temperature records of Barrow, Alaska (71.30° N, 156.78° W) and Mys Uelen, Russia (66.17° N, 169.83° W, hereafter referred to as Uelen) are examined from 1951-2007 (n = 57) in conjunction with the sea ice data described below. The raw monthly Arctic SAT data is from the Global Historical Climate Network Monthly Version 2 (GHCN2), which was obtained from the National Climatic Data Center (NCDC). All temperatures taken from these land based observation stations are gathered from the standard height of two meters. The aforementioned western Arctic coastal locations were selected based on the integrity of their records, i.e. their temperature and sea ice time series are nearly or entirely complete without notable discontinuous periods. The Polyakov et al. (2002, 2003a) Arctic SAT dataset, consolidated from WMO land stations, Russian NP stations and drifting buoys (from the International Arctic Buoy Programme (IABP)), was used to fill missing monthly temperature values through the year 2002. Remaining gaps from 2003-2007 were filled with the individual station’s monthly mean SAT values from the study period. Mean seasonal temperatures for each year were constructed as follows: winter (wi/DJF), spring (sp/MAM), summer (su/JJA)
and autumn (SON). In the final seasonal analysis, autumn indices were not included with the other seasonal values because of the assumption that the future indices would not have an impact on preceding summer sea ice and SAT. Separate analyses using summer and annual teleconnections were also conducted. The summer temperatures and sea ice conditions (described below) are analyzed against multi-seasonal (winter, spring, summer or wss) and summer-only (su) atmospheric and SST teleconnection indices while annual temperatures (ann) are analyzed against annual teleconnection indices (average of all four seasonal indices).

The derived sea ice data has been obtained from the Hadley Center Sea Ice and Sea Surface Temperatures (HadISST) monthly median sea ice concentration (SIC) fields on a 1° x 1° grid from 1951-2007, available from the Hadley Center Meteorological Office (Rogers and Hung, 2008; Rayner et al., 2003). The main HadISST source of ice data prior to 1978 was the Walsh (1978) end of month SIC charts composed of various sources including early satellite observations, aircraft and ship reports, which were adjusted to create mid-month HadISST SIC fields (Rogers and Hung, 2008; Stroeve et al., 2007; Rayner et al., 2003). Beginning in October 1978, HadISST SIC fields are primarily composed of Scanning Multichannel Microwave Radiometer (SMMR) and the Special Sensor Microwave Imager (SSM/I) passive microwave satellite data outputs (Rogers and Hung, 2008).

The summer ice retreat latitudes examined represent the approximate locations of sea ice extent along lines of longitude extending from the Alaskan and Siberian coasts and analyzed on September 15 of each year, which is the approximate climatological
peak of the melt season in the Arctic near the time when maximum open water occurs. The latitude to which the ice retreats on September 15 of each year, 1951-2007, was obtained at eleven different longitudes from the eastern portion of the Chukchi to the eastern Beaufort Sea (Figure 1, Table 1). For purposes of identification in this paper, the coordinates are labeled by their approximate longitudes from the farthest western longitude, 176.27° W, recognized as L176, to the furthest eastern longitude, 126.23° W, recognized as L126, with each coordinate separated by approximately 5° longitude. The longitudes were arranged such that the longitude extending north from Barrow, Alaska (L156) would be included. The datasets were composed with both the ice and temperature histories in mind. The Barrow (1895-2007) and Uelen (1928-2007) temperature records are amended to encapsulate the sea ice data period of record, 1951-2007 as used by Rogers and Hung (2008). All eleven HadISST ice latitudes will also be examined and compared in following sections of this paper.

The impacts of teleconnections have long studied by the physical science community. Ångström (1935) coined the term *teleconnection* in regards to patterns of climatic fluctuations and Bjerknes (1969) later used it to describe patterns of atmospheric response to a remote surface forcing (Barry and Carleton, 2001). It is important to note that the term *teleconnections* will be loosely used to describe both atmospheric circulation and SST indices within the context of this paper and will be used to evaluate SAT and sea ice variability. The indices are composed of mean seasonal values following the same divisions as the temperature data previously described. Ten regional teleconnections consisting of five atmospheric and five SST indices were used for this
<table>
<thead>
<tr>
<th>Ice Location</th>
<th>Latitude in Degrees North (°N)</th>
<th>Longitude in Degrees West (°W)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L176</td>
<td>67.70</td>
<td>176.27</td>
</tr>
<tr>
<td>L171</td>
<td>66.70</td>
<td>171.25</td>
</tr>
<tr>
<td>L165</td>
<td>68.86</td>
<td>165.86</td>
</tr>
<tr>
<td>L161</td>
<td>70.52</td>
<td>161.11</td>
</tr>
<tr>
<td>L156</td>
<td>71.30</td>
<td>156.78</td>
</tr>
<tr>
<td>L151</td>
<td>70.61</td>
<td>151.09</td>
</tr>
<tr>
<td>L146</td>
<td>70.32</td>
<td>146.05</td>
</tr>
<tr>
<td>L141</td>
<td>69.67</td>
<td>141.13</td>
</tr>
<tr>
<td>L136</td>
<td>69.32</td>
<td>136.58</td>
</tr>
<tr>
<td>L131</td>
<td>70.19</td>
<td>131.36</td>
</tr>
<tr>
<td>L126</td>
<td>69.77</td>
<td>126.23</td>
</tr>
</tbody>
</table>

Table 1. HadISST sea ice coordinates.
thesis. The atmospheric indices include the North Atlantic Oscillation (NAO), Arctic Oscillation (AO), North Pacific Index (NPI), Pacific North American Pattern (PNA) and Southern Oscillation Index (SOI), while the SST indices include the Atlantic Multidecadal Oscillation (AMO), Pacific Decadal Oscillation (PDO), the Niño 3.4 Index (N34), Cold Tongue Index (CTI) and Tropical Pacific Index (TPI) as referenced in Table 2.

The NAO is the raw sea level pressure (SLP) anomaly (hPa) between the Ponta Delgadas, Azores and Akureyri, Iceland, and is comprised of the Azores High and Icelandic Low (Rogers, 1984). Thompson and Wallace (1998) have argued the NAO is actually part of a larger mode of sea level pressure variability called the AO, which is the first eigenvector of Northern Hemisphere SLP from 20°N to 90°N, measuring the surface signature of the modulations in the strength of the polar vortex aloft (50 hPa), i.e. the strength of the mid-latitude westerlies, most notably over the winter season. The NPI also relates the subtropics to the subpolar regions from 30° N to 65° N and 160° E to 140° W via an area-weighted mean SLP (hPa) over the region (Trenberth and Hurrell, 1994). Similar to the NPI, the PNA is the monthly mean 500 hPa geopotential height over four centers of action which include Hawaii, the North Pacific Ocean, Alberta, Canada and the Gulf Coast region of the United States (Wallace and Gutzler, 1981). The NPI is highly correlated to the PNA in winter months (r ≈ -0.92), but the SLP-based index extends to 1899. The dominant Southern Hemisphere atmospheric teleconnection is the SOI, which is the SLP anomaly difference (hPa) between Tahiti and Darwin, Australia (Chen, 1982).
<table>
<thead>
<tr>
<th>Index Name</th>
<th>Abbreviation</th>
<th>Period of Record</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>North Atlantic Oscillation</td>
<td>NAO</td>
<td>1895-2007</td>
<td>Rogers, 1984 (updated)</td>
</tr>
<tr>
<td>Arctic Oscillation</td>
<td>AO</td>
<td>1899-2007</td>
<td><a href="http://jisao.washington.edu/ao/#data">http://jisao.washington.edu/ao/#data</a></td>
</tr>
<tr>
<td>North Pacific Index</td>
<td>NPI</td>
<td>1899-2007</td>
<td><a href="http://www.cgd.ucar.edu/cas/jhurrell/indices.data.html#npmon">http://www.cgd.ucar.edu/cas/jhurrell/indices.data.html#npmon</a></td>
</tr>
<tr>
<td>Southern Oscillation Index</td>
<td>SOI</td>
<td>1895-2007</td>
<td><a href="http://www.cgd.ucar.edu/cas/catalog/climind/SOI.signal.ascii">http://www.cgd.ucar.edu/cas/catalog/climind/SOI.signal.ascii</a></td>
</tr>
<tr>
<td>Atlantic Multidecadal Oscillation</td>
<td>AMO</td>
<td>1895-2007</td>
<td><a href="http://www.esrl.noaa.gov/psd/data/climateindices/list/#AMO">http://www.esrl.noaa.gov/psd/data/climateindices/list/#AMO</a></td>
</tr>
<tr>
<td>Pacific Decadal Oscillation</td>
<td>PDO</td>
<td>1900-2007</td>
<td><a href="http://jisao.washington.edu/pdo/PDO.latest">http://jisao.washington.edu/pdo/PDO.latest</a></td>
</tr>
<tr>
<td>Niño 3.4 SST Index</td>
<td>N34</td>
<td>1895-2007</td>
<td><a href="http://gcmd.nasa.gov">http://gcmd.nasa.gov</a></td>
</tr>
<tr>
<td>Cold Tongue SST Index</td>
<td>CTI</td>
<td>1895-2007</td>
<td>Jisao.washington.edu/data/cti/#data</td>
</tr>
<tr>
<td>Tropical Pacific SST Index</td>
<td>TPI</td>
<td>1895-2007</td>
<td>Obtained from COADS</td>
</tr>
</tbody>
</table>

Table 2. List of teleconnection indices used in analysis with sea ice and surface air temperature data. The PNA winter and spring indices date back to 1948, while the summer and autumn indices date to 1950.
The AMO is a measure of the North Atlantic Ocean SST anomaly (°C) from the equator to 60°N (Enfield et al., 2001). The PDO is the leading principal component of North Pacific Ocean (poleward of 20°N) monthly SST (Mantua et al., 1997). The Niño 3.4 Index (N34) is the mean SST over the eastern equatorial Pacific Ocean spanning 5°N to 5°S and 170° W to 120° W (Rasmusson and Carpenter, 1982). The CTI measures (°C) the cold water of the eastern tropical Pacific between 6°N and 6°S and 180-90°W (Deser and Wallace, 1990). The TPI is defined by Zhang et al. (1997) as the SSTs (°C) averaged from 20°N to 20° S and from 160°E to 80°W, an area associated with “ENSO-like” conditions.
Figure 1. Map of western Arctic sea ice and temperature coordinates. The blue arrow represents the Uelen temperature station and the green arrow represents the Barrow sea ice and temperature location.
3.2 Methodology

The foundation of this thesis is grounded on two primary statistical methods, principal component analysis (PCA) and stepwise multiple linear regression (SMLR). PCA is useful because it reduces the multivariate teleconnection dataset into a smaller multivariate dataset constructed of new orthogonal variables. These orthogonal variables are linear combinations of the original ones and represent a large fraction of the variability contained within the original dataset. The initial principal component (PC) exhibits the largest variance and subsequent PCs represent the largest remaining variances of the dataset. Initial runs were completed using unrotated and rotated principal component analysis (RPCA) methods before varimax rotation was ultimately chosen to simplify the structure while maximizing the sum of the explained variances (Wilks, 2006). The decision of how many factors to retain is based on the scree plot of the eigenvalues. The scree plot graphs the eigenvalue against the component number and where the eigenvalues level off to nearly constant values, or where noticeable ledges occur in the data, determines the number of components selected. This procedure will be discussed in greater detail in Chapter 4.

The RPCs are composed of scores, which represent the components’ time series, and loadings, which represent the spatial patterns of the component. Loading thresholds are set at \( r \geq 0.70 \) because this assumes that each loading accounts for nearly half of the explained variance \( (r^2 = 0.49) \). RPC names were assigned based on teleconnection indices that fit this loading criteria. Typically, the RPCs are based on one dominant loading pattern blended with all others to create an uncorrelated data set. However, some
RPCs are composed of multiple indices that fit the loading threshold (as seen in Table 4, 6 and 8 of the next chapter). After being labeled accordingly, these RPCs are then used as independent variables (predictors) in the SMLR analysis and regressed against the dependent sea ice and temperature variables (predictands). The use of RPCA in constructing new orthogonal teleconnection functions negates the potential for multicollinearity in the SMLR that could arise due to high correlation between teleconnections such as the AMO and NAO. In this analysis, for example, components representing the AMO and NAO are separate orthogonal (uncorrelated) patterns.

To conclude the bulk of the statistical analysis, SMLR is used to identify the best combination of predictors (teleconnection based RPCs) that explain the variance of the predictands (surface air temperatures and sea ice retreat latitudes). This can be represented by the model equation as:

\[ Y = a + b_1x_1 + b_2x_2 + \ldots + b_nx_n \]

where \( Y \) is the predictand value, \( a \) is the constant, values \( b_1 \ldots b_n \) are the regression coefficients for the predictor variables \( x_1 \ldots x_n \). The SMLR forward selection process starts by choosing the predictor variable explaining the most predictand variance. Second and subsequent predictors retained in the prediction equation must explain the largest amount of remaining predictand variance with 95% confidence, thereby increasing the coefficient of determination \( (r^2) \) with \( Y \) by the greatest amount. The SMLR stops the entry of variables when new independent variables no longer explain significant levels of residual variance. Regression coefficients are re-calculated as each new predictor is entered and the number of degrees of freedom is reduced by one in each step, leading to a final \( r^2 \)
value adjusted for the reduction in degrees of freedom (Rogers, 2010, personal
communication).

The model estimates are conducted by a least-squares regression approach, which
produces unstandardized predicted values that minimize the sum of squares errors. Since
the true model is unknown, errors, or unstandardized residuals, will result after the model
has been estimated. These residuals are equal to the difference between the observed and
predicted value of the predictand for a certain year. Further, they measure the closeness
of fit of the predicted values and the observed predictands and the smaller the residuals
the better the statistical model fits the data. Least-squares regression is also used to
identify trends in the observed, predicted and residual values by regressing the
independent time (year) variable against those three values. The resulting trends are
multiplied by ten to produce decadal trends. The predicted and residual values will each
be analyzed with the aforementioned predictands via Pearson bivariate correlations to
measure the degree of linear relation between the two variables over the duration of the
time series. The time series of the multi-seasonal, summer and annual (temperatures
only) observed, predicted and residual sea ice and temperature values are presented in
Figures 5-31. T-values and F-ratios will be mentioned as a means of initially evaluating
the model significance in terms of its multiple linear regression slope significantly
differing from zero. Percent significance for t-values, F-ratios and trends correspond to
these significance intervals: 95% (0.025 < x ≤ 0.055), 99% (0.005 < x ≤ 0.025) and
99.9% (0.000 ≤ x ≤ 0.005).
Analysis of the residuals will be carried out including examination of their standard deviations and lag-1 autocorrelations ($r_1$), which measures the correlation of the series with itself at a one year lagged interval (for instance, previous multi-seasonal, summer, annual value). The corresponding Ljung-Box (L-B) statistic, an increasingly common portmanteau test, will be used to assess the significance of the $r_1$ and whether the residuals are random or persistence (autocorrelation) is unresolved in the model. The null hypothesis for this test is that the residuals are random, indicative of a stochastic process. Therefore, a non-statistically significant $r_1$ (L-B < 95%), is an indication that the residuals are likely random and normally distributed (with 95% confidence), as they should be in a regression analysis. A significant $r_1$ (L-B ≥ 95%) indicates that there is still some element of non-randomness (autocorrelation) remaining in the residuals beyond the trend and therefore this non-randomness is not adequately explained by the regression analysis (Rogers, 2011, personal communication).

