Multi-regime states of arctic atmospheric circulation

by

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ABSTRACT

Ensemble simulations of arctic circulation can develop multiple dynamical regimes. We use ensemble simulations of June – December 2007 by the WRF-ARW model to examine regime development, and to understand the differences in the atmospheric circulation caused by changes in sea ice and how it is represented. Multiple regimes are common in our ensemble simulations, although there are differences through the period. There is a slight tendency for two or three regimes to be preferred more in June-July-August than October-November-December. September has the fewest multiple-regime periods. September is also the month of sea-ice minimum, suggesting that open ocean may inhibit the occurrence of multiple regimes in ensemble simulations compared to periods when substantial sea ice is present. Differences in sea-ice treatment have little influence on model results. The regime behavior occurring here suggests that as future summer ice cover wanes in the Arctic, the predictability of the atmosphere may increase.
CHAPTER 1. GENERAL INTRODUCTION

Introduction

Arctic atmospheric circulation is of great interest to the atmospheric science community due to the recent rapid decline of sea ice [Serreze et al., 2007, Stroeve et al., 2007; Comiso et al., 2008; Deser and Teng, 2008]. Reductions in sea-ice area allow added solar radiation to be absorbed by the ocean, warming the ocean and delaying winter freezing, which causes thinner sea ice that is more likely to melt the following spring; this ice-albedo feedback allows for further reductions in summer sea ice [Francis and Hunter, 2007; Perovich et al., 2007; Screen and Simmonds, 2010]. Additionally, sea ice acts to regulate heat interactions between the ocean and atmosphere, whereby declines in arctic sea ice allow for larger energy fluxes between the ocean and atmosphere [Deser et al., 2010], which affect atmospheric circulation.

Observations of large energy exchanges between the ocean and atmosphere were found during periods of reduced sea ice [Walsh, 1983]. Other, recent observational studies found that areas with reduced sea ice had substantial energy exchanges between the ocean and atmosphere, influencing atmospheric circulation [Honda et al., 1996; Slonosky et al., 1997; Deser et al., 2000; Francis et al., 2009].

Previous studies have used atmospheric models to examine the role of reduced sea-ice area on atmospheric circulation. Parkinson et al. [2001] used a global climate model to examine sensitivities of simulated regional and global climate to changes in sea ice for the years 1979 – 1986. They found large differences in winter, whereby reductions in arctic sea ice led to warmer arctic surface temperatures. Two similar studies used an atmospheric global climate model (AGCM) to investigate the wintertime atmospheric response to reductions in sea-ice area. Deser et al. [2004] found reductions in sea ice produced warming confined to the bound-
ary layer that affected atmospheric circulation across the Greenland Sea. However, they note that the atmospheric response was largely dominated by model internal variability, which produced a 500 hPa geopotential height response larger than expected with respect to the shallow forcing. Alexander et al. [2004] also identified a similar shallow, warming response to reductions in sea ice that was also found to affect atmospheric circulation for the 1982 – 1983 and 1995 – 1996 winters. They also note that the wintertime atmospheric response is influenced by other modes of variability. Bhatt et al. [2008] used an AGCM to examine the atmospheric response to reductions in summer sea ice for the months April – October 1995 and also found shallow warming and weak circulation responses across areas of reduced sea ice.

More recent studies examined the effect of 2007/2008 sea-ice minimums on atmospheric circulation. Strey et al. [2010] found a significant warming response in October that contributed to a large atmospheric circulation response. Additionally, they note that years with substantial reductions in summer sea ice largely influence atmospheric circulation, with a lag time of approximately one month. Balmaseda et al. [2010] used an European Center for Medium Range Forecasts (ECMWF) coupled ocean-atmosphere model to examine the 2007 and 2008 reduced summer sea-ice impacts on atmospheric circulation. They found that sea-surface temperatures (SST) largely precondition the atmospheric response to sea-ice differences; i.e., the magnitude of the response is strongly dependent upon SSTs rather than the atmospheric sensitivity to changes in sea ice.

Other studies have examined the impacts of reduced sea-ice scenarios on atmospheric circulation for the twenty-first century and found large changes in arctic winter atmospheric circulation [Singarayer et al., 2006; Higgins and Cassano, 2009; Deser et al., 2010].

In this study, ensemble simulations of arctic atmospheric circulation from a regional mesoscale model are used to examine changes to lower boundary conditions (e.g. sea-ice) and their effect on the development of dynamic circulation regimes. The susceptibility of arctic atmospheric circulation to developing multiple dynamic regimes produces implications regarding the predictability of future arctic atmospheric circulation.
Thesis Organization

In this study, I analyzed ensemble simulations of arctic atmospheric circulation using a regional atmospheric model to investigate multiple dynamical regimes and to understand differences in atmospheric circulation caused by changes in sea-ice treatment. The development of multiple regimes was simultaneous across ensemble members, although there were differences through the period. During periods with large sea-ice cover, there were more frequent episodes of multiple regimes in ensemble simulations, revealing times when the predictability of the atmosphere is low. In Chapter 1, I state the research problem and provide a literature review of past research. Chapter 2 describes the analysis of multiple dynamical regimes and how changes to sea-ice treatment had little effect on the emergent differences in atmospheric circulation among ensemble simulations. This chapter was submitted in a paper to The Journal of Geophysical Research Atmospheres with the help of co-authors, William J. Gutowski, Jr., Jonathan M. Hobbs and John J. Cassano. William J. Gutowski, Jr., my major professor, provided guidance for this research and writing of this thesis, and John J. Cassano provided the initial idea for this research. Jonathan M. Hobbs provided me with the statistical approach to identify when multiple regimes occur and how to assess the statistical significance of the features found. Chapter 3 summarizes the research analysis from this work and discusses the implications that multiple regime behavior may have on future arctic atmospheric circulation.