All statistical procedures were performed using Statistical Package for the Social Sciences (SPSS Statistics 17.0 and 19.0). Interactive Data Language (IDL) Student Edition 5.5 was used to create the map schematic and generate the time series for this thesis.
CHAPTER 4
RESULTS

4.1 History of Sea Ice and Temperature: 1951-2007

The sensitivity of the Arctic cryosphere to natural and anthropogenic forcing mechanisms is undeniable. This is especially well documented in the western Arctic, where sea ice and surface air temperature have reached new extremes in recent years. Table 3 displays summary statistics that include the latitude of the mean ice retreat extent (mean SAT), standard deviation and maximum and minimum values of these latitudes (and their respective years when the extremes occurred) for all eleven HadISST longitudes and both surface air temperature stations for the 1951-2007 study period. Some interesting features of the dataset are first examined before the more complex statistical procedures and outcomes are explored.

Examining the 57 years of September 15 ice extent latitudes revealed some similar patterns. All maximum retreat years, i.e. the year in which the poleward retreat of the ice was greatest, correspond to the last ten years (1998-2007) of the dataset. In fact, the extreme ice decline of 2007 was represented in the six westernmost HadISST longitudes spanning from the far eastern extent of the Chukchi Sea to the far western portion of the Beaufort Sea. Ice retreat maxima in the final five longitudes takes place
Table 3. Summary statistics for sea ice extents and summer surface air temperatures at Uelen and Barrow. Sea ice extents are in latitudes (°N) as are standard deviations. Surface air temperatures at Uelen and Barrow are in °C. Asterisks (*) indicate multiple years with similar values.
from 1998-2002. The Uelen temperature maximum follows a similar pattern, with highest summer temperature in 2004, while Barrow was warmest instead in 1989. Further, the greatest maximum retreat of any single longitude in the dataset also occurred at L176 during the summer of 2007 when the ice retreated to 85.60°N, nearly 13°N beyond the 1951-2007 mean sea ice latitude. The standard deviations of the ice retreat latitudes along the 11 longitudes generally decrease eastward. This means that the greatest interannual variability of the sea ice coordinates occurs in the Chukchi and western Beaufort Seas. Plots of sea ice variability, found corresponding to the results of Sections 4.3 and 4.3.1, substantiate this fact.


A few of these locations produced physically perplexing results. For instance, L151 (70.61 °N) had minimum retreat values that breached the coastline origin from which the ice retreat is measured (70.50°N). This could be attributed to a landfast sea ice scenario (or near landfast phenomena). While a cold summer and landfast ice on
September 15 is possible, overlap on extents for non-landfast scenarios (L176, L156, L141, L136) could be caused by a lack of decimal precision stemming from SSMR/SSM/I resolution estimates or the integrative measurements taken in the period before October 1978. Nevertheless, these estimates are fairly clustered together in the twenty seven years comprising the pre-satellite era of the data used for this project. Further, the rough periods where minimum (1951-1978) and maximum retreat (1979-2007) observations of the given longitudes fit in the context of the global temperature record over the last century. With a period of cooling temperatures ending in the 1970s and a transition into rapid temperature increases of the last thirty years, the maxima and minima ice retreats of the observation period seem to distinctly fit into the context of the global temperature time series.

4.2 Composition of the Principal Components

In the multi-seasonal analysis (wi, sp and su) principal component analysis was performed on the teleconnection indices to make them orthogonal to each other. A set of eigenvalues and eigenvectors were obtained. The scree plot of the eigenvalues (Figure 2) shows a couple of noticeable ledges, namely between components one and three (eigenvalue $\lambda = 9.43$ and $2.86$ respectively) and components six and eight ($\lambda = 2.08$ and $0.82$ respectively). Experimentation was conducted to see whether the best solution was to save between seven and ten components. Although a higher percentage of the total variance is explained with more components, the associations between the teleconnections are not as robust, meeting the critical threshold of eigenvector loading values exceeding absolute 0.7. Based on the rotated eigenvector loading matrix (Table
the teleconnection indices that meet and exceed the threshold were identified and they represent the component and are labeled accordingly (Table 5). For example, rotated principle component eight is comprised of the summer NAO and AO, the two indices that had the highest loadings on that component. Experiments using seven and eight components produced odd combinations of indices, but nine components resolved more of the total variance ($r^2 = 0.88$) while capturing regional homogenous (multicollinear) patterns that seemed to best fit physical reality. A trial retaining a tenth component has a component created that had no indices exceeding loadings of 0.7, suggesting that retaining ten components was over rotation. Tables 4 and 5 present the results for the best fit analysis in which nine components are retained.

The summer-only scree plot (Figure 3) shows a significant ledge between components one and two ($\lambda = 4.00$ and 1.36) and a slight ledge between components four and five ($\lambda = 1.11$ and 0.63). Experimentation saving between five and seven components was initially completed. Keeping consistent with the threshold, six components were ultimately selected to best describe the summer teleconnections dataset after scanning the rotated component matrix (Table 6). These components represent a large majority of the cumulative variance ($r^2 = 0.93$) and capture the essence of the regional teleconnections patterns better than additional or fewer components (Table 7). While simpler, this analysis also resolves more of the explained variance with three fewer components ($r^2 = 0.93$) compared with the multi-seasonal analysis above ($r^2 = 0.88$).
Table 4. Eigenvectors loadings of the individual multi-seasonal teleconnection indices on the nine rotated principle components chosen as best fit for the analysis. Loadings greater than absolute 0.7 are used to identify the teleconnections by which the component is named in Table 5.

<table>
<thead>
<tr>
<th>Component</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPI wi</td>
<td>-.242</td>
<td>-.077</td>
<td>-.886</td>
<td>-.055</td>
<td>.005</td>
<td>.043</td>
<td>.015</td>
<td>.166</td>
<td>.073</td>
</tr>
<tr>
<td>NPI sp</td>
<td>-.165</td>
<td>-.163</td>
<td>-.043</td>
<td>-.034</td>
<td>-.866</td>
<td>-.172</td>
<td>.186</td>
<td>.058</td>
<td>.108</td>
</tr>
<tr>
<td>NPI su</td>
<td>.051</td>
<td>-.210</td>
<td>-.019</td>
<td>.226</td>
<td>.042</td>
<td>-.155</td>
<td>-.114</td>
<td>.221</td>
<td>-.769</td>
</tr>
<tr>
<td>AO wi</td>
<td>.005</td>
<td>-.033</td>
<td>-.115</td>
<td>.031</td>
<td>.140</td>
<td>.898</td>
<td>.213</td>
<td>.112</td>
<td>.049</td>
</tr>
<tr>
<td>AO sp</td>
<td>-.058</td>
<td>.083</td>
<td>.083</td>
<td>-.123</td>
<td>-.243</td>
<td>.136</td>
<td>.854</td>
<td>.079</td>
<td>.073</td>
</tr>
<tr>
<td>AO su</td>
<td>-.073</td>
<td>-.178</td>
<td>.043</td>
<td>-.061</td>
<td>-.035</td>
<td>.349</td>
<td>.049</td>
<td>.758</td>
<td>-.274</td>
</tr>
<tr>
<td>PDO wi</td>
<td>.215</td>
<td>.019</td>
<td>.817</td>
<td>.105</td>
<td>.229</td>
<td>-.210</td>
<td>.079</td>
<td>.133</td>
<td>.081</td>
</tr>
<tr>
<td>PDO sp</td>
<td>.254</td>
<td>.210</td>
<td>.668</td>
<td>.122</td>
<td>.592</td>
<td>-.014</td>
<td>-.013</td>
<td>.017</td>
<td>-.047</td>
</tr>
<tr>
<td>PDO su</td>
<td>.258</td>
<td>.458</td>
<td>.372</td>
<td>-.027</td>
<td>.508</td>
<td>.166</td>
<td>.048</td>
<td>-.112</td>
<td>.273</td>
</tr>
<tr>
<td>N34 wi</td>
<td>.951</td>
<td>.028</td>
<td>.194</td>
<td>.120</td>
<td>.045</td>
<td>-.035</td>
<td>-.047</td>
<td>-.022</td>
<td>.092</td>
</tr>
<tr>
<td>N34 sp</td>
<td>.794</td>
<td>.525</td>
<td>.044</td>
<td>.074</td>
<td>.202</td>
<td>-.032</td>
<td>.005</td>
<td>-.020</td>
<td>.051</td>
</tr>
<tr>
<td>N34 su</td>
<td>.016</td>
<td>.951</td>
<td>-.036</td>
<td>-.008</td>
<td>-.028</td>
<td>-.109</td>
<td>.043</td>
<td>-.133</td>
<td>.070</td>
</tr>
<tr>
<td>AMO wi</td>
<td>.015</td>
<td>-.069</td>
<td>-.035</td>
<td>.911</td>
<td>-.087</td>
<td>.000</td>
<td>-.037</td>
<td>-.015</td>
<td>.010</td>
</tr>
<tr>
<td>AMO sp</td>
<td>.216</td>
<td>.019</td>
<td>.180</td>
<td>.900</td>
<td>-.003</td>
<td>-.033</td>
<td>-.197</td>
<td>-.074</td>
<td>-.038</td>
</tr>
<tr>
<td>AMO su</td>
<td>.073</td>
<td>.022</td>
<td>.205</td>
<td>.827</td>
<td>.079</td>
<td>.096</td>
<td>-.187</td>
<td>-.102</td>
<td>-.031</td>
</tr>
<tr>
<td>SOI wi</td>
<td>-.870</td>
<td>.021</td>
<td>-.239</td>
<td>-.035</td>
<td>-.224</td>
<td>.017</td>
<td>-.091</td>
<td>-.064</td>
<td>-.042</td>
</tr>
<tr>
<td>SOI sp</td>
<td>-.587</td>
<td>-.623</td>
<td>-.261</td>
<td>-.102</td>
<td>-.131</td>
<td>-.043</td>
<td>.045</td>
<td>-.064</td>
<td>.090</td>
</tr>
<tr>
<td>SOI su</td>
<td>.015</td>
<td>-.863</td>
<td>-.101</td>
<td>-.003</td>
<td>-.059</td>
<td>.082</td>
<td>-.167</td>
<td>-.066</td>
<td>-.156</td>
</tr>
<tr>
<td>PNA wi</td>
<td>.196</td>
<td>-.096</td>
<td>.912</td>
<td>.176</td>
<td>-.082</td>
<td>.084</td>
<td>.026</td>
<td>-.027</td>
<td>.039</td>
</tr>
<tr>
<td>PNA sp</td>
<td>.232</td>
<td>.039</td>
<td>.041</td>
<td>-.068</td>
<td>.842</td>
<td>.168</td>
<td>-.271</td>
<td>-.072</td>
<td>.003</td>
</tr>
<tr>
<td>PNA su</td>
<td>.440</td>
<td>.050</td>
<td>.004</td>
<td>.218</td>
<td>-.039</td>
<td>-.182</td>
<td>-.003</td>
<td>-.046</td>
<td>.754</td>
</tr>
<tr>
<td>NAO win</td>
<td>-.075</td>
<td>-.087</td>
<td>-.002</td>
<td>.030</td>
<td>.166</td>
<td>.910</td>
<td>.012</td>
<td>.160</td>
<td>-.026</td>
</tr>
<tr>
<td>NAO sp</td>
<td>.042</td>
<td>.147</td>
<td>-.006</td>
<td>-.245</td>
<td>-.128</td>
<td>.094</td>
<td>.868</td>
<td>.036</td>
<td>.025</td>
</tr>
<tr>
<td>NAO su</td>
<td>.133</td>
<td>-.063</td>
<td>-.088</td>
<td>-.109</td>
<td>-.093</td>
<td>.061</td>
<td>.074</td>
<td>.910</td>
<td>-.033</td>
</tr>
<tr>
<td>CTI wi</td>
<td>.944</td>
<td>.025</td>
<td>.207</td>
<td>.039</td>
<td>.033</td>
<td>-.015</td>
<td>-.081</td>
<td>.017</td>
<td>.083</td>
</tr>
<tr>
<td>CTI sp</td>
<td>.630</td>
<td>.628</td>
<td>-.079</td>
<td>-.133</td>
<td>.182</td>
<td>.040</td>
<td>-.076</td>
<td>-.085</td>
<td>-.028</td>
</tr>
<tr>
<td>CTI su</td>
<td>.046</td>
<td>.921</td>
<td>-.167</td>
<td>-.198</td>
<td>.047</td>
<td>.009</td>
<td>-.018</td>
<td>-.159</td>
<td>.040</td>
</tr>
<tr>
<td>TPI wi</td>
<td>.703</td>
<td>.071</td>
<td>.395</td>
<td>.401</td>
<td>.248</td>
<td>-.057</td>
<td>.039</td>
<td>.126</td>
<td>.092</td>
</tr>
<tr>
<td>TPI sp</td>
<td>.549</td>
<td>.450</td>
<td>.281</td>
<td>.451</td>
<td>.320</td>
<td>-.032</td>
<td>.160</td>
<td>.114</td>
<td>.045</td>
</tr>
<tr>
<td>TPI su</td>
<td>.265</td>
<td>.759</td>
<td>.190</td>
<td>.349</td>
<td>.243</td>
<td>-.016</td>
<td>.176</td>
<td>-.049</td>
<td>.038</td>
</tr>
<tr>
<td>Component Name</td>
<td>Description</td>
<td>$\lambda$</td>
<td>$r^2$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>----------------</td>
<td>---------------------------------------------------------------</td>
<td>-----------</td>
<td>-------</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC 1</td>
<td>Equatorial Pacific wi/sp (N34 wi/sp, SOI wi, CTI wi, TPI wi)</td>
<td>9.43</td>
<td>0.31</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC 2</td>
<td>Equatorial Pacific su (N34, SOI, CTI, TPI)</td>
<td>4.25</td>
<td>0.14</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC 3</td>
<td>Pacific Ocean-Atmosphere wi (NPI, PNA, PDO)</td>
<td>2.86</td>
<td>0.10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC 4</td>
<td>AMO wi, sp and su</td>
<td>2.59</td>
<td>0.09</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC 5</td>
<td>NPI and PNA sp</td>
<td>2.20</td>
<td>0.07</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC 6</td>
<td>AO and NAO wi</td>
<td>2.08</td>
<td>0.07</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC 7</td>
<td>AO and NAO sp</td>
<td>1.54</td>
<td>0.05</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC 8</td>
<td>AO and NAO su</td>
<td>0.82</td>
<td>0.03</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC 9</td>
<td>NPI and PNA su</td>
<td>0.73</td>
<td>0.02</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5. The descriptive names of the rotated principal components from Table 4 and the individual indices that comprise them. Eigenvalues ($\lambda$) and the total dataset variance explained ($r^2$) of the components are also included.
<table>
<thead>
<tr>
<th>Component</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPI su</td>
<td>-.171</td>
<td>.135</td>
<td>.136</td>
<td>-.192</td>
<td>-.084</td>
<td>.937</td>
</tr>
<tr>
<td>AO su</td>
<td>-.196</td>
<td>.856</td>
<td>.081</td>
<td>-.378</td>
<td>.007</td>
<td>.003</td>
</tr>
<tr>
<td>PDO su</td>
<td>.325</td>
<td>-.080</td>
<td>.065</td>
<td>.145</td>
<td>.913</td>
<td>-.101</td>
</tr>
<tr>
<td>N34 su</td>
<td>.952</td>
<td>-.156</td>
<td>-.010</td>
<td>.024</td>
<td>.090</td>
<td>-.089</td>
</tr>
<tr>
<td>AMO su</td>
<td>-.023</td>
<td>-.096</td>
<td>.964</td>
<td>.104</td>
<td>.068</td>
<td>.121</td>
</tr>
<tr>
<td>SOI su</td>
<td>-.883</td>
<td>-.020</td>
<td>-.023</td>
<td>-.075</td>
<td>-.110</td>
<td>.126</td>
</tr>
<tr>
<td>PNA su</td>
<td>.056</td>
<td>-.080</td>
<td>.125</td>
<td>.938</td>
<td>.144</td>
<td>-.188</td>
</tr>
<tr>
<td>NAO su</td>
<td>-.030</td>
<td>.911</td>
<td>-.195</td>
<td>.158</td>
<td>-.100</td>
<td>.158</td>
</tr>
<tr>
<td>CTI su</td>
<td>.897</td>
<td>-.135</td>
<td>-.160</td>
<td>-.009</td>
<td>.165</td>
<td>-.077</td>
</tr>
<tr>
<td>TPI su</td>
<td>.731</td>
<td>-.032</td>
<td>.371</td>
<td>.131</td>
<td>.442</td>
<td>.046</td>
</tr>
</tbody>
</table>

Table 6. Same as Table 4 but for the summer-only teleconnection index analysis. Principal component names are in Table 7.
<table>
<thead>
<tr>
<th>Component Name</th>
<th>Description</th>
<th>$\lambda$</th>
<th>$r^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC 1</td>
<td>Equatorial Pacific (N34, SOI, CTI, TPI)</td>
<td>4.00</td>
<td>0.40</td>
</tr>
<tr>
<td>PC 2</td>
<td>AO and NAO</td>
<td>1.65</td>
<td>0.17</td>
</tr>
<tr>
<td>PC 3</td>
<td>AMO</td>
<td>1.36</td>
<td>0.14</td>
</tr>
<tr>
<td>PC 4</td>
<td>PNA</td>
<td>1.11</td>
<td>0.11</td>
</tr>
<tr>
<td>PC 5</td>
<td>PDO</td>
<td>0.63</td>
<td>0.06</td>
</tr>
<tr>
<td>PC 6</td>
<td>NPI</td>
<td>0.53</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Table 7. Same as Table 5 but for summer-only principal components.
The annual scree plot (Figure 4) shows a significant ledge between components one and two (\(\lambda = 4.52\) and 2.05) with other slight ledges between the remaining components until they flatten out to constant values in the scree from component five onward. Again, between five and seven components were initially examined via the rotated component matrix (Table 8) before six were ultimately retained for the analysis based the previously chosen loading threshold. These six components represent the greatest amount of explained variance of any subset examined (\(r^2 = 0.97\)) and well capture regional patterns, nearly mirroring the summer components composition with the exception of a reversal of components five and six (Table 9).
Table 8. Same as Table 4 but for the annual averaged teleconnection indices. Principal components are named in Table 9.
<table>
<thead>
<tr>
<th>Component Name</th>
<th>Description</th>
<th>$\lambda$</th>
<th>$r^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC 1</td>
<td>Equatorial Pacific (N34, SOI, CTI, TPI)</td>
<td>4.52</td>
<td>0.45</td>
</tr>
<tr>
<td>PC 2</td>
<td>AO and NAO</td>
<td>2.05</td>
<td>0.21</td>
</tr>
<tr>
<td>PC 3</td>
<td>AMO</td>
<td>1.46</td>
<td>0.15</td>
</tr>
<tr>
<td>PC 4</td>
<td>PNA</td>
<td>0.95</td>
<td>0.09</td>
</tr>
<tr>
<td>PC 5</td>
<td>NPI</td>
<td>0.38</td>
<td>0.04</td>
</tr>
<tr>
<td>PC 6</td>
<td>PDO</td>
<td>0.25</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Table 9. Same as Table 5 but for annual principal components.
Figure 2. Scree plot for multi-seasonal teleconnection indices.
Figure 3. Same as Figure 2 but for summer-only teleconnection indices.
Figure 4. Same as Figure 2 but for annual teleconnections indices.
4.3 Multi-Seasonal Teleconnections and Sea Ice

Each of the eleven sea ice predictands, including Uelen and Barrow temperatures, were analyzed using the principal component teleconnection predictors (Tables 5, 7 and 9). Multi-seasonal teleconnections and sea ice results reveal primarily between two and four predictors for each SMLR run (Table 10) with the exception of the furthest eastern longitude L126, which did not produce any significant predictors for its sea ice extents. The full results are described below. Test statistics for the regression models are provided in Table 11. The trends for observed, predicted and residual time series as well as the resulting correlations between the observed, predicted and residual time series are shown in Table 12. Test statistics for the model residuals are presented in Table 13. The SMLR multi-seasonal model outputs show an obvious pattern that will be expanded upon in the forthcoming analysis (Section 4.5).

The farthest western Arctic coordinates, located in the eastern Chukchi Sea, L176 and L171 produce similar results that indicate the model was a reasonable fit. Each are represented by same four predictors (PC 4, PC 7, PC 9, and PC 5 in Table 5) which cumulatively both account for 40% of the explained variance respectively ($r^2 = 0.40$). For L176, the initial predictor, PC 4 (AMO) accounts for 18% of the explained variance, $r^2 = 0.18$, while PC 7 (AO and NAO spring) has an $r^2 = 0.09$. L171 had a higher initial predictor value, $r^2 = 0.24$, compared with its Chukchi counterpart noted above and its two initial components account for about 32% of the total dataset variance. The model significance tests (Table 11) were also similar as L176 has a t-value = 2.59 (significant at
<table>
<thead>
<tr>
<th>Location</th>
<th>Predictor 1</th>
<th>Predictor 2</th>
<th>Predictor 3</th>
<th>Predictor 4</th>
<th>Constant (a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L176</td>
<td>PC 4</td>
<td>PC 7</td>
<td>PC 9</td>
<td>PC 5</td>
<td>72.83</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.18/1.22</td>
<td>0.27/0.89</td>
<td>0.33/0.75</td>
<td>0.40/0.75</td>
<td></td>
</tr>
<tr>
<td>L171</td>
<td>PC 4</td>
<td>PC 7</td>
<td>PC 9</td>
<td>PC 5</td>
<td>73.43</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.24/1.22</td>
<td>0.32/0.76</td>
<td>0.36/0.56</td>
<td>0.40/0.53</td>
<td></td>
</tr>
<tr>
<td>L166</td>
<td>PC 4</td>
<td>PC 7</td>
<td></td>
<td></td>
<td>73.60</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.21/1.03</td>
<td>0.33/0.79</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L161</td>
<td>PC 4</td>
<td>PC 7</td>
<td></td>
<td></td>
<td>73.44</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.25/1.06</td>
<td>0.35/0.70</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L156</td>
<td>PC 4</td>
<td>PC 7</td>
<td></td>
<td></td>
<td>73.41</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.32/1.06</td>
<td>0.40/0.55</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L151</td>
<td>PC 4</td>
<td>PC 7</td>
<td></td>
<td></td>
<td>72.78</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.35/1.12</td>
<td>0.48/0.68</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L146</td>
<td>PC 4</td>
<td>PC 7</td>
<td>PC 9</td>
<td>PC 8</td>
<td>72.45</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.41/1.20</td>
<td>0.51/0.61</td>
<td>0.57/0.46</td>
<td>0.59/-0.33</td>
<td></td>
</tr>
<tr>
<td>L141</td>
<td>PC 4</td>
<td>PC 7</td>
<td>PC 9</td>
<td>PC 8</td>
<td>72.27</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.25/0.79</td>
<td>0.41/0.61</td>
<td>0.46/0.39</td>
<td>0.50/-0.33</td>
<td></td>
</tr>
<tr>
<td>L136</td>
<td>PC 4</td>
<td>PC 7</td>
<td></td>
<td></td>
<td>71.86</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.23/0.66</td>
<td>0.30/0.40</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L131</td>
<td>PC 4</td>
<td></td>
<td></td>
<td></td>
<td>72.05</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.13/0.39</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L126</td>
<td>NO</td>
<td>RESULTS</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 10. Summary of the multi-seasonal orthogonal teleconnection predictors in the SMLR that best explain the variance of the sea ice retreat latitude at the 11 longitudes. The numbered PCs refer to the teleconnection groups identified in Table 5. Results include the explained variance ($r^2$) and regression coefficient ($\pm b$) for each predictor as well as the regression equation constant ($a$).
<table>
<thead>
<tr>
<th>Location</th>
<th>t-value</th>
<th>F-ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>L176</td>
<td>2.59</td>
<td>10.30</td>
</tr>
<tr>
<td>L171</td>
<td>2.10</td>
<td>10.44</td>
</tr>
<tr>
<td>L166</td>
<td>3.29</td>
<td>14.56</td>
</tr>
<tr>
<td>L161</td>
<td>3.15</td>
<td>16.38</td>
</tr>
<tr>
<td>L156</td>
<td>2.91</td>
<td>19.92</td>
</tr>
<tr>
<td>L151</td>
<td>3.78</td>
<td>26.52</td>
</tr>
<tr>
<td>L146</td>
<td>-2.07</td>
<td>21.23</td>
</tr>
<tr>
<td>L141</td>
<td>-2.24</td>
<td>14.91</td>
</tr>
<tr>
<td>L136</td>
<td>2.66</td>
<td>13.13</td>
</tr>
<tr>
<td>L131</td>
<td>3.02</td>
<td>9.12</td>
</tr>
<tr>
<td>L126</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 11. Test statistics (t-value and F-ratio) for the multi-seasonal sea ice regression model. Significance at 95% is italicized, significance at 99% is bold and significance at 99.9% is italicized and bold.
<table>
<thead>
<tr>
<th>Location</th>
<th>Observed trend (dec⁻¹)</th>
<th>Predicted trend (dec⁻¹)</th>
<th>Residual trend (dec⁻¹)</th>
<th>r (ob and pred)</th>
<th>r (ob and res)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L176</td>
<td>1.14</td>
<td>0.65</td>
<td>0.49</td>
<td>0.67</td>
<td>0.75</td>
</tr>
<tr>
<td>L171</td>
<td>0.93</td>
<td>0.56</td>
<td>0.37</td>
<td>0.67</td>
<td>0.75</td>
</tr>
<tr>
<td>L166</td>
<td>0.84</td>
<td>0.39</td>
<td>0.45</td>
<td>0.59</td>
<td>0.81</td>
</tr>
<tr>
<td>L161</td>
<td>0.73</td>
<td>0.38</td>
<td>0.36</td>
<td>0.61</td>
<td>0.79</td>
</tr>
<tr>
<td>L156</td>
<td>0.61</td>
<td>0.34</td>
<td>0.27</td>
<td>0.65</td>
<td>0.76</td>
</tr>
<tr>
<td>L151</td>
<td>0.68</td>
<td>0.38</td>
<td>0.29</td>
<td>0.70</td>
<td>0.71</td>
</tr>
<tr>
<td>L146</td>
<td>0.59</td>
<td>0.38</td>
<td>0.21</td>
<td>0.79</td>
<td>0.62</td>
</tr>
<tr>
<td>L141</td>
<td>0.52</td>
<td>0.29</td>
<td>0.23</td>
<td>0.73</td>
<td>0.68</td>
</tr>
<tr>
<td>L136</td>
<td>0.41</td>
<td>0.23</td>
<td>0.18</td>
<td>0.57</td>
<td>0.82</td>
</tr>
<tr>
<td>L131</td>
<td>0.15</td>
<td>0.08</td>
<td>0.07</td>
<td>0.38</td>
<td>0.93</td>
</tr>
<tr>
<td>L126</td>
<td>0.17</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 12. Multi-seasonal observed, predicted and residual decadal trends and correlations (r) between observed and predicted (ob and pred) and observed and residual (ob and res) time series.
<table>
<thead>
<tr>
<th>Location</th>
<th>$\sigma_e$</th>
<th>$r_1$ (L-B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L176</td>
<td>2.08</td>
<td>0.30 (98%)</td>
</tr>
<tr>
<td>L171</td>
<td>1.82</td>
<td>0.33 (99%)</td>
</tr>
<tr>
<td>L166</td>
<td>1.77</td>
<td>0.24 (93%)</td>
</tr>
<tr>
<td>L161</td>
<td>1.63</td>
<td>0.07 (39%)</td>
</tr>
<tr>
<td>L156</td>
<td>1.38</td>
<td>0.06 (35%)</td>
</tr>
<tr>
<td>L151</td>
<td>1.32</td>
<td>0.14 (73%)</td>
</tr>
<tr>
<td>L146</td>
<td>1.14</td>
<td>0.15 (74%)</td>
</tr>
<tr>
<td>L141</td>
<td>1.05</td>
<td>0.28 (97%)</td>
</tr>
<tr>
<td>L136</td>
<td>1.11</td>
<td>0.12 (66%)</td>
</tr>
<tr>
<td>L131</td>
<td>0.96</td>
<td>0.18 (83%)</td>
</tr>
<tr>
<td>L126</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 13. Test statistics for the multi-seasonal model residuals. Standard deviation of the residuals ($\sigma_e$) and lag-1 autocorrelation ($r_1$) with corresponding Ljung-Box (L-B) statistic indicated with percent significance.
99%) and F-ratio = 10.30 significant at 99.9%), while L171 has a t-value = 2.10 (significant at 95%) and F-ratio = 10.44 (significant at 99.9%).