References


Bhatt, U. S., M. A. Alexander, C. Deser, J. E. Walsh, J. S. Miller, M. S. Timlin, J. Scott, and
R. A. Tomas (2008), The atmospheric response to realistic reduced summer arctic sea ice

Comiso, J. C., C. L. Parkinson, R. Gersten, and L. Stock (2008), Accelerated decline in the

Deser, C., and H. Teng (2008), Evolution of Arctic sea ice concentration trends and the

Deser, C., J. E. Walsh, and M. S. Timlin (2000), Arctic sea ice variability in the context of

SST and sea ice anomalies on the winter circulation in CCM3. Part II: direct and indirect

Deser, C., R. Tomas, M. Alexander, and D. Lawrence (2010), The seasonal atmospheric re-
sponse to projected Arctic sea ice loss in the late twenty-first century, J. Clim., 23,


Francis, J. A., W. Chan, D. Leathers, J. Miller, and D. Veron (2009), Winter northern hemi-
sphere weather patterns remember summer arctic sea-ice extent, Geophys. Res. Lett., 36,

Higgins, M. E., and J. J. Cassano (2009), Impacts of reduced sea ice on winter arctic at-
mospheric circulation, precipitation, and temperature, J. Geophys. Res., 114, D16107,


CHAPTER 2. MULTI-REGIME STATES OF ARCTIC ATMOSPHERIC CIRCULATION


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Abstract

Ensemble simulations of arctic circulation can develop multiple dynamical regimes. We use ensemble simulations of June – December 2007 by the WRF-ARW model to examine regime development, and to understand the differences in the atmospheric circulation caused by changes in sea ice and how it is represented. Multiple regimes are common in our ensemble simulations, although there are differences through the period. There is a slight tendency for two or three regimes to be preferred more in June-July-August than October-November-December. September has the fewest multiple-regime periods. September is also the month of sea-ice minimum, suggesting that open ocean may inhibit the occurrence of multiple regimes in ensemble simulations compared to periods when substantial sea ice is present. Differences in sea-ice treatment have little influence on model results. The regime behavior occurring here suggests that as future summer ice cover wanes in the Arctic, the predictability of the atmosphere may increase.

Introduction

Previous work has shown arctic atmospheric circulation responds to changes in forcing as a dynamical system, wherein the response is not a simple cause and effect relationship, but rather a change in circulation patterns [Gutowski et al., 2007]. An example where surface conditions
can change is through the behavior of arctic sea ice, which acts to regulate the strength of energy fluxes linking the ocean and atmosphere. In this study, we examine the effects of sea ice on the development of circulation regimes in the Western Arctic Ocean.

In the last decade, multiyear arctic sea ice has been rapidly declining [Comiso, 2006], a behavior attributed to natural and anthropogenic causes [Serreze et al., 2007]. Climate models participating in the Intergovernmental Panel on Climate Change Fourth Assessment Report (IPCC AR4) are in agreement with the recent decline in arctic sea-ice cover [Zhang and Walsh, 2006], though observations show sea ice declining faster than simulated [Stroeve et al., 2007]. During the summer of 2007, a record minimum occurred in arctic sea-ice extent, thus raising concerns regarding rapid sea ice loss in the future [Comiso et al., 2008]. Comiso et al. [2008] attributes the loss of arctic sea ice to an increased area of summer open ocean, whereby more solar radiation is absorbed, warming the ocean and creating thinner first-year sea ice that is likely to completely melt the following summer.

Various observational studies have investigated the decline of arctic sea ice and its effect on the atmospheric circulation. Walsh and Johnson [1979] found an anomalous warming of the polar atmosphere during periods of reduced ice concentrations north of 60° N. Later, Alexander et al. [2004] found large anomalies in surface air temperatures and air-sea heat fluxes during two winters with reduced ice concentrations in the Greenland Sea. Similarly, Slonosky et al. [1997] found decreased 500 hPa heights and mean sea-level pressure (MSLP) in the Greenland Sea with reduced sea-ice concentrations. Other studies suggested that reductions in sea ice produce substantially large energy exchanges between the ocean and atmosphere [Walsh, 1983; Honda et al., 1996; Francis et al., 2009].

Recent modeling studies have also examined the atmospheric response to changes in sea ice. Using the Goddard Institute for Space Studies global climate model, Parkinson et al. [2001] found areas with reduced (increased) sea-ice concentrations had increased (decreased) arctic surface air temperatures. Deser et al. [2004] investigated the wintertime atmospheric response to sea-ice trends using the Community Climate Model, Version 3.0 (CCM3.0). They found a shallow, anomalous 500 hPa ridge that developed along areas of reduced ice cover in the Greenland Sea, in response to heating confined in the lower troposphere as a result of large
static stability. In a similar study, Alexander et al. [2004] also found for areas of reduced ice cover a local but shallow response in surface air temperatures and decreases in sea-level pressure. Additionally, they note that changes in sea ice occurring along storm tracks in the Greenland Sea may affect the low-level baroclinicity, allowing for shifts in storm tracks. Bhatt et al. [2008], using CCM3.6, investigated the atmospheric response in the Arctic during a period with small sea-ice area, for the months April – October 1995. The largest response occurred in August when arctic sea-ice area was near its minimum. During this period, the Arctic displayed a shallow temperature response with small decreases in sea-level pressure. One further experiment limited ice reduction to only the Beaufort Sea, in which they found a similar but smaller response. Additionally, they found changes in sea ice have an influence on the storm tracks in the North Pacific region. Singarayer et al. [2006] examined the impacts of a twenty-first century, reduced sea-ice scenario using the Hadley Centre Atmospheric Model, Version 3 (HaDAM3). The impact was stronger in winter with warming over the Arctic basin and reductions in sea-level pressure extending into the North Pacific and North Atlantic regions. Higgins and Cassano [2009] examined the influence of projected late twenty-first century reductions of sea ice on atmospheric circulation and found changes across the Arctic resulting from changes in the frequency of high and low pressure centers and overall deepening of the Aleutian Low. Strey et al. [2010] simulated the effects of reduced sea ice in 2007 compared to the 1984 distribution for the period September – December 2007 and found significant atmospheric differences resulting from the changed ice distribution in October.

In this study we examine differences between ensemble simulations allowing fractional sea-ice cover in a model grid box versus those for which sea ice is prescribed simply as binary; e.g. 0% or 100%, respectively. Our study is primarily motivated by thinning arctic sea ice, which as sea ice thins is more likely to break apart, spread and compress under the influence of atmosphere and ocean circulations, potentially creating greater area within model grid boxes that is only partially ice covered. The intent of this study was to discern differences in the atmospheric circulation due to the behavior of sea ice. However, we find that the emergent differences are governed weakly by the choice of ice treatment, and that the key factor appears to be the susceptibility of arctic atmospheric circulation to developing multiple dynamic regimes.
There is a tendency for MSLP to evolve differently among ensemble members, allowing for a splitting behavior into multiple dynamic regimes, which arises from our understanding that there is an unforced, nonlinear variability of the system. The development of multiple regimes implies that there is not a single circulation evolution that one would be able to forecast, which allows for possible implications about the predictability of the flow. We note that dynamic regimes as discussed in this work is contrary to the orographically forced multiple equilibrium states work performed by Charney and Straus [1980], and the distribution of bimodal wave states work by Hansen [1988].

Data and Methodology

Model Design

For our ensemble simulations, we used the Weather Research and Forecast model – Advanced Research WRF (WRF-ARW), Version 3.1.0 [Skamarock et al., 2008]. An important consideration for the WRF-ARW simulations was the selection of physical parameterizations appropriate to the Arctic. The ensemble simulations here used parameterization choices similar to Cassano et al. [2011] with further modifications based on additional model testing and evaluation provided by M. Seefeldt (unpublished data, 2010). These include the sub-grid cumulus scheme of Grell and Devenyi [2002], the NCAR Community Atmosphere Model (CAM 3.0) spectral-band scheme [Collins et al., 2004; Mlawer et al., 1997] for shortwave and longwave radiation, the Goddard Cumulus Ensemble (GCE) models [Tao and Simpson, 1993] cloud microphysics scheme using a three-category ice-phase scheme, with the Rutledge and Hobbs [1984] graupel ice physics as the third class of ice. For the planetary boundary layer (PBL), we used the Mellor-Yamada-Janjic (MYJ) scheme [Janjic, 2001], which is based on eta surface similarity theory [Monin and Obukhov, 1954].

We used the 4-layer Noah [Chen and Dudhia, 2001] land surface model (LSM) with polar modifications for snow and ice [Hines et al., 2011]. Updates include the representation of sea ice as a fractional field in a grid box. Additionally, sea-ice albedo and emissivity were set at 0.80 and 0.98, respectively. In the work here, we treat sea ice using two different methods: one
set of simulations allows for an ocean grid box to have ice cover anywhere in the range 0 – 100% (fractional) and, the other set of simulations allow sea-ice cover to be either 0% or 100% in a grid box (binary).

The simulations used 40 terrain-following vertical levels between Earth's surface and the model top at 50 hPa. In order to resolve the boundary layer well, the model used 10 levels between the ground and 800 m. The model domain (Figure 1) is a polar-stereographic projection of the Arctic specified by the Coordinated Regional Downscaling Experiment (CORDEX) (unpublished data, 2010) available from the World Climate Research Program (http://wcrp.ipsl.jussieu.fr/RCD_CORDEX.html). The domain is spanned by a $126 \times 136$ array of grid points with 50 km grid spacing, centered over the Arctic Ocean and covering portions of the arctic North America and Eurasia. The arctic circumpolar vortex is generally contained within the domain, allowing for simulations to establish a response to differences in the lower boundary conditions that is not strongly constrained by the lateral boundary conditions [Gutowski et al., 2007].