The decadal trends of the time series are fairly similar throughout (Table 12). The observed trend for L176, 1.14°N retreat dec⁻¹, is the largest retreat for any longitude, followed by L171, 0.93° dec⁻¹ (both significant at 99.9%). The SMLR predicted multi-seasonal trends for L176 and L171 are not as steep (0.65° latitude dec⁻¹ versus 0.56° latitude dec⁻¹, both significant at 99.9%) and they have trends in their residuals (0.49° latitude dec⁻¹, significant at 99.9%, versus 0.37° latitude dec⁻¹, significant at 99%). This is a common theme that generally persists throughout the seasonal sea ice analysis.

Analysis of the L176 residuals’ time series shows (Figures 5) a slight positive trend from around 1955 to 1979 and a steeper positive trend from the late 1980s through 2007. Moreover, the relationship between the observed and predicted L176 time series values clearly shows that the SMLR under predicts (observed > predicted values) the retreat by 5-10° latitude near the end of the time series (Figure 5). The overall spread (standard deviation) of the residuals throughout the time series is the highest of any single longitude (σₑ = 2.08, Table 13). The residuals represent the unexplained variance and are better correlated (r = 0.75, significant at 99%) to the derived sea ice extents (Table 12) as opposed to the predicted values (r = 0.67, significant at 99%). More telling of the model result, the lag-1 autocorrelation (r₁) indicates there is some measureable autocorrelation, or persistence, in the residuals (Table 13) that the model did not resolve as we might expect with an r₁ = 0.30 and corresponding L-B = 98%.
For L171, there is some variation of the residuals about the mean \( \mu_e = 0, \sigma_e = 1.82 \) as most values drift between \( \pm 4^\circ \) latitude, until the very end of the time series when under prediction is apparent and positive residuals occur (Figure 6). The unexplained variance is captured by the residuals, which are better correlated with the sea ice \( r = 0.75 \), significant at 99% versus the predicted values \( r = 0.67 \), significant at 99%. This theme of sizeable SMLR model under prediction at the conclusion of the time series persists through all longitudes of the sea ice analysis, though the fit of predicted values on a multidecadal basis does improve as seen by the general decrease in residual standard deviation (Table 13). Further, despite the statistical methods employed to establish independence amongst the residuals, there is still an amount of unexplained autocorrelation in the residuals at L171 with an \( r_1 = 0.33 \) and L-B = 99%. Both L176 and L171 exhibit residual non-randomness that is fairly substantial and probably indicate other factors are at work in the model than those explained by the trend. These could be scrutinized further by spectral techniques to test whether any periodicity occurs in the residuals, but will not be further examined in this paper.

Moving across the Bering Strait to the northern coast of Alaska and the far western extent of the Beaufort Sea, L166 is represented only by the predictors PC4 and PC7 \( r^2 = 0.33 \). The L166 SMLR significance tests (Table 11) are notable for t-value = 3.29 (significant at 99.9%) and F-ratio = 14.56 (significant at 99.9%). The observed trend (Table 12) for L166 is 0.84\(^\circ\) latitude retreat dec\(^{-1}\) (99.9% significance), the third largest in the analysis. The SMLR predicted seasonal trend is again slightly less steep than the residual trend \( 0.39^\circ \) latitude dec\(^{-1}\) compared to \( 0.45^\circ \) latitude dec\(^{-1}\), both
significant at 99.9%). The predicted values are a better fit relative to the previous model estimates as the residual values fluctuate between ±2-4° latitude until approximately the last five years of the residual time series when under prediction is most noticeable (Figure 7). The residuals represent the unexplained variance and are much better correlated ($r = 0.81$, significant at 99%) to the derived sea ice extents (Table 12) relative to the predicted values ($r = 0.59$, significant 99%). Further, the residual standard deviation = 1.77, $r_1 = 0.24$ and L-B = 93% (Table 13) show that the model residuals are slightly random in contrast to the first two longitudes.

Continuing eastward across the southern Beaufort Sea noticeable patterns persist and the explained variance by the regression model improves in the L161, L156 and L151 results. PCs 4 and 7 persist as the only two predictors revealed by the model, but the cumulative amount of explained variance by the respective models noticeably increases from L161 ($r^2 = 0.33$), to L156 ($r^2 = 0.43$) and finally to L151 ($r^2 = 0.48$) with all three notably significant in terms of their t-values (Table 11) and F-ratios (significant at 99.9%). L151 has a t-value = 3.78 and F-ratio of 26.52 (both significant at 99.9%). A coefficient of determination approaching 0.50 is significant from the standpoint that nearly half of the variance can be explained with a significant amount of that contributed to by the AMO multi-seasonal predictor. The predicted values from the SMLR equation for all three locations match the observations generally within about ±2° until about 1990, when the residual time series becomes slightly more variable. The ability of the SMLR models to reasonably capture the observed trends at these locations is impressive, especially given that all three vary between 0.61 and 0.73° latitude dec$^{-1}$ (all significant at
Similar to the far western longitude time series there is very noticeable underprediction in the model shortly after 2000 for L166, L161 and L156 as the observed extents retreat northward beyond what the model predicts that they should do (Figures 8-10).

The residuals for L161 are better correlated ($r = 0.79$, significant at 99%) to the derived sea ice extents as opposed to the predicted values ($r = 0.61$, significant at 99%). This location has an $r_1 = 0.07$, indicating that the residuals are not well correlated at one year lagged time interval. The corresponding L-B = 39% is also statistically insignificant for the purpose of residual testing and is much more insignificant than the previous result at L166 (L-B = 93%). This non-significant result validates the statistical model by preserving the theory of randomness or independence of the residuals as expected a priori. The L156 residuals are also better correlated (Table 12) with observed values ($r = 0.76$, significant at 99%) in contrast to predicted SMLR values ($r = 0.65$, significant at 99%). L156 (Barrow) has an $r_1 = 0.06$ and a corresponding L-B = 35%, the most non-significant multi-seasonal test statistic, which compared with its western neighbor, L161, L156 strongly supports non-randomness in the model residuals. Like the longitudes before it, L151 derived observations are better correlated with their residuals ($r = 0.71$, significant at 99%) compared to their predicted values ($r = 0.70$, significant at 99%). The residual analysis for L151 favors randomness of the residuals because of the lack of significance in the residual analysis, $r_1 = 0.14$ and L-B = 73%, but the argument is not as compelling as the previous examples. Nevertheless, these three longitudes are the best
multi-seasonal examples of fulfilling the requirements set forth to validate and analyze the SMLR model.

L146 marks the highest explained variance of the entire multi-seasonal study. This longitude is expressed by four components (PC 4, PC 7, PC 9, PC 8) that cumulatively have a coefficient of determination, $r^2 = 0.59$, explaining over half the variance for the location. The observed trend in ice retreat is $0.59^\circ$ latitude dec$^{-1}$ (significant at 99.9%) with a steeper predicted ($0.38^\circ$ latitude dec$^{-1}$, significant at 99.9%) versus residual trend $0.21^\circ$ latitude dec$^{-1}$ (significant at 99%). Similar to previous results, Figure 11 shows the predicted values closely match the observations within ±2$^\circ$ latitude throughout until 1990 when the residuals become increasing positive as the model generally under predicts the anomalous post-1990 sea ice retreats. The regression model test statistics indicate the SMLR slope is non-zero as the t-value = -2.07 (significant at 95%) and F-ratio = 21.23 (significant at 99.9%). In contrast to the previous six longitudes, L146 observations are better correlated to the predicted values of the SMLR ($r = 0.79$, significant at 99%) as opposed to the residuals ($r = 0.62$, significant at 99%). Again, the residuals appear random ($r_1 = 0.15$ and L-B = 74%), which further validates the statistical model. Further, the fact that the initial component, AMO, has an explained variance of $r^2 = 0.41$ is also substantial for this multi-seasonal analysis. Previous longitudes L156 and L151 initial predictors, also the AMO, account for the second and third highest initial predictor values at $r^2 = 0.35$ and $r^2 = 0.32$ respectively. With high coefficients of determination coupled with significant regression model and non-significant L-B statistics, the SMLR model seems to indicate an increasingly strong,
consistent relationship between the AMO, and AO/NAO spring as well, between L166 and L146.

Continuing eastward across the Beaufort Sea coastline, L141 possesses the second highest explained variance of any sea ice location thus far with a total $r^2 = 0.50$, while accounting for the same variables as L146 (PC 4, PC 7, PC 9, PC 8). The AMO component (PC 4) represents 25% ($r^2 = 0.25$) of the explained variance itself. Further, L141 signifies the fifth consecutive longitude where the foremost predictor, AMO, accounts for at least a quarter of the explained variance (Table 10). This outcome is significant ($t$-value $=-2.24$ (significant at 95%) and $F$-ratio $=14.91$ (significant at 99.9%) and the predicted and observed values again match fairly well, but become more variable and increasingly positive around 1990, indicative of model under prediction in conjunction with previously mentioned causes (Figure 12). The observed trend is $0.52^\circ$ latitude dec$^{-1}$, while the predicted and residual trends are $0.29^\circ$ latitude dec$^{-1}$ and $0.23^\circ$ latitude dec$^{-1}$ respectively (all significant at 99.9%). The predicted values show a slightly stronger relationship to the sea ice extents ($r = 0.73$, significant at 99%) versus the residuals ($r = 0.68$, significant at 99%). The predicted values are better correlated with the observations at L146 and L141 than the residuals (Table 12). This is a function of model fit because the explained variance is at least 50% for those longitudes and therefore the relationship between the predicted values and observations intuitively should be stronger. However, unlike the previous four longitudes, the residual test statistics differ in defense of the model. While the standard deviation of the residuals is the second lowest of all locations analyzed, the $r_1 = 0.28$ (Table 13) is noticeably higher.
than the previous several longitudes. Also, the L-B = 97% is significant, similar to L176 and L171 and indicative of red noise, which contrasts greatly with the four previously well-explained and verified longitudinal model results. As a result, there is likely some element of non-randomness of the residuals, or some dependence amongst them, that is not resolved in the model.

The multi-seasonal analysis concludes with L136 and L131. L136 ice retreat latitude variability is represented by a combination of familiar predictors in PCs 4 and 7 (AMO and NAO/AO spring). These two predictors explain 30% of the variance ($r^2 = 0.30$), while the AMO explains nearly two-thirds of that total, ($r^2 = 0.23$). This result is significant (t-value = 2.66 (significant at 99%), F-ratio = 13.13 (significant at 99.9%)). L136 from 2005-2007 was under predicted by the statistical model, but there are some spots, such as the mid to late 1970s (L136) that clearly exhibit greater residual values compared to the tail end of the time series (Figure 13). The observed trend for L136 is $0.41^\circ$ latitude dec$^{-1}$ (significant at 99.9%), the predicted trend is $0.23^\circ$ latitude dec$^{-1}$ (significant at 99.9%) and the residual trend is $0.18^\circ$ latitude dec$^{-1}$ (significant at 95%)

There is a much stronger relationship between the L136 residuals and observations ($r = 0.82$, significant at 99%) compared to the predicted values ($r = 0.57$, significant at 99%). The residual standard deviation for L136 is 1.11, while the $r_1$ = 0.12 with a subsequent L-B = 66%. This non-significant L-B statistic again means that the model residuals appear random and normally distributed (at 95% confidence) as expected.

At L131, the AMO is the only component accounting for the smallest amount of explained variance by an initial predictor of any of the previous locations ($r^2 = 0.12$).
Though the explained variance at this location is small, it is significant (t-value = 3.02, F-ratio = 9.12 (both significant at 99.9%). L131 shows SMLR under prediction from the mid to late 1970s/1990s (Figure 14), however this longitude has the smallest residual standard deviation of any location in the seasonal dataset ($\sigma_e = 0.96$) indicating that the residual values are tightly bunched around the residual mean (which again, $\mu_e = 0$). L131 has the smallest observed (0.15º latitude dec$^{-1}$, non-significant), predicted (0.08º latitude dec$^{-1}$, significant at 99%) and residual (0.07º latitude dec$^{-1}$, non-significant) trends of the analysis (Table 12). The residual and observed values are very highly correlated ($r = 0.93$, significant at 99%) as opposed to the predicted values (0.38, significant at 99%). However, more importantly, the $r_1 = 0.18$ and the L-B = 83% indicate that the SMLR residuals are likely random and well-resolved by the statistical model.
Figure 5. Time series of L176 sea ice extents for (a) observed (solid) and predicted (dashed) values, based on multi-seasonal teleconnections, and corresponding (b) residuals.
Figure 6. Same as Figure 5 but for L171.
Figure 7. Same as Figure 5 but for L166.
Figure 8. Same as Figure 5 but for L161.
Figure 9. Same as Figure 5 but for L156.
Figure 10. Same as Figure 5 but for L151.
Figure 11. Same as Figure 5 but for L146.
Figure 12. Same as Figure 5 but for L141.
Figure 13. Same as Figure 5 but for L136.
Figure 14. Same as Figure 5 but for L131.
4.3.1 Summer Teleconnections and Sea Ice

Similarly, all eleven sea ice longitudes are examined using summer-only teleconnection indices to test whether the end of summer ice variability can be better linked to that season’s teleconnections (Table 14) than the multi-season regression results. Test statistics for the regression models are provided in Table 15. The trends for observed, predicted and residual time series as well as the resulting correlations between the observed, predicted and residual time series are presented in Table 16. Finally, test statistics for the model residuals are displayed in Table 17. As previously mentioned, this is a simplified analysis with only six orthogonal components retained for the SMLR model. Although the total variance explained by retaining six components is fairly robust ($r^2 = 0.93$), the use of these PCs as components in the SMLR equation produces predictors not nearly as robust as those previously described in Section 4.3. However, some common predictors that show up in the multi-seasonal analysis also show up in the summer SMLR models as well.