**Data**

The ensemble simulations used initial and lateral boundary conditions for the atmospheric fields provided by the European Center for Medium Range Forecasts (ECMWF) Interim Re-analysis (ERA-Interim), available every 6 hours at T255 (approximately 0.7°) horizontal resolution [Simmons et al., 2007; Berrisford et al., 2009]. The ERA-Interim re-analysis is similar to that of the ERA-40 [Uppala et al., 2005] with the exception of improvements made to model physics and the assimilation system. Noteworthy improvements made to the data assimilation include: increased horizontal resolution from T159 to T255, corrections made to satellite radiance data, and corrections made to surface pressure data because of errors in station height and buoy data [Simmons et al., 2007].

ERA-Interim re-analysis was also used to assess the quality of our ensemble simulations. Although the same data are supplying lateral boundary conditions, for a pan-arctic domain that encompasses most of the circumpolar vortex, the lateral boundary conditions exert relatively small influence on the model's interior circulation [Gutowski et al., 2007]. This is in contrast to
regional simulations in the mid-latitudes, where westerly flow sweeps across the entire domain [Giorgi and Bi, 2000].

We prescribe fractional sea-ice coverage using daily sea-ice concentrations from the National Snow and Ice Data Center (NSIDC) Special Sensor Microwave/Imager (SSM/I) observations, available every 12 hours at 25 km resolution [Comiso, 2008]. In the Arctic, sea-ice concentrations are not available poleward of 87.2° N, so we assume a concentration there of 100%. Additionally, to account for potential errors associated with data retrieval and summer melt ponding [Comiso and Kwok, 1996; Comiso et al., 1997], we follow the recommendation of Comiso and Parkinson [2008] and set ice concentrations of 10% or less to open-ocean (0% ice cover). The WRF-ARW Preprocessing System (WPS) interpolate the sea-ice concentrations on the NSIDC grid to values for each grid box in our ensemble simulations. For ensemble simulations with binary sea ice, we then adjust the sea-ice fraction to 100% for grid boxes with NSIDC ice cover greater than or equal to 50%, and to 0% for grid boxes with NSIDC ice cover less than 50%.

Simulations

We constructed a pair of ensembles that simulated two sets of sensitivity runs. The first ensemble set included binary sea ice everywhere and the second set used binary sea-ice treatment everywhere, except for a portion of the Arctic Ocean that had fractional sea-ice coverage in its grid boxes. From consideration of the times and locations for which the area for fractional ice cover is greater than 0% but less than 90%, the portion of the Arctic Ocean with prescribed fractional ice cover is an area north of 70° N that includes portions of the Arctic, Beaufort and Chukchi (ABCH) seas (Figure 1). This region is also the focus of our analysis.

In order to obtain a clear climate response above noise levels and to avoid excessive computation expense, we used ensembles consisting of eight members, which were determined to be an appropriate size to accurately obtain a model’s seasonal response [Taschetto and England, 2008]. The ensemble simulations ran from 00 UTC 24 May 2007 through 31 December 2007, with start times for each ensemble member staggered 12 hours during the period, 24 – 30 May 2007 (Table 1). Our period of analysis began 15 June, allowing time for the ensemble simula-
tions to spin-up and potentially reach distinctly different atmospheric states by the start of the analysis period. We chose this period for simulations due to the large area of sea-ice fraction between 50% and 90%. In our study, the binary ensemble treats ice fractions larger than 50% in a grid box as closed (100% ice cover), which reduces the heat fluxes between ocean and atmosphere; conversely, the fractional ensemble will retain a portion of open ocean in these grid boxes, thus allowing potentially much greater heat fluxes between the ocean and atmosphere.

**Regime Analysis**

Analysis of our simulations shows periods when ensemble members collectively show two or more circulation regimes in our target region. We identify these regimes using model-based clustering, which is a common technique for systematically identifying combinations of similar components in multivariate data. For example, Smyth et al. [1999] use model-based clustering to identify multiple regimes in seasonal geopotential height anomaly patterns. Model-based clustering characterizes the data as a finite-mixture stochastic model. A finite mixture model assumes that the probability density function (PDF) for the data is a weighted average of a fixed set $j = 1, 2, \ldots, k$ component PDFs $f_j$

$$f(y_{i,t}) = \sum_{j=1}^{k} w_j f_j(y_{i,t}|\theta_j)$$  \hspace{1cm} (1)

Here $y_{i,t}$ is the MSLP for ensemble member $i$ at time $t$. Each component of the model (1) is characterized by its own set of parameters $\theta_j$ and a weight $w_j$. For the ensemble MSLP time series, we assume that each ensemble member belongs to one of the $k$ components, or regimes. However, the regime membership of each ensemble member, the regime weights and the regime-specific PDFs are unknown and need to be estimated from the data. This requires further assumptions about the nature of the individual PDFs.

We adopt a time series stochastic model for the individual PDFs $f_j$. Specifically, if ensemble member $i$ is in regime $j$, the observed time series follows a first-order autoregressive process

$$y_{i,t} = \mu_{j,t} + \rho_j (y_{i,t-1} - \mu_{j,t-1}) + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} \sim \text{Gaussian}(0, \sigma_{j}^2),$$  \hspace{1cm} (2)
with autocorrelation parameter $\rho_j$ and Gaussian-distributed random shocks $\varepsilon_{i,t}$. Thus, each regime has its own autocorrelation parameter and variance. In addition, to allow the time series mean to vary with time, we add some flexibility to the mean parameters $\mu_{j,t}$. These are linear combinations of a set of b-spline basis functions, with the number of basis functions depending on the length of the time series. This allows the overall mean for each regime to vary smoothly with time, meaning that regimes could differ not only in their overall mean over the entire time series, but also in their trends over time. Regimes can also differ in their overall variability. For a given number of regimes, the data are used to identify the most likely parameter values for each regime and the most likely regime membership for each ensemble member.

**Estimation**

For a specified number of regimes $k$, parameters are estimated by maximizing the likelihood function, denoted as $L(\theta|y)$ and the resulting estimates are known as the maximum likelihood estimates (MLE). The likelihood function is equivalent to the joint probability distribution for the data given the parameters. For a single regime and the Gaussian time series model in (2), the time series for a single ensemble member has a multivariate Gaussian joint distribution. In contrast, for multiple regimes the joint distribution is a mixture of multivariate Gaussian distributions. For a mixture model such as (1), the expectation-maximization (EM) algorithm is a convenient tool for finding the MLE. The EM algorithm is an iterative search procedure that is designed to converge to the MLE and generally performs well in practice. Raftery et al. [2005] outline the general steps for each iteration of the algorithm for a mixture model with Gaussian component distributions. Once the parameter estimates that maximize the likelihood are found, the most probable regime membership for the individual ensemble members can also be computed.

**Model selection**

Maximum likelihood estimation also provides information about the relative quality of a model's fit to the data. Competing statistical models can be compared by evaluating the likelihood function at the MLE for each model. However, a more complex model with more
parameters will tend to provide a better fit, so a model comparison criterion should also incorporate model complexity. The Bayesian Information Criterion (BIC) provides a summary of model fit that also includes a penalty for the number of parameters in the model. In the context of model-based clustering, Fraley and Raftery [2002] define

\[
\text{BIC} = 2 \ln (L(\theta_{\text{MLE}}|y)) - p \ln n,
\]

where \( p \) is the number of model parameters, \( n \) is the sample size (the number of ensemble members), and \( L(\theta_{\text{MLE}}|y) \) is the value of the likelihood function at the MLE. The BIC can be used to compare the fit of mixture models for varying numbers of components. One primary comparison we make is a one-component mixture versus a two-component mixture. In the form of (3), a model with higher BIC is favored.

**Time windows**

We are interested in circulation regimes that persist beyond a synoptic time scale but wish to avoid examining long time series where transitions from one dynamic regime to another would be increasingly likely. Therefore, we perform the mixture model estimation on time series of MSLP that are 7 or 11 days long, with one observation per ensemble member per day. With 16 ensemble members present, there are generally sufficient data to estimate the mixture model parameters with precision for up to three regimes, while still including more than one ensemble member in a regime. The estimation is performed separately for every available 7 and 11-day time window. Each time window is identified by its starting date. For example, the 7-day dataset for 1 July consists of MSLP for 1 – 7 July and the 7-day dataset for 31 July consists of MSLP for 31 July – 6 August.

**Results**

**Model Performance**

Using the ERA-Interim re-analysis that supplied our initial and boundary conditions as our reference simulation, we calculated performance statistics (Table 2) to determine how well our ensemble simulations were reproducing arctic atmospheric circulation. We first computed the
bias as the difference between the monthly, spatially averaged binary and fractional simulations, and re-analysis. The errors between our ensemble simulations and the ERA-Interim re-analysis were small (± 2 hPa) for the months simulated. For a small domain (e.g. CORDEX domain), the small bias between model simulations was expected. We were also interested in how our model ensemble simulations performed with respect to the noise level of natural variability. We compared the variance for each daily-averaged ensemble member to that of the monthly-averaged ERA-Interim re-analysis. Then for each ensemble-averaged variance the monthly, domain-averaged variance was computed whereby the root-mean-square difference (RMSD) could then be easily found by taking the square root of the variance. For comparison, the natural variability of the ERA-Interim re-analysis was calculated by finding the square root of the variance between the daily-averaged and monthly-averaged MSLP. Overall, the binary and fractional ensemble RMSDs are similar to the ERA-Interim natural variability. Further, the differences in RMSD are small, with errors estimated to be the bias as previously discussed. This is indicative that our ensemble simulations are reproducing arctic atmospheric circulation within the noise level of natural variability during the six-month simulation.

**Regime Behavior**

Multiple regimes are common in our simulations, although there are differences through the period. This behavior occurs when daily MSLP traces are significantly separated or when pressure traces show differing trends (Figure 2), which often occur in sequence, with differing trends leading to separated pressure traces that then have differing trends as the traces merge into one regime later. Table 3 shows the percentage of days in each month when the BIC preferred two or three-regime behavior over one-regime behavior. There is a slight tendency for two or three regimes to be preferred more in June-July-August (JJA) than October-November-December (OND). However, the clearest feature in Table 3 is the September minimum, which coincides with the month that has the least amount of sea ice. Sea-surface temperatures are specified in both ensembles, which may act to constrain the atmospheric behavior [Parkinson et al., 2001] and inhibit model variability during periods when little sea ice is present. In contrast, when there is substantial sea-ice area, surface temperature is determined internally.
by the model, potentially allowing for more freedom in its evolution.