HadISST longitudes L176 and L171 produce similar results. L176 is represented by one predictor (PC 3, summer AMO, Table 7) with a corresponding $r^2 = 0.11$ (t-value = 2.82 and F-ratio = 7.97 (both significant at 99%)), while L171 is represented by the AMO with a comparable $r^2 = 0.13$ (t-value = 3.05 and F-ratio = 9.32 (both significant at 99.9%)). Starting at L176 and continuing throughout the summer sea ice/teleconnection analysis, there is a weak association between the summer predictors and their respective longitudes, which contrasts the strong affiliation between the residuals and the derived values. The good connection between the residuals and observations is indicative of poor
<table>
<thead>
<tr>
<th>Location</th>
<th>Predictor 1</th>
<th>Predictor 2</th>
<th>Constant</th>
</tr>
</thead>
<tbody>
<tr>
<td>L176</td>
<td>PC 3</td>
<td></td>
<td>72.83</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.11/0.99</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L171</td>
<td>PC 3</td>
<td></td>
<td>73.43</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.13/0.93</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L166</td>
<td>PC 3</td>
<td></td>
<td>73.60</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.10/0.76</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L161</td>
<td>PC 3</td>
<td></td>
<td>73.44</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.13/0.80</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L156</td>
<td>PC 3</td>
<td>PC 4</td>
<td>73.41</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.20/0.84</td>
<td>0.25/0.44</td>
<td></td>
</tr>
<tr>
<td>L151</td>
<td>PC 3</td>
<td></td>
<td>72.78</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.23/0.91</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L146</td>
<td>PC 3</td>
<td>PC 4</td>
<td>72.45</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.29/1.02</td>
<td>0.35/0.52</td>
<td></td>
</tr>
<tr>
<td>L141</td>
<td>PC 3</td>
<td></td>
<td>72.27</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.19/0.70</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L136</td>
<td>PC 3</td>
<td></td>
<td>71.86</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.16/0.57</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L131</td>
<td>PC 4</td>
<td>PC 3</td>
<td>72.05</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.10/0.36</td>
<td>0.17/0.29</td>
<td></td>
</tr>
<tr>
<td>L126</td>
<td>PC 4</td>
<td></td>
<td>73.02</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.07/0.36</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 14. Same as Table 10 but for summer-only.
<table>
<thead>
<tr>
<th>Location</th>
<th>t-value</th>
<th>F –ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>L176</td>
<td>2.82</td>
<td>7.97</td>
</tr>
<tr>
<td>L171</td>
<td>3.05</td>
<td>9.32</td>
</tr>
<tr>
<td>L166</td>
<td>2.72</td>
<td>7.40</td>
</tr>
<tr>
<td>L161</td>
<td>3.10</td>
<td>9.62</td>
</tr>
<tr>
<td>L156</td>
<td>2.08</td>
<td>10.09</td>
</tr>
<tr>
<td>L151</td>
<td>4.18</td>
<td>17.48</td>
</tr>
<tr>
<td>L146</td>
<td>2.59</td>
<td>16.35</td>
</tr>
<tr>
<td>L141</td>
<td>3.78</td>
<td>14.31</td>
</tr>
<tr>
<td>L136</td>
<td>3.45</td>
<td>11.82</td>
</tr>
<tr>
<td>L131</td>
<td>2.31</td>
<td>6.66</td>
</tr>
<tr>
<td>L126</td>
<td>2.22</td>
<td>4.91</td>
</tr>
</tbody>
</table>

Table 15. Same as Table 11 but for summer-only.
<table>
<thead>
<tr>
<th>Location</th>
<th>Observed trend (dec(^{-1}))</th>
<th>Predicted trend (dec(^{-1}))</th>
<th>Residual trend (dec(^{-1}))</th>
<th>r (ob and pre)</th>
<th>r (ob and res)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L176</td>
<td>1.14</td>
<td>0.25</td>
<td>0.89</td>
<td>0.36</td>
<td>0.94</td>
</tr>
<tr>
<td>L171</td>
<td>0.93</td>
<td>0.24</td>
<td>0.69</td>
<td>0.38</td>
<td>0.93</td>
</tr>
<tr>
<td>L166</td>
<td>0.84</td>
<td>0.19</td>
<td>0.65</td>
<td>0.34</td>
<td>0.94</td>
</tr>
<tr>
<td>L161</td>
<td>0.73</td>
<td>0.20</td>
<td>0.53</td>
<td>0.39</td>
<td>0.92</td>
</tr>
<tr>
<td>L156</td>
<td>0.61</td>
<td>0.19</td>
<td>0.42</td>
<td>0.52</td>
<td>0.85</td>
</tr>
<tr>
<td>L151</td>
<td>0.68</td>
<td>0.23</td>
<td>0.45</td>
<td>0.49</td>
<td>0.87</td>
</tr>
<tr>
<td>L146</td>
<td>0.59</td>
<td>0.23</td>
<td>0.36</td>
<td>0.61</td>
<td>0.79</td>
</tr>
<tr>
<td>L141</td>
<td>0.53</td>
<td>0.18</td>
<td>0.35</td>
<td>0.45</td>
<td>0.89</td>
</tr>
<tr>
<td>L136</td>
<td>0.40</td>
<td>0.14</td>
<td>0.26</td>
<td>0.42</td>
<td>0.91</td>
</tr>
<tr>
<td>L131</td>
<td>0.15</td>
<td>0.05</td>
<td>0.10</td>
<td>0.25</td>
<td>0.90</td>
</tr>
<tr>
<td>L126</td>
<td>0.17</td>
<td>-0.02</td>
<td>0.19</td>
<td>0.29</td>
<td>0.96</td>
</tr>
</tbody>
</table>

Table 16. Same as Table 12 but for summer-only.
<table>
<thead>
<tr>
<th>Location</th>
<th>$\sigma_e$</th>
<th>$r_1$ (L-B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L176</td>
<td>2.60</td>
<td>0.22 (90%)</td>
</tr>
<tr>
<td>L171</td>
<td>2.26</td>
<td>0.19 (86%)</td>
</tr>
<tr>
<td>L166</td>
<td>2.07</td>
<td>0.22 (92%)</td>
</tr>
<tr>
<td>L161</td>
<td>1.90</td>
<td>0.12 (66%)</td>
</tr>
<tr>
<td>L156</td>
<td>1.56</td>
<td>0.13 (69%)</td>
</tr>
<tr>
<td>L151</td>
<td>1.62</td>
<td>0.20 (87%)</td>
</tr>
<tr>
<td>L146</td>
<td>1.46</td>
<td>0.17 (81%)</td>
</tr>
<tr>
<td>L141</td>
<td>1.37</td>
<td>0.15 (75%)</td>
</tr>
<tr>
<td>L136</td>
<td>1.23</td>
<td>0.17 (82%)</td>
</tr>
<tr>
<td>L131</td>
<td>0.93</td>
<td>0.20 (88%)</td>
</tr>
<tr>
<td>L126</td>
<td>1.20</td>
<td>0.04 (22%)</td>
</tr>
</tbody>
</table>

Table 17. Same as Table 13 but for summer-only.
SMLR model fit for the data, resulting in such high error (residual) terms and trends. Whereas the predicted trends (versus the residual trends) more closely resembled the observational data in Section 4.3, the opposite transpires in this summer analysis as a greater proportion of the observed trends are accounted for by the residual trends. This can be viewed in more detail in Table 16. For instance, L176 shows a fairly steep and significant trend in the residuals (0.89° latitude dec⁻¹, significant at 99.9%) relative to the predicted trend (0.25° latitude dec⁻¹, significant at 99.9%). Overall, the residual trends, like the observations trends, generally decrease from this longitude forward in the summer analysis.

L176 and L171 residuals are quite large throughout (±5° latitude) and reach their maximum at the end of the time series as they approach +10° latitude deviation from the observations (Figures 15-16). As previously stated, these values correlate much better (Table 16) to the observed time series (r = 0.94 (L176) and r = 0.93 (L171), both significant at 99%) as opposed to their predicted counterparts (r = 0.36 and r = 0.38 respectively, both significant at 99%). Visually, the first part of the time series generally displays over prediction (negative residuals), while the opposite effect (positive residuals) is more apparent from the early 1990s onward (Figures 15-16). Overall, toward the conclusion of the time series the furthest western coordinates (L176 and L171) have the greatest poleward retreats and largest under predicted values. Both of these locations have standard deviations in their residuals above two (2.60 and 2.26 respectively) that reflect the large residuals produced by the SMLR model. Further, L176 has an r₁ = 0.22
that is slightly random due to a L-B = 90%. Similarly, L171 has an $r_1 = 0.19$ and L-B = 86% that also displays a slightly random pattern of residuals (Table 17).

Moving eastward across the Bering Strait to L166 and L161, PC 3 (AMO) continues as the initial and sole predictor. L166 has an $r^2 = 0.10$ (t-value = 2.72 and F-ratio = 7.40 (both significant at 99%), while L161 $r^2 = 0.13$ (t-value = 3.10 and F-ratio = 9.62 (both significant at 99.9%), which equates roughly 90% unexplained variance by the SMLR model. While this is not satisfactory, compared with the two previous longitudes, the residual range is slightly smaller (±4° latitude) throughout most of the time series and therefore the residual standard deviations are less (Figures 17-18). Again, the residuals are much better correlated with the observation ($r = 0.94$ and $r = 0.92$, both significant at 99%) compared to the predicted values ($r = 0.34$ and $r = 0.39$, both significant at 99%). L166 has an $r_1 = 0.22$ with a L-B = 92%, which is marginally acceptable to pass the test for randomness. L161 has an $r_1 = 0.12$ and a L-B = 66% that is substantially improved from the previous residual test results.

The stepwise model for L156 is comprised of two predictors, PC 3 (AMO) and PC 4 (PNA), whose cumulative $r^2 = 0.25$ (t-value = 2.08 (significant at 95%), F-ratio = 10.09 (significant at 99.9%)), is the second highest explained variance of the summer series of SMLR model runs. The predicted values match the observed values within ±2-4° for most of the time series, though the residuals slightly increase from the early 1990s to 2007 (Figure 19). Again, the residual values are better correlated to the observed values ($r = 0.85$, significant at 99%) than the predicted values ($r = 0.52$, significant at 99%). However, this SMLR model captures a better fit of the predictors relative to the
previous longitudes of this section, as substantiated by the decreased residual standard deviation \( \sigma_e = 1.56 \). The \( r_1 = 0.13 \) and the L-B = 69\% verifies that the weak lagged relationship between the model residuals is likely random. Whereas the multi-seasonal residual L-B tests at L161 and L156 were the highest at these longitudes, the summer-only residual test results at these longitudes are the second and third highest respectively. Therefore, the resolution of non-randomness in the residuals is best for these longitudes.

L151 is represented by one sole predictor, PC 3, whose \( r^2 = 0.23 \) is the second highest initial predictor value of the summer-only dataset. More importantly, the model significance tests for this location exhibit an ideal level of significance in terms of t-value = 4.18 (significant at 99.9\%). The F-ratio = 17.48 (significant at 99.9\%) is also the most significant of any location in the summer analysis. The smallest residuals of the dataset are roughly found from the early 1970s until the early 1990s (±2°) with larger residuals found on the tails of the time series (Figure 20). These residual values are well correlated to the observations (\( r = 0.87 \), significant at 99\%) versus the predicted values (\( r = 0.49 \), significant at 99\%). Further, there is fairly small dispersion about the zero residual mean as shown by \( \sigma_e = 1.62 \) while the residual tests promote model randomness in the residuals as the \( r_1 = 0.20 \) and the L-B = 87\%.

The L146 SMLR result is similar to its L156 (Barrow) counterpart. This longitude is represented by two predictors, PC 3 and PC 4 (Table 7), that cumulatively account for an \( r^2 = 0.35 \) (t-value = 2.59, significant at 99\%, F-ratio = 16.35, significant at 99.9\%). However, PC 3 has an \( r^2 = 0.29 \) which by far accounts for the majority of the explained variance at this location. There is very good cohesion between the predicted
and observed values throughout parts of the time series, especially during most of the 1970s when the residuals are especially small (Figure 21), though the residuals are still better correlated with the observations ($r = 0.79$, significant at 99%) compared to the predicted values ($r = 0.61$, significant at 99%). The biggest disparities again persist at the onset of the time series, where there is about 4° over prediction initially by the model, and towards the conclusion of the time series, where there is about 3° under prediction by the model that is prompted by anomalous retreat years. Overall, the residual standard deviation throughout the dataset is 1.46. The residuals do appear non-random in accordance with the test results, $r_1 = 0.17$ and L-B = 81%. Importantly, this location in both the summer-only and multi-seasonal analyses produced multiple predictors, led by the AMO, which explained the premier amount of dataset variance relative to the other locations. Further, both of these outcomes were adequately validated by their respective test results indicating that L146, located off the north/central Alaskan coast in the Beaufort Sea, best relates the available teleconnection indices to observed sea ice variability relative to all other SMLR sea ice model runs completed in this statistical analysis.

The next two longitudes moving eastward, L141 and L136, are both characterized by PC 3 and share similar $r^2$ values of 0.19 (t-value = 3.78, F-ratio = 14.31, both significant at 99.9%) and 0.16 (t-value = 3.45, F-ratio = 11.82, also both significant at 99.9%) respectively. At the onset of the time series, L141 has small residual values that fluctuate around 0, indicative of good predictor fit to the observed values (Figure 22). However, as the time series progresses the predicted and observed values deviate most
(+2-4º residuals) around the aforementioned years of the most recent minima, post-2000, i.e. 2005, 2007). Despite the appearance of good fit through parts of the time series, the correlations are still much stronger regarding the residuals and observations (r = 0.89, significant at 99%) versus the predicted values (r = 0.45, significant at 99%). The same scenario transpires for L136, however the residuals are slightly more compact within the range of about ±2º throughout the majority of the time series with no clear trend of over predicted or under predicted values (Figure 23), but the relationships between the residuals and the observed values is very strong (r = 0.91, significant at 99%) relative to the predicted values (r = 0.42, significant at 99%). The residual standard deviations for L141 (σₑ = 1.37) and L136 (σₑ = 1.23) are indicative of relatively small dispersion of residuals. The L141 rₑ = 0.15 with a L-B = 75% and L136 has an rₑ = 0.18 with a L-B = 82%. The consistently insignificant Ljung-Box statistic acts to verify the lack of residual autocorrelation in the regression model, though the low adjusted r² continues to explain little of the variance in the model results.

The final two longitudes of this summer-only teleconnection and sea ice analysis reveal unique patterns, though much like the previous longitudes their explained variance is not substantial. All of the previous longitudes for both the seasonal and summer multidecadal analysis present the AMO as the foremost predictor that explains the most variance of any single predictor in the dataset. However, at L131 the AMO is not the ultimate predictor, but rather the PNA (PC 4) weakly assumes this role (r² = 0.10) followed by the AMO (r² = 0.07, cumulative r² = 0.17). The t-value = 2.31 (significant at 99%) and F-ratio = 6.66 (significant at 99.9%) indicate that the slope of the regression
line significantly deviates from zero, though the SMLR slope is becoming increasingly flat relative to the previous sea ice longitudes. The predicted and observed values arguably appear the best fit to the observations at this longitude as evidenced by their nearly identical time series modulations and subsequent narrow range of residuals as seen in the plots of Figure 24. Though the predicted fit appears reasonable the relationship between the predicted and observed values is substantially weaker (r = 0.45, significant at 99%) relative to the residuals (r = 0.90, significant at 99%) indicating that in actuality the residuals behavior closely mirrors that of the observations. The residual standard deviation is less than one sigma (0.93), which is the lowest value of the entire sea ice analysis. Finally, there appears to be randomness in the residuals as referenced by an $r_1 = 0.20$ and a L-B = 88%.