Our simulations show that there is little model variability during JJA and September, a period when sea-ice area is declining. Table 4 shows the inter-quartile differences (75th - 25th quartiles) of the daily MSLP for our 6-month ensemble simulations. There is a wider range of variability occurring in OND (> 8 hPa) than JJA and September (<8 hPa), which supports the concept that as sea-ice area decreases, model variability becomes small. The number of consecutive days (streaks) when two or three-regime behavior is preferred to one-regime behavior (Table 5) is also important in recognizing periods when model variability is small. Consecutive-day streaks are more persistent during JJA, which suggests that the model has a greater tendency to remain in one mode of regime behavior during JJA. Less frequent transitions between different modes of regime behavior suggests that the flow evolves more slowly in summer. In contrast, during periods with greater sea-ice area in the model, whether as fractional or binary, the interactive ice surface appears to allow the modeled atmosphere to have more freedom in its variability and to transition more frequently between different regime modes.

Recent studies examined the seasonal cyclone variability and found differences in duration time and frequency of arctic cyclones throughout the year [Zhang et al., 2004; Sorteberg and Walsh, 2008; Asplin et al., 2009]. During summer they found arctic atmospheric circulation developed more persistent behavior with arctic cyclones having a longer residence time than in colder months, which may have been the result of enhanced baroclinic instability when more open ocean was present. This is in line with our results that identified the JJA and September circulations as persisting longer. In contrast, in winter, periods with large sea-ice area, arctic cyclones were observed to be more frequent but have shorter duration times, which may be attributed to the reinforcement of anticyclonic circulations over the increasing sea-ice area [Asplin et al., 2009]. Our results are similar in that there were more streak episodes with shorter length (Table 5) in OND than JJA.
Ice Treatment Differences

An original motivation for this work was to analyze differences in arctic atmospheric circulation due to differences in sea-ice treatment (fractional versus binary). The motivation beyond the modeling differences was recognition that as sea ice thins, it can break up more easily and produce more fractional behavior. In this section, we focus on differences that emerged as a result of our choice in the treatment of sea ice. Although we ultimately found no significant differences in atmospheric circulation resulting from sea-ice treatment, we document briefly here the basis for arriving at this conclusion.

During periods when there is substantial sea-ice area with fractional concentrations between 50% and 90%, the fractional treatment allows heat exchange between the ocean and atmosphere. In contrast, the binary treatment with sea ice prescribed at 100% for ice concentrations larger than 50% would have very small heat exchange between ocean and atmosphere; thereby having reduced sensible and latent heat fluxes, which would allow for large differences between fractional and binary sea-ice simulations. October would be an ideal time for strong differences to emerge, because ocean and sea-ice temperatures are substantially different as the Arctic Ocean refreezes but does not approach 100% sea-ice cover in the ABCH seas.

Indeed, the largest differences in MSLP between the ensembles occur in October, although August shows comparable differences in the ABCH seas (Figure 3). However, monthly mean 2 m temperature differences are negligible in August (Figure 4), suggesting that emergent differences in August MSLP are not the result of differences in ice treatment. For October, Figure 4 shows small sensible heat flux and 2 m temperature monthly mean differences. These differences are a consequence of changes in the direction in which the ensemble mean winds (not shown) are blowing over ice-free areas. Small differences in the surface circulation may move cold air originating over sea ice to areas of open ocean, and conversely warm air over open ocean to areas with sea ice. Ice treatment differences may also affect the low-level baroclinicity, which may influence storm tracks entering the ABCH seas region. To examine this possibility, we calculated storm tracks using a 31-point, Lanczos band-pass filter that gives frequencies between 2.5 and 6-days [Blackmon, 1976; Duchon, 1979]. Differences in storm tracks between
fractional and binary ice treatments for the month of October were negligible (Figure 5). Overall, the results suggest that October mean MSLP differences were not the result of changes in ice treatment, but rather the ensembles falling into different regimes, with no significant forcing differences (e.g. differences in surface sensible heat flux). We note that our work specifies different changes to the lower boundary conditions and does not contradict previous studies [Parkinson et al., 2001; Alexander et al., 2004; Deser et al., 2004; Singarayer et al., 2006; Bhatt et al., 2008; Strey et al., 2010] that have shown an atmospheric response to develop with substantial changes in sea-ice concentrations.

Conclusions and Discussion

In this study, we examined the susceptibility of an arctic atmospheric-circulation ensemble to developing multiple dynamic regimes. We used the WRF-ARW model to construct a pair of ensembles with each containing eight members in order to obtain a climate response above noise levels. The first ensemble set included binary sea ice everywhere and the second set used binary sea-ice treatment everywhere, except for a portion of the Arctic Ocean that had fractional sea-ice coverage in its grid boxes. Initial and boundary conditions were supplied by the ERA-Interim re-analysis. Our simulations ran from late May 2007 through December 2007 with our period of analysis beginning 15 June, allowing time for the ensemble simulations to spin-up and potentially reach distinctly different atmospheric states by the start of the analysis period. From our simulation output, we constructed daily MSLP time series to analyze for multiple dynamic regimes.

For our regime analysis, we used a Bayesian Information Criterion to determine when multiple regimes persisted for 7 or 11 days. The analysis thus identified multi-regime states that persisted beyond synoptic, auto-regressive time scales (≈ 5 days). We found that multiple dynamic regimes were common during our simulation period. When sea-ice area was declining (JJA) there was a tendency for more persistent multiple-regime behavior, which may be due to sea-surface temperatures constraining variability of atmospheric circulation. In contrast, during periods when there is a large sea-ice area present (OND), the interactive ice surface allows the modeled atmosphere more freedom in its variability, allowing less persistent multiple-regime
behavior. However, the clearest feature in our simulations occurred in September, which was when the sea-ice area reached a minimum. September had the largest percentage of consecutive days when 1-regime behavior was preferred to 2 or 3-regime behavior.