The summer PNA is the only predictor for the easternmost longitude, L126, accounting for a cumulative $r^2 = 0.07$ (t-value = 2.22, F-ratio = 4.91), which is the smallest explained variance of any single predictor across the sea ice analysis. The F-ratio = 4.91, the lowest of this analysis, combined with a t-value = 2.22 (both significant at 95%) would indicate that the significance of the model is deteriorating relative to the previous statistical confirmations. Visual inspection of the predicted/observed model fit is more comparable to the westernmost predicted/residual fits from L176-L156 ($\sigma_e = 1.20$) with residuals ranging between ±3º latitude with mainly over prediction (negative residuals) dominating the first half of the time series and under prediction (positive residuals) dominating the other half of the time series (Figure 25). In fact, the behavior of the residuals is nearly perfectly in step with the observations ($r = 0.96$, significant at
99%) compared to the predicted values (r = 0.29, significant at 99%). The predictors largely fail to match the observations and therefore the relationships between the residuals and observations are very good. Despite the low adjusted variance of the model, the residual tests are very striking. The $r_1 = 0.04$ and $L-B = 22\%$, which is the lowest L-B statistic of the analysis, is indicative of extremely weak spatial autocorrelation and makes the strongest argument thus far for residual randomness.
Figure 15. Time series of L176 sea ice extents for (a) observed (solid) and predicted (dashed) values, based on summer-only teleconnections, and corresponding (b) residuals.
Figure 16. Same as Figure 15 but for L171.
Figure 17. Same as Figure 15 but for L166.
Figure 18. Same as Figure 15 but for L161.
Figure 19. Same as Figure 15 but for L156.
Figure 20. Same as Figure 15 but for L151.
Figure 21. Same as Figure 15 but for L146.
Figure 22. Same as Figure 15 but for L141.
Figure 23. Same as Figure 15 but for L136.
Figure 24. Same as Figure 15 but for L131.
Figure 25. Same as Figure 15 but for L126.
4.4 Multi-Seasonal Teleconnections and Surface Air Temperatures

The raw temperatures are analyzed in much the same fashion as the derived sea ice values from previous sections. The same multi-seasonal teleconnections analyzed in Section 4.3 (descriptions found in Table 5) are methodically analyzed against the raw summer (JJA) surface air temperatures (SAT) for Uelen and Barrow. All principal component predictors (multi-seasonal (wss), summer-only (su) and annual (ann)) for each SMLR run are displayed in Table 18. The regression model test statistics are shown in Table 19. The trends for observed, predicted and residual time series are listed as well as their correlations in Table 20, while the residual test statistics are presented in Table 21.

These temperature results contrast the uniform results of the sea ice study. Uelen, located just south of the Arctic Circle, is summarized by three predictors (PC 7, PC 4 and PC 9) that cumulatively account for an $r^2 = 0.27$ (t-value = 2.52 (significant at 99%), F-ratio = 7.81 (significant at 99.9%)). Individually, PC 7 (AO and NAO spring) represents roughly 11% of the total variance, while PC 4 (AMO), the predominant initial rotated component for the sea ice analysis, accounts for about 9% of the variance and PC 9 (PNA/NPI summer) concludes the trio of Uelen predictors explaining 7% of the variance. The summer raw temperature time series shows an approximate $0.29^\circ$C dec$^{-1}$ (significant at 99.9%) increase over the study period, with a predicted trend ($0.15^\circ$C dec$^{-1}$, significant at 99.9%) approximately equal to the residual trend ($0.14^\circ$C dec$^{-1}$, significant at 95%). The residuals are fairly small, mostly fluctuating between ±1°C (Figure 26), and are better correlated with the observations ($r = 0.83$, significant at 99%) compared to the predicted values ($r = 0.55$, significant at 99%). The narrow range of modulating residuals
<table>
<thead>
<tr>
<th>Location</th>
<th>Predictor 1</th>
<th>Predictor 2</th>
<th>Predictor 3</th>
<th>Constant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uelen (wss)</td>
<td>PC 7</td>
<td>PC 4</td>
<td>PC 9</td>
<td>4.93</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.11/0.33</td>
<td>0.20/0.31</td>
<td>0.27/0.27</td>
<td></td>
</tr>
<tr>
<td>Barrow (wss)</td>
<td>PC 6</td>
<td>PC 4</td>
<td>PC 5</td>
<td>3.13</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.07/0.35</td>
<td>0.12/0.31</td>
<td>0.17/0.30</td>
<td></td>
</tr>
<tr>
<td>Uelen (su)</td>
<td>PC 5</td>
<td></td>
<td></td>
<td>4.93</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.06/0.26</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Barrow (su)</td>
<td>PC 3</td>
<td>PC 5</td>
<td></td>
<td>3.13</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.07/0.35</td>
<td>0.14/0.34</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Uelen (ann)</td>
<td>PC 3</td>
<td>PC 6</td>
<td></td>
<td>-7.40</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.10/0.44</td>
<td>0.18/0.40</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Barrow (ann)</td>
<td>PC 3</td>
<td>PC 6</td>
<td></td>
<td>-12.12</td>
</tr>
<tr>
<td>$r^2/b$</td>
<td>0.19/0.61</td>
<td>0.30/0.48</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 18. Same as Table 10 but for multi-seasonal (wss), summer-only (su) and annual (ann) temperature results.
<table>
<thead>
<tr>
<th>Location</th>
<th>t-value</th>
<th>F –ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uelen (wss)</td>
<td>2.52</td>
<td>7.81</td>
</tr>
<tr>
<td>Barrow (wss)</td>
<td>2.08</td>
<td>4.83</td>
</tr>
<tr>
<td>Uelen (su)</td>
<td>2.14</td>
<td>4.56</td>
</tr>
<tr>
<td>Barrow (su)</td>
<td>2.28</td>
<td>5.43</td>
</tr>
<tr>
<td>Uelen (ann)</td>
<td>2.57</td>
<td>7.21</td>
</tr>
<tr>
<td>Barrow (ann)</td>
<td>3.17</td>
<td>13.16</td>
</tr>
</tbody>
</table>

Table 19. Same as Table 11 but for multi-seasonal (wss), summer-only (su) and annual (ann) temperature results.
<table>
<thead>
<tr>
<th>Location</th>
<th>Observed trend (dec(^{-1}))</th>
<th>Predicted trend (dec(^{-1}))</th>
<th>Residual trend (dec(^{-1}))</th>
<th>(r) (ob and pre)</th>
<th>(r) (ob and res)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uelen (wss)</td>
<td>0.29</td>
<td>0.15</td>
<td>0.14</td>
<td>0.55</td>
<td>0.83</td>
</tr>
<tr>
<td>Barrow (wss)</td>
<td>0.32</td>
<td>0.17</td>
<td>0.15</td>
<td>0.46</td>
<td>0.89</td>
</tr>
<tr>
<td>Uelen (su)</td>
<td>0.29</td>
<td>0.06</td>
<td>0.23</td>
<td>0.28</td>
<td>0.96</td>
</tr>
<tr>
<td>Barrow (su)</td>
<td>0.32</td>
<td>0.17</td>
<td>0.15</td>
<td>0.41</td>
<td>0.91</td>
</tr>
<tr>
<td>Uelen (ann)</td>
<td>0.26</td>
<td>0.20</td>
<td>0.06</td>
<td>0.46</td>
<td>0.89</td>
</tr>
<tr>
<td>Barrow (ann)</td>
<td>0.47</td>
<td>0.24</td>
<td>0.23</td>
<td>0.57</td>
<td>0.82</td>
</tr>
</tbody>
</table>

Table 20. Same as Table 12 but for multi-seasonal (wss), summer (su) and annual (ann) temperature results.
<table>
<thead>
<tr>
<th>Location</th>
<th>$(\sigma_e)$</th>
<th>$r_1$ (L-B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uelen (wss)</td>
<td>0.79</td>
<td>0.15 (75%)</td>
</tr>
<tr>
<td>Barrow (wss)</td>
<td>1.06</td>
<td>-0.09 (51%)</td>
</tr>
<tr>
<td>Uelen (su)</td>
<td>0.91</td>
<td>0.22 (91%)</td>
</tr>
<tr>
<td>Barrow (su)</td>
<td>1.09</td>
<td>-0.07 (40%)</td>
</tr>
<tr>
<td>Uelen (ann)</td>
<td>1.16</td>
<td>-0.08 (48%)</td>
</tr>
<tr>
<td>Barrow (ann)</td>
<td>1.12</td>
<td>0.03 (17%)</td>
</tr>
</tbody>
</table>

Table 21. Same as Table 13 but for multi-seasonal (wss), summer-only (su) and annual (ann) temperature results.
with no obvious pattern of over/under prediction is substantiated by a small residual standard deviation ($\sigma_e = 0.79$). Further the $r_1 = 0.15$ with a L-B statistic = 75% supports the theory that the residuals are random and normally distributed with 95% confidence.

Barrow is also represented by three predictors (PC 6, PC 4 and PC 5) that account for an adjusted $r^2 = 0.17$ (t-value = 2.08 (significant at 95%), F-ratio = 4.83 (significant at 99.9%). PC 6 (AO and NAO winter) explains about 7% of the total variance, while the second predictor PC 4 (AMO) and final predictor PC 5 (NPI and PNA spring) both account for 5% of the variance. Compared to the Uelen temperature trend over the time period, the Barrow trend is slightly steeper ($0.32^\circ$C dec$^{-1}$) and just as significant. The predicted trend ($0.17^\circ$C dec$^{-1}$, significant at 99.9%) and residual trend ($0.15^\circ$C dec$^{-1}$, significant at 95%) are also approximately the same. The residuals are slightly larger for Barrow than Uelen, consistent with under prediction by the model (Figure 27). The residual standard deviation ($\sigma_e = 1.06$) is higher than at Uelen. The multi-seasonal Barrow predictors do not capture the summer temperature variability as well as the Uelen model predictors. Similar to the Uelen temperatures, the residual values are much better correlated to the raw values ($r = 0.89$, significant at 99%) compared to the regression model residuals ($r = 0.46$, significant at 99%). The $r_1 = -0.09$ with a L-B = 51% shows that no residual persistence is taking place for this data.
Figure 26. Time series of Uelen summer SATs for (a) observed (solid) and predicted (dashed) values, based on multi-seasonal teleconnections, and corresponding (b) residuals.
Figure 27. Same as Figure 26 but for Barrow.
4.4.1 Summer Teleconnections and Surface Air Temperatures

The summer temperatures are regressed against the summer teleconnections (refer back to Table 7). Uelen is represented solely by PC 5 (PDO) which has an adjusted $r^2 = 0.06$ (t-value = 2.14, F-ratio = 4.56 (both significant at 95%)). Using the same temperature data as the previous section, the observed trend remains the same ($0.29^\circ{\text{C}} \text{dec}^{-1}$, significant at 99.9%). The predicted trends are $0.06^\circ{\text{C}} \text{dec}^{-1}$ (significant at 99%) relative to the seasonal temperature trends while the residual trends are somewhat steeper at $0.23^\circ{\text{C}} \text{dec}^{-1}$ (significant at 99.9%). The time series shows residuals fluctuating between $\pm1^\circ{\text{C}}$ ($\sigma_e = 0.91$), until the early/mid 2000s, but this looks as though the increase (and large model under prediction) is a manifestation of the temperature maximum ($8.2^\circ{\text{C}}$) that occurred in 2004 (Figure 28). The weak predictability of the model lends itself to large residuals that closely mirror the observations. This is substantiated by the strong correlations of the residuals to the observations ($r = 0.96$, significant at 99%) versus the predicted values ($r = 0.28$, significant at 95%). Further, the lag-1 = 0.22 and L-B = 91% act to show that randomness is narrowly resolved in the residuals though the $r^2$ is so weak.

Barrow summer temperatures correspond to two predictors, PC 3 (AMO) and PC 5 (PDO) both of which have $r^2$ values = 0.07 (cumulative $r^2 = 0.14$, t-value = 2.28, significant at 95%, F-ratio = 5.43, significant at 99%). The observed trend of Barrow multidecadal temperatures is unchanged from the previous analysis, as are the predicted ($0.17^\circ{\text{C}} \text{dec}^{-1}$, significant at 99.9%) and residual trends ($0.15^\circ{\text{C}} \text{dec}^{-1}$, significant at 95%). The predicted and observed correlations are still weak ($r = 0.41$, significant at
99%) relative to the residual counterpart (r = 0.91, significant at 99%). The higher residual standard deviation ($\sigma_e = 1.09$) is a product of slightly more variability in the summer temperatures than Uelen, although the time series appears balanced by both slight over and under prediction by the model (Figure 29). Finally, the $r_1 = -0.07$ is weak and the corresponding L-B test (40%) strongly supports randomness in the residuals.
Figure 28. Time series of Uelen summer SATs for (a) observed (solid) and predicted (dashed) values, based on summer-only teleconnections, and corresponding (b) residuals.
Figure 29. Same as Figure 28 but for Barrow.
4.4.2 Annual Teleconnections and Surface Air Temperatures

Unlike the preceding sections that examine sea ice and temperature variability in the context of seasonal or summer teleconnections indices, this section briefly examines annual temperatures at Uelen and Barrow against annual teleconnections indices, which are described in Table 9. For the study period, Uelen’s mean annual SAT was -7.4°C (σ = 1.30). Its warmest year of the period is 2007 when temperatures were -4.4°C on average, nearly 3°C warmer than the 1951-2007 climatological mean. The coldest year occurred in 1955 and during that year the temperature average -9.7 °C, which was 2.3°C degrees colder than the mean. The winter that year was the coldest of the study period, -24.4°C, or nearly a degree colder than the next coldest winter (1965). Barrow’s average temperature for the period was -12.1 °C (σ = 1.36). During the warmest year of the period, 1998, the average temperature was -8.3°C, which was about 3.8°C warmer than average. This year was aided by the warmest spring (-11.6°C) by nearly two degrees and warmest fall (-3.3°C) by about half a degree of the study period. The coldest year was 1964 when the average annual temperature was -15.2°C or about 3.1°C below average.

The SMLR produces the same predictor variables for both Uelen and Barrow run. Uelen is represented by PC 3 (AMO), $r^2 = 0.10$, and PC 6 (PDO), $r^2 = 0.08$ (t-value = 2.57, significant at 99%, F-ratio = 7.21, significant at 99.9%). The annual time series shows a trend of 0.26°C dec$^{-1}$ (significant at 99%), while the predicted trend is 0.20°C dec$^{-1}$ (significant at 99.9%) and the residual trend is 0.06°C dec$^{-1}$ (non-significant). Visual interpretation of the time series shows residual between ±2°C ($\sigma_e = 1.16$) indicating the model does not fit the data well throughout. Further, no obvious consistent
patterns of over/under prediction are exhibited (Figure 30). The observations and residuals are better correlated (r = 0.89, significant at 99%) versus the predicted values (r = 0.46, significant at 99%). Finally, the $r_1 = -0.08$ is very weak and the L-B = 48% shows the residuals are likely randomly distributed.

Similarly, Barrow’s predictor variables are also PC 3 (AMO), $r^2 = 0.19$, and PC 6 (PDO), $r^2 = 0.11$. The t-value = 3.17 and F-ratio = 13.16 (both significant at 99.9%) strongly indicate that the slope of the regression line is different from zero. Further, the raw annual values show a trend of 0.47°C dec$^{-1}$ (significant at 99.9%), a predicted value trend of 0.24°C dec$^{-1}$ (significant at 99.9%), and a residual trend of 0.23°C dec$^{-1}$ (significant at 99%). The residuals fluctuate between ±2°C until 1990, then are slightly positive through 2007 ($\sigma_e = 1.12$), as seen in Figure 31. This model under prediction of the warming trend at the tail end of the time series occurs again in this time series. The observations are better correlated with the residuals (r = 0.82, significant at 99%) than the predicted values (r = 0.57, significant at 99%), which is another consistent feature of the temperature analysis. Lastly, the $r_1 = 0.03$ with a L-B = 17% very strongly supports residual randomness.
Figure 30. Time series of Uelen annual SATs for (a) observed (solid) and predicted (dashed) values, based on annual teleconnections, and corresponding (b) residuals.
Figure 31. Same as Figure 30 but for Barrow.
4.5 Comparisons to the Teleconnection Indices

The statistical results in the previous sections were presented in a pretty methodical and straightforward manner without much tangential analysis. This section looks to expound upon the most robust predictors, in terms of $r^2$ values, and their physical connection to the western Arctic temperatures and sea ice. Undoubtedly, the most well explained variance is captured in Section 4.3 where the sea ice retreats for September 15 are examined in the context of principal components comprised of variations of three seasons. Overall, the AMO, whose principal component (PC 4, Table 5) was a combination of the winter, spring and summer values, and the AO/NAO combination spring principal component (PC 7, Table 5) proved to be the most consistently high performing predictors. Therefore, these predictors will be evaluated at sea ice longitudes L151, L146 and L141, the three locations possessing the largest explained dataset variances (Table 10). Barrow annual temperatures and teleconnections, AMO (PC 3) and PDO (PC 6), will also be evaluated as this temperature output possessed the highest explained variance of the two stations (Table 18).

The latitude of the sea ice retreat, surface air temperatures and teleconnection indices varied in terms of units and their means and standard deviations, which made direct visual comparisons of the data difficult. Therefore, in order to assess their co-variability with respect to time, their data were adjusted and standardized so that they all had the same means and standard deviations. First, the standard deviations of the respective seasonal and annual principal components (Tables 5 and 9) and ice longitudes’/temperatures’ time series were obtained. Then, the ratio of the data with the
higher standard deviation to the lower standard deviation was used as a multiplier on the
data with the lower standard deviation (always the PCs) in order to make a new dataset.
Further, the mean values of the observations and new dataset ($\mu = 0.00$) were found and
the difference between the two were taken. Finally, the values of the new dataset were
adjusted by the aforementioned difference so that the variables’ behavior could be examined.

The SMLR model for L151 had two predictor variables, the AMO ($r^2 = 0.35$) and
AO/NAO ($r^2 = 0.13$) that cumulatively account for about 48% of the explained variance.
The time series separately comparing the AMO and AO/NAO principal components with
L151 ice retreat are found in Figures 32 and 33. As one might expect, there are periods
were the AMO signal matches well with the ice retreat (late 1950s, early/mid 1980s,
mid/late 1990s) and periods where the AMO is noticeably out of phase with the sea ice
behavior (early 1960s, early/mid 1970s, mid 2000s). The AO/NAO component rarely
matches the September 15 retreat observations, but their high frequency movement is
similar to some degree. The bivariate correlation coefficient for the ice retreat and AMO
multi-seasonal component is about 0.60 (significant at 99%), while the correlation
between the AO/NAO multi-seasonal component and the ice retreat at L151 is 0.37
(significant at 99%) throughout the 57 year period.

The stepwise model for L146 also had the same predictors with the AMO
seasonal ($r^2 = 0.41$) and AO/NAO ($r^2 = 0.10$) component explaining a majority of the
total explained variance ($r^2 = 0.59$). The comparisons between the ice retreats and these
oscillations can be viewed in Figures 34 and 35. The AMO component and L146 sea ice
match well over similar periods (mid 1960s, mid 1980s, late 1990s) and contrast over similar periods (early 1950s, early/mid 1970s, mid 1990s, mid 2000s) as the previous ice longitude L151. The correlation between the signal and the component is slightly stronger L146 over the multidecadal period (r = 0.65, significant at 99%). The AO/NAO (collectively termed the Northern Annular Mode or NAM) component rarely mirrors the ice retreat for a given year beyond 73°N. However years where the observed ice retreat consistently hovers near the coastline, 70.32°N are well traced at times by this component (≈1955, 1965, 1995). Nevertheless, the correlation between the ice and AO/NAO components is fairly weak over the 57 years (r = 0.33, significant at 95%).

Similarly, the predictors for the AMO ($r^2 = 0.25$) and AO/NAO ($r^2 = 0.16$) explain about 80% of the cumulative explained variance for L141 ($r^2 = 0.50$). These comparisons can be viewed in Figures 36-37. The AMO and L141 ice retreat appear congruent in the mid 1960s, early 1980s and late 1990s and look incompatible in the early 1960s, early 1970s, mid 1980s and mid 1990s. The multidecadal correlation for the sea ice and AMO component is about 0.52 (significant at 99%), the weakest of the sea ice comparisons to the AMO. The AO/NAO component and L141 also share somewhat similar interannual variation throughout, though with an $r = 0.40$ (significant at 99%) this relationship is again not as strong as that concerning the AMO.

For Barrow annual temperatures, the AMO ($r^2 = 0.19$) and PDO ($r^2 = 0.11$) teleconnections are the lone variables that explain any variance. These comparisons are depicted in Figures 38 and 39. Barrow temperature and the AMO are well matched in the mid 1970s and late 1990s. Otherwise, Barrow annual temperature and the AMO do not
correspond as strongly \((r = 0.45, \text{ significant at } 99\%)\) as the sea ice longitudes 151-141 \((r = 0.60, 0.65 \text{ and } 0.52 \text{ respectively})\) in Figures 32, 34 and 36. The PDO and temperatures overlap in the late 1960s and early 1990s and otherwise vary throughout the time series \((r = 0.35, \text{ significant at } 99\%)\).

Since the orthogonal teleconnection components are comprised of small parts of all the other teleconnections, with each component primarily represented by teleconnection loading patterns of \(r \geq \pm 0.70\) that it is named after, comparing these teleconnections with the sea ice and temperatures only gives an idea of whether these are congruent over the time series. Taking this a step further, Figure 40, shows the behaviors of all three ice longitudes in comparison to the raw AMO values. These were calculated as the average of winter, spring and summer AMO indices and then adjusted with the same correction procedure as described earlier in the section (using highest \(\sigma = 1.86\) and \(\mu = 72.78\) from L151). The relationships between sea ice longitudes are very good at times as L146 (purple) and L141 (teal) often overlap. Most importantly, the raw values are well correlated to the sea ice observations. L151 is correlated with the raw-averaged AMO at \(r = 0.54\), L146 is correlated at \(r = 0.60\) and L141 is correlated at \(r = 0.47\) (all significant at 99\%). These correlations are relatively strong, however they are less than their L151 \((r = 0.60)\), L146 \((r = 0.65)\) and L141 \((r = 0.52)\) previously discussed orthogonal PC counterparts illustrated in Figures 32, 34 and 36.
Figure 32. Time series of L151 sea ice (solid) compared to the AMO multi-seasonal component (dashed). The AMO index data have been adjusted to the same mean and standard deviation as the sea ice latitude data.
Figure 33. Time series of L151 sea ice (solid) compared to the AO/NAO multi-seasonal component (dashed). The AO/NAO index data have been adjusted to the same mean and standard deviation as the sea ice latitude data.
Figure 34. Same as Figure 32 except for L146.
Figure 35. Same as Figure 33 except for L146.
Figure 36. Same as Figure 32 except for L141.
Figure 37. Same as Figure 33 except for L141.
Figure 38. Time series of Barrow annual temperatures compared to the AMO annual component (dashed). The AMO index data have been adjusted to the same mean and standard deviation as the temperature data.
Figure 39. Time series of Barrow annual temperatures compared to the PDO annual component (dashed). The PDO index data have been adjusted to the same mean and standard deviation as the temperature data.
Figure 40. Overplot of the L151 (green), L146 (purple) and L141 (teal) sea ice extents and raw-averaged (winter, spring and summer) AMO (red, dashed). The AMO index data have been adjusted to the same mean and standard deviation as the sea ice latitude data.
4.6 Discussion

The AMO and to a lesser extent the AO/NAO and PDO contribute to the majority of the total variance calculations for the well explained sea ice and temperature SMLR model runs. Statistical rationale does not by itself imply causality, but one of the main questions to be answered by this thesis involves how well these connections can be explained not only statistically, but also physically. Namely, a major point of contention is whether the AMO and AO/NAO can be explained in conjunction with one another as contributors to western Arctic sea ice decline. Researchers have in fact attributed the AMO and AO/NAO (or NAM) to anomalous summer ice retreat events. Past studies have shown a probable link between the AMO and the behavior of the Thermohaline Circulation (THC) (Knight et al., 2005). For instance, when the AMO is in positive phase the THC is enhanced. Further, climate simulations have shown an enhanced THC, and therefore positive AMO, has been partially attributed to persistent positive phases of the NAO (Delworth and Knutson, 2000).

The physical connection requires some explanation. North Atlantic water enters the Arctic through the Fram Strait and Barents Sea. This transport is aided by SLP variability in the region, which is largely dictated by the strength of the NAO (Frankcombe et al., 2010; Rogers et al., 2004). Since the 1980s the NAO has been slightly positive overall. Therefore, more often than not over the past 30 years a deepened Icelandic low has persisted in the region producing anomalous westerly surface winds and a strengthened North Atlantic storm track. This climatological pressure feature acts to propel anomalously warm North Atlantic SSTs (evident by the positive
AMO) into the Arctic (Francombe et al., 2010). Polyakov and Johnson (2000) found that a positive AMO (warm SSTs, Figure 41) roughly corresponds to a positive AO (found in the 1940s-1950s and 1980s-1990s) and, like the NAO, also corresponds to a strong Icelandic low (enhanced cyclonic winds) and a slackened western Arctic high pressure field. These separate studies show the congruent behavior of the positive AO/NAO and Icelandic low. Taking the argument one step further, Polyakov et al. (2004) found a positive AMO precedes a sea ice minimum largely because an influx of warm Atlantic water penetrates into the Arctic. Therefore, these oceanic/atmospheric teleconnections have thus been shown as co-contributors to sea ice decline, though more evidence is warranted.

Specifically, the multidecadal AMO index and August ice extent trends (significant at 95%) were found to be strongest in the Kara Sea through 2000 (Polyakov et al., 2003b). However the relationship between the AMO, AO/NAO and sea ice generally decays eastward toward the Bering Strait (Polyakov et al., 2003b). This study finds evidence to dispute this claim. While the Kara Sea is not part of the analysis domain, as previously mentioned the highest variance explained of the whole analysis can be mainly accounted for by the AMO and AO/NAO multi-seasonal principle components for L151-L141 over 1951-2007 (Table 10). The three seasons (winter, spring, summer) of AMO indices that primarily comprise PC 4, which precede the climatological peak in the melt season, are thereby shown to statistically contribute to a large amount of variance in the ice well into the Beaufort Sea. In terms of correlation,
the ice longitudes are best correlated to the AMO for 1951-2007, but when the time period is separated into 1951-2000 and 2000-2007 some interesting patterns emerge.

As seen in Table 22, during 1951-2000 the AMO was better correlated (especially as a principle component than raw-averaged value) with the notable ice longitudes than the AO/NAO. However, from 2000-2007, the AO/NAO (raw-average) is much better correlated with the ice retreats than the AMO. The large amount of divergence in the AMO and ice time series versus the AO/NAO and ice time series visually makes this apparent (Figures 32-37). Though the AMO has remained positive (warm phase) through the end of 2007, its correlation to the ice variability has substantially declined. On the other hand, the AO/NAO whose physical mechanisms have been accredited to forcing the warm SSTs of the North Atlantic into the region correlates well with the ice variability. This calls into question the co-contributing nature of both the AMO and AO/NAO from a statistical standpoint. However, it is vital to remember that because the statistical behavior of the indices is mismatched over these amended time scales that does not necessarily imply that a physical connection does not exist. Rather, more exploration regarding spectrum of ocean-atmosphere interactions needs to be considered.

Maslanik et al. (2007b) found that even though the AO/NAO switched back to neutral in the mid-1990s, central Arctic low pressure and positive dipole patterns were strong through 2004 and more attributable to ice variability than the AO/NAO. Wang et al. (2009) confirmed the presence of positive dipole patterns (strong meridional wind anomalies) and historical record low ice extents in conjunction with positive AO phases.
<table>
<thead>
<tr>
<th>Location</th>
<th>Year</th>
<th>Predictors (1\textsuperscript{st} and 2\textsuperscript{nd})</th>
<th>$r_{pc}$</th>
<th>$r_{raw}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>L151</td>
<td>1951-2007</td>
<td>AMO/AO-NAO</td>
<td>0.60/0.37</td>
<td>0.54/0.21</td>
</tr>
<tr>
<td>L146</td>
<td>1951-2007</td>
<td>AMO/AO-NAO</td>
<td>0.65/0.33</td>
<td>0.60/0.14</td>
</tr>
<tr>
<td>L141</td>
<td>1951-2007</td>
<td>AMO/AO-NAO</td>
<td>0.52/0.40</td>
<td>0.47/0.16</td>
</tr>
<tr>
<td>L151</td>
<td>1951-2000</td>
<td>AMO/AO-NAO</td>
<td>0.49/0.26</td>
<td>0.41/0.17</td>
</tr>
<tr>
<td>L146</td>
<td>1951-2000</td>
<td>AMO/AO-NAO</td>
<td>0.54/0.22</td>
<td>0.49/0.08</td>
</tr>
<tr>
<td>L141</td>
<td>1951-2000</td>
<td>AMO/AO-NAO</td>
<td>0.34/0.31</td>
<td>0.30/0.08</td>
</tr>
<tr>
<td>L151</td>
<td>2000-2007</td>
<td>AMO/AO-NAO</td>
<td>0.14/0.92</td>
<td>-0.05/0.51</td>
</tr>
<tr>
<td>L146</td>
<td>2000-2007</td>
<td>AMO/AO-NAO</td>
<td>0.24/0.91</td>
<td>0.01/0.51</td>
</tr>
<tr>
<td>L141</td>
<td>2000-2007</td>
<td>AMO/AO-NAO</td>
<td>0.44/0.81</td>
<td>0.22/0.43</td>
</tr>
</tbody>
</table>

Table 22. Correlations based on most significantly explained variances ($r^2$) of the dataset. The AMO and AO/NAO principle components ($r_{pc}$) from Table 5 and their raw-averaged equivalent values are correlated with the ice longitudes at L151-L141 and separated by the slash marks. Significance at 95% is italicized; significance at 99% is bold.
in 1995 and 2002 and negative AO phases in 1999, 2005 and 2007. As previously
mentioned, these strong southerly wind anomalies out of the Pacific aid ice advection and
propagate the transport of warm SSTs into the western Arctic in a similar fashion as one
could expect with a positive AO/NAO, but from a different direction.