When comparing the percentage of days with 1-regime present in binary and fractional sea-ice ensembles we found there was a tendency for the binary simulations to have more 1-regime days in JJA. In contrast, there was a tendency for the fractional ensemble to have more 1-regime days in OND. Results from multiple years are needed to assess whether or not this is a meaningful difference.

MSLP differences between fractional and binary sea-ice ensembles were largest for October. However, although October differences may be statistically significant they lack any clear forcing mechanism. Only small differences occurred between ensembles in 2 m air temperature, surface sensible heat flux and storm tracks, suggesting the differences between ensembles are not physically meaningful. Longer simulations may be necessary to give a more significant result, although the physical meaningfulness would still be in question.

The regime behavior seen here has implications for the predictability of arctic atmospheric circulations. Further changes in sea-ice area may affect the degree to which multiple persistent regimes appear in ensemble simulations. In the last decade, the Arctic has seen reductions in summer sea-ice area [Serreze et al., 2003; Stroeve et al., 2007; Comiso et al., 2008]. The trend may continue in the future [Zhang and Walsh, 2006], leading to more 1-regime behavior as less sea ice is present. This behavior may allow for more accurate prediction of future arctic atmospheric circulation in summer because there would be fewer multi-regime periods.

Uncertainties in model variability exist due to our use of specified sea-surface temperatures, which prevent interactive changes in ocean temperature. This behavior would be more common, of course, during periods of low sea-ice; i.e., late summer. Using a coupled ocean-atmosphere model may produce more multiple-regime states during low ice periods than our specified sea-surface temperature simulations because there would be more interaction between the ocean and atmosphere. However, ocean temperatures tend to evolve more slowly than ice-surface temperatures, which may lessen the effects of an interactive ocean.
Acknowledgments

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References


Janjic, Z. I. (2001), Nonsingular implementation of the Mellor-Yamada Level 2.5 Scheme in the NCEP Meso Model, *NCEP Office Note*, No. 437, 61 pp., NOAA Science Cent., Camp Springs, Maryland, USA.


Figure Captions

**Figure 1** Map of the WRF model domain showing the land-sea mask at the model’s 50 km resolution. Sea ice in the red triangle was subject to fractional sea-ice treatment.

**Figure 2** Daily MSLP traces with (a) 1-regime, (b) two separated regimes and (c) two regimes with different trends.

**Figure 3** Daily MSLP differences for fractional – binary ensembles for (a) August and (b) October.

**Figure 4** Fractional – binary ensemble differences for monthly averaged 2 m temperature (top) and sensible heat flux (bottom) differences for (a), (c) August and (b), (d) October.

**Figure 5** Monthly averaged October band-pass filtered 500 hPa heights for (a) fractional and (b) binary ensembles. The filter gives frequencies between 2.5 and 6 days.
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Figure 5 Monthly averaged October band-pass filtered 500 hPa heights for (a) fractional and (b) binary ensembles. The filter gives frequencies between 2.5 and 6 days.
Table 1  List of ensemble member starting times.

<table>
<thead>
<tr>
<th>Ensemble</th>
<th>Start Times</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fraction</td>
<td>05/24 12Z, 05/25 12Z, 05/26 12Z, 05/27 12Z,</td>
</tr>
<tr>
<td></td>
<td>05/28 12Z, 05/29 00Z, 05/29 12Z, 05/30 00Z</td>
</tr>
<tr>
<td>Binary</td>
<td>05/25 00Z, 05/26 00Z, 05/27 00Z, 05/28 00Z,</td>
</tr>
<tr>
<td></td>
<td>05/28 12Z, 05/29 00Z, 05/29 12Z, 05/30 00Z</td>
</tr>
</tbody>
</table>
Table 2  Performance statistics of WRF compared with ERA-Interim using MSLP (hPa). \( F \) = fractional sea-ice ensemble, \( B \) = binary sea-ice ensemble.

<table>
<thead>
<tr>
<th>Month</th>
<th>RMSD(ERA)</th>
<th>RMSD(F-ERA)</th>
<th>RMSD(B-ERA)</th>
<th>Bias(F-ERA)</th>
<th>Bias(B-ERA)</th>
</tr>
</thead>
<tbody>
<tr>
<td>June(15-30)</td>
<td>7.1</td>
<td>8.1</td>
<td>8.1</td>
<td>-0.6</td>
<td>-1.0</td>
</tr>
<tr>
<td>July</td>
<td>5.8</td>
<td>6.6</td>
<td>6.8</td>
<td>-0.1</td>
<td>0.6</td>
</tr>
<tr>
<td>August</td>
<td>6.4</td>
<td>8.5</td>
<td>7.8</td>
<td>2.2</td>
<td>1.7</td>
</tr>
<tr>
<td>September</td>
<td>5.6</td>
<td>8.3</td>
<td>8.3</td>
<td>-1.8</td>
<td>-1.7</td>
</tr>
<tr>
<td>October</td>
<td>9.1</td>
<td>10.4</td>
<td>10.4</td>
<td>-0.8</td>
<td>-1.1</td>
</tr>
<tr>
<td>November</td>
<td>9.5</td>
<td>11.9</td>
<td>12.3</td>
<td>-1.3</td>
<td>-0.6</td>
</tr>
<tr>
<td>December</td>
<td>12.0</td>
<td>13.6</td>
<td>13.7</td>
<td>-0.3</td>
<td>-0.6</td>
</tr>
</tbody>
</table>
Table 3  Percentage of days in each month when 2 or 3-regimes are preferred to 1-regime.