Past research has explained multidecadal sea ice variability in the Laptev, East
Siberian and Chukchi Seas in terms of synoptically forced winds and surface currents in
the absence of positive AMO and AO/NAO (NAM) forcings (Maslanik et al., 2007b;
Polyakov et al., 2003b). Other authors have also connected strong easterly zonal wind
climatologies, created by a pronounced Beaufort High, to summer sea ice losses in the
Beaufort Sea (Ogi et al., 2008; Nghiem et al., 2006). Previously not mentioned, Wendler
et al. (2010) found Pacific (PCI) and East Atlantic (EA) atmospheric indices correlated to
southern Beaufort Sea ice concentration (1972-2007) at $r = -0.59$ and $r = -0.47$
respectively. However, an established North Atlantic SST connection to Beaufort and
Chukchi Sea climate variability has previously been absent on multidecadal scales.

The results of this thesis dispute the findings of previous researchers and indicate
an AMO signal not only in the Chukchi Sea, but also in Beaufort Sea. While the sea ice
extent trends (primarily significant at 99.9%, see Tables 12 and 16) decrease eastward,
the amount of explained variance by the AMO actually increases toward the Canadian
Arctic Archipelago until it peaks at L146 and thereafter declines. At L146, both seasonal
and summer AMO (Tables 10 and 14) explain the maximum amount of the sea ice
variance found in this study ($r^2 = 0.41$ and $r^2 = 0.29$). Further, the multi-seasonal AMO is
coupled with the AO/NAO to explain 51% of the variance at L146, with surrounding ice
locations L151 and L141 displaying variances of at least 41% relating both teleconnection components. These regression equations (t and F tests) are also statistically significant. Not only does the AMO signal strengthen eastward to L146 in the central Beaufort Sea, but the connection to the AO/NAO is undeniable. This connection, aided by the influence of a summer synoptic high pressure system over the Beaufort Sea, could explain a majority of the multidecadal variability in these western Arctic seas.

The Barrow annual temperature results, though not as strongly connected to sea ice, also attract the AMO ($r^2 = 0.19$) as well as the PDO ($r^2 = 0.11$). Explaining the AMO forcing in terms of the PDO (with a periodicity of 20-30 years) or a PDO-like forcing mechanism is difficult. Since the relationship between the former teleconnection and the region was previously established, mentioning the PDO’s physical linkage to Barrow temperatures is appropriate. The abrupt shift of the PDO from negative to positive phase in 1976, corresponding to a deepened Aleutian low that promoted advection of warm, moist air into the Alaskan interior, appears to be one reason why Barrow’s temperatures could be weakly attracted to this oscillation (Hartman and Wendler, 2005). Papineau (2001) found that north of the Brooks Range the ENSO signal, which is largely modulated by the PDO, is not particularly strong albeit present. Although, the winter PDO and Barrow temperatures (both constructed as Nov-March mean values) are correlated at $r = 0.41$.

Several Alaskan temperature station records, especially at interior locations in the state, have been better correlated to the PDO than Barrow (Papineau, 2001).
Nevertheless, this study acknowledges a connection between the PDO and Barrow annual temperatures. Hartman and Wendler (2005) further conclude the high latitude Alaska temperature variability is more likely a function of Arctic variability (AO) than the PDO. The results of the seasonal teleconnections and temperatures show a weak statistical connection to AO and NAO winter at Barrow, while the more robust Barrow annual temperature values reflect the AMO and PDO signals exclusively (Table 18). Therefore, most of the results of this thesis support the conclusion that low-frequency climate variability, mainly in terms of the AMO, AO/NAO (NAM) and even the PDO, is partially responsible for the observed sea ice and SAT changes that have taken place over the last several decades in the western Arctic (Serreze and Francis, 2006).
Figure 41. Atlantic Multidecadal Oscillation index from 1850 to 2005 represented by annual anomalies of SST in the extratropical North Atlantic (30–65°N; top), and in a more muted fashion in the tropical Atlantic (10°N–20°N) SST anomalies (bottom). Both time series come from HadSST2 and are relative to the 1961 to 1990 mean (°C). The smooth blue curves show decadal variations (image from IPCC, 2007).
CHAPTER 5
SUMMARY AND CONCLUSIONS

5.1 Key Findings

The western Arctic sea ice retreat latitudes regressed against the multi-seasonal (winter-summer) teleconnections produced the most robust low-frequency teleconnection relationships found in this thesis (Section 4.3). Foremost, the AMO multi-seasonal component (PC 4) is the primary predictor of ice latitude in the SMLR analyses. Moreover, the AMO component alone accounts for roughly between 12-41% of the total explained variance of the statistical models produced at each longitude. At eight of the eleven longitudes the AMO accounts solely for ≥ 20% of the explained variance. It is noteworthy that this SST index is so prominent and persistent in the model outputs considering it only explains 9% of the 88% explained variance of the nine components used for this analysis (Table 4). Given the many scholarly studies (as reviewed in Section 4.5), the AMO’s impact on the Arctic sea ice overall is not surprising, although the extent of its eastward impact into the Chukchi and Beaufort Seas on a multidecadal temporal scale is unparalleled. Further the AMO $r^2$ value generally increases across the Chukchi and Beaufort Sea to L146 ($r^2 = 0.41$) and then declines toward the Canadian Arctic Archipelago.
Another common theme to the multi-seasonal teleconnections/sea ice study is that the AO/NAO spring component (PC 7) also shows up as the second predictor in nine of the ten stepwise analyses. Though this component only explains between roughly 8-15% of the explained variance, its consistent appearance is important to note. The fit of the models again consistently improves eastward, evidenced by decreasing standard deviation residuals, decreasing trend in the sea ice observations and decreasing unexplained variance through L146 (Tables 10-13). Still, the unexplained variance in the residuals is quite high through the analyses as they are noticeably better correlated to the observations than the predicted values.

For the multi-seasonal analysis, L176, L171 and L141 have cumulative variances of at least 40% and lag-1 autocorrelations of at least 0.28 which are significant by Ljung-Box test. These are not large non-zero lags, but this result presumes that the residual time series still exhibits some degree of persistence contrary to methods employed to dissuade such from occurring. There may be internal factors and/or autoregressive or moving-average complexities acting to offset the techniques employed to resolve autocorrelation. The middle latitudes from L161 to L146 produced the most telling statistical returns with substantially insignificant Ljung-Box statistics between 0.26 (L146) and 0.65 (L156). Further, the validation of L146 is important because nearly 60% of the variance is explained by the four predictors of the model, and especially by the AMO dominated PC 4, which explains nearly 40% of the variance by itself.

Similar to the multi-seasonal analysis, the AMO is the predominant multidecadal predictor in the summer-only teleconnections/sea ice analysis (Section 4.3.1) for the first
nine longitudes while the easternmost longitudes, L131 and L126, revealed the PNA as the primary predictor. While the connection of the AMO to the ice retreat cannot be understated, the coefficients of determination for the summer-only analysis relative to the multi-seasonal analysis are not nearly as robust. The results indicate that the concurrent summer AMO is not able to explain as much variance in ice retreat as in an analysis with precursor AMO values (and AO/NAO values).

Nevertheless, it is important to note that despite the low explanation of cumulative explained variance throughout the summer-only dataset (no longitude was explained by > 35% variance). Overall, the summer SMLR model’s ability to predict sea ice retreat is much more acceptable in the middle longitudes (L161-L141) versus the farthest eastern and western coordinates that oddly enough show the greatest and least amount of sea ice variability. The summer teleconnection and sea ice comparisons were insignificant in their respective tests for residual autocorrelation and prove to be random. Compared to the multi-seasonal analysis, where only eight of the ten longitudes passed this test, the summer-only teleconnections passed the test on every occasion indicating that the regression model resolves persistence and the variability of the residuals is in keeping with a white noise process. For example, the location that explained the largest amount of explained variance for both analyses was located at L146, although the explained variance for summer-only ($r^2 = 0.35$) pales in comparison to the multi-seasonal result ($r^2 = 0.59$).

Correlations between the initial and second seasonal predictors of the ice retreat latitudes at L151, L146 and L141, those explaining the highest cumulative variances ($r^2$),
yielded some interesting results (Table 22). Over the entire study period of 1951-2007, the correlations between the AMO based principle components and raw-averaged values and all three sea ice longitudes were reasonable ($\approx r \geq 0.50$, significant at 99%), while the spring AO/NAO is substantially weaker ($r \leq 0.37$, varying significances). The physical connection between the warm waters of the Atlantic (positive AMO) being propagated by the positive spring AO/NAO over the course of several decades was covered in Section 4.5. Both teleconnections patterns could be arguable as co-contributing factors depending on a subjective assessment of a reasonable correlation coefficient to connect them to the sea ice (physicality aside). Over the last decade of the study, the AO-NAO pattern became relatively neutral while the AMO has continued to remain positive. On that basis correlations pre and post 2000 were carried out to assess the relationships between these indices and the sea ice variability in order to try to assess their contribution in light of these studies.

From 1951-2000, the AMO, better correlated as the principle component than the raw-averaged value, was somewhat correlated to sea ice variability at L151-L141, while the AO-NAO was much more weakly correlated to the same longitudes. From 2000-2007, the opposite can be said as the AMO is very weakly correlated to L151-L141 sea ice longitudes and the AO/NAO component is very strongly correlated to the ice variability ($r \geq 0.81$ and significant at least at 95%). The raw-averaged and principle component correlations largely do not match in either 1951-2000 or 2000-2007 (Table 22). For instance, the AO/NAO principle component is very highly correlated with the ice in 2000-2007 but the AO/NAO raw-averaged values are not (Table 22). Whereas,
Wang et al. (2009) and Maslanik et al. (2007b) both connect dipole patterns and meridional wind anomalies to sea ice variability as opposed to the AO/NAO, interpretation of these results could argue that the AO/NAO combination could still possibly have statistically contributed to the ice variability. Lack of support from the literature and observed neutrality of the AO/NAO indices largely points to a lack of connection in support of the raw-averaged 2000-2007 conclusion. Similarly, a positive AMO without a strong North Atlantic SLP presence (i.e. fueled by the AO/NAO) also equates to a weak connection to the sea ice through the more recent period, though again it is important to keep in mind that statistical connections do not necessarily imply causal relationships.

The relationship between the temperatures and teleconnections varies. Overall the annual values yield the most robust explained variances (Barrow cumulative $r^2 = 0.30$, Table 18). Though these are not as robust as the sea ice results, they continue the pattern of an AMO initial predictor. The temperature residuals are far better a correlated with the observational values than with the predicted values for both temperature locales. Different initial predictors are also introduced in the temperature analyses that contrast the consistent AMO pattern found in the sea ice results. For the multi-seasonal temperature analysis, the AO/NAO spring explains 11% of the variance at Uelen and AO/NAO winter explains 7% of the total variance at Barrow. The AMO still has a presence in this analysis, but its adjusted $r^2$ values are very low ($r^2 = 0.09$ at Uelen and $r^2 = 0.05$ at Barrow). The summer-only analysis introduces the PDO as the sole predictor at Uelen, though the explained variance by that sole predictor is miniscule ($r^2 = 0.06$). In
contrast, Barrow’s summer temperatures reconvene the pattern of the AMO as an initial predictor with the PDO contributing an equal part of the explained variance ($r^2 = 0.07$). All locations have non-significant $r_1$ values indicating a lack of residual autocorrelation. Even though the residuals prove to be random, the small adjusted $r^2$ for each predictor and the large amount of unexplained variance for Uelen and Barrow temperatures in terms of the oceanic and atmospheric teleconnections employed makes definitive multidecadal statistical conclusions an impossible task.

5.2 Future Implications

Statistical forecasting on multidecadal scales is challenging, especially as it pertains to deciphering an anthropogenically forced climate shift versus natural variability or a combination of the two (Solomon et al., 2011). This thesis strictly analyzes teleconnection relationships with sea ice and SAT independent of anthropogenic factors. Therefore, these results neither provide absolute answers nor do they capture the entire picture regarding the forcing mechanisms of western Arctic climate change. On the other hand, the results of this thesis do provide insight that the AMO signal, previously not felt to be of influence in the parts of the Chukchi and Beaufort Seas, does statistically relate to sea ice in the western Arctic in those marginal Arctic seas (Polyakov et al., 2003).

Future work could utilize a similar methodology to spatially expand this research in a Circum-Arctic sense in order to compare and contrast teleconnection signals across all marginal Arctic seas and test where the AMO signal is most pronounced relative to the Chukchi/Beaufort results. Expanding the temporal scale of the sea ice record further
into the future, thereby lengthening the reliability of the sea ice data via the passive microwave satellite observations, should only increase the integrity of the multidecadal sea ice forecasts with respect to teleconnection behaviors.

In terms of variables, this analysis could possibly be improved by adding GHG concentrations, especially carbon dioxide (CO$_2$), as predictors. However, separating the GHG forcing from the natural forcing is difficult on decadal scales, let alone multidecadal scales (Hoerling et al., 2011). Perhaps more prudent and practical additions to the analysis would include the Beaufort High and Dipole Anomaly (DA). The Beaufort High represents such an interannual presence effecting Beaufort Sea climate that adding this mean summer 1000 millibar pressure feature as another predictor could potentially help explain more of the sea ice and temperature variance in the region. It would also be wise to add this persistent feature since synoptic climatological pressure features, like those that compose the NAO, AO and PDO for instance, form the crux of this analysis. Adding the DA as a predictor and examining its influence on the western Arctic, especially in regards to sea ice, over the study period of this thesis and recent decades may also prove useful. Further studies could also examine and expand the temperature analysis in a similar fashion to the aforementioned sea ice. Focus on annual and/or other seasonal temperature combinations could potentially yield noteworthy results.

The research scope of this thesis satisfies the objectives laid out in Chapter 1. Over 1951-2007, the AMO was the initial, most pronounced predictor of sea ice and SAT variability across the study area. The sea ice results were robust and largely significant
for a few longitudes in the central Beaufort Sea (L151-L141). Likewise, Barrow’s annual temperatures were the most robust and significant of the temperature analysis. Importantly, many of the results of this thesis can be explained both statistically and physically in the Arctic climate system. As a result, this analysis serves as a baseline methodology that can be expanded upon in the future to statistically explain and provide insight into the complexities of atmosphere-ocean interactions as contributors to northern high latitude climate change.
REFERENCES