<table>
<thead>
<tr>
<th>Month</th>
<th>7-Day</th>
<th>11-Day</th>
</tr>
</thead>
<tbody>
<tr>
<td>June</td>
<td>93%</td>
<td>100%</td>
</tr>
<tr>
<td>July</td>
<td>71%</td>
<td>87%</td>
</tr>
<tr>
<td>August</td>
<td>84%</td>
<td>97%</td>
</tr>
<tr>
<td>September</td>
<td>33%</td>
<td>30%</td>
</tr>
<tr>
<td>October</td>
<td>74%</td>
<td>94%</td>
</tr>
<tr>
<td>November</td>
<td>63%</td>
<td>83%</td>
</tr>
<tr>
<td>December</td>
<td>96%</td>
<td>100%</td>
</tr>
</tbody>
</table>
Table 4  Monthly averaged inter-quartile differences of the daily MSLP.

<table>
<thead>
<tr>
<th>Month</th>
<th>75th - 25th Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>June(15-30)</td>
<td>6.1</td>
</tr>
<tr>
<td>July</td>
<td>4.9</td>
</tr>
<tr>
<td>August</td>
<td>8.1</td>
</tr>
<tr>
<td>September</td>
<td>5.7</td>
</tr>
<tr>
<td>October</td>
<td>10.1</td>
</tr>
<tr>
<td>November</td>
<td>9.0</td>
</tr>
<tr>
<td>December</td>
<td>9.8</td>
</tr>
</tbody>
</table>
Table 5 Length (in days) of persistent streaks when multiple regimes are preferred with a 7 or 11-day window during JJA and OND.

<table>
<thead>
<tr>
<th>Season</th>
<th>Streaks</th>
<th>Mean Length</th>
</tr>
</thead>
<tbody>
<tr>
<td>JJA(7-day)</td>
<td>1, 4, 5, 5, 6, 13, 13, 16</td>
<td>7.9</td>
</tr>
<tr>
<td>JJA(11-day)</td>
<td>18, 19, 35</td>
<td>24.0</td>
</tr>
<tr>
<td>OND(7-day)</td>
<td>1, 1, 1, 3, 4, 6, 7, 8, 9, 18</td>
<td>6.0</td>
</tr>
<tr>
<td>OND(11-day)</td>
<td>1, 11, 12, 25, 26</td>
<td>15.0</td>
</tr>
</tbody>
</table>
CHAPTER 3. GENERAL CONCLUSIONS

General Discussion

In this study, I used a regional mesoscale model to examine the effects of changing sea ice on the development of multiple dynamic regimes in a regional mesoscale model. I also examined how differences in sea-ice treatment influence atmospheric circulation.

Chapter 2 provided the results from the regime analysis that were used to determine when multiple dynamic regimes were common. During periods of declining sea ice, June-July-August (JJA), there was a tendency for more persistent multiple dynamic regimes. This persistent behavior may be due to specified sea-surface temperatures (SST), preventing ocean-atmosphere interactions, which constrains the variability of the models atmospheric circulation. In contrast, during colder months with a larger sea-ice area, October-November-December (OND), there was a tendency for less persistent multiple dynamic regime behavior that may be due to the larger interactive ice surface, which allows for more freedom in the variability of the models atmospheric circulation. However, September witnessed a large change in regime behavior, in which more persistent 1-regime behavior was preferred to multiple regime behavior. The sea-ice minimum also occurred in September, in which a substantially large open-ocean area would greatly constrain the variability of the models atmospheric circulation, allowing for more persistent regime behavior.

The regime behavior examined in this study suggests that changing sea-ice area affects the predictability of atmospheric circulation, which has implications for the predictability of future arctic atmospheric circulation. Future reductions in summer sea ice may continue [Zhang and Walsh, 2006; Zhang et al., 2010; among many others], which may affect the persistence of multiple regimes, whereby more persistent 1-regime behavior will become the norm, allow-
ing for a more predictable future summer arctic atmosphere. However, uncertainties exist in model variability due to prescribed SSTs, which constrain the variability of the models atmospheric circulation. Balmaseda et al. [2010] performed a sensitivity study on the influence of SSTs on atmospheric circulation during periods with large changes in sea ice. They compared output from a fully coupled ocean-atmosphere model and an atmospheric model that used prescribed SSTs, and found SSTs significantly precondition atmospheric circulation, influencing the sensitivity of the atmosphere to changes in sea ice. This suggests that a fully coupled ocean-atmosphere model may be necessary to understand future regime behavior and its effect on the predictability of the future atmospheric mean state, especially during the warm months when open-ocean area is greatest. However, care should be taken in ensuring that the oceanic state is adequately represented (e.g. the slow evolution of SSTs) [Peng et al., 2009; Balmaseda et al., 2010], allowing for accurate prediction of atmospheric circulation.

Sensitivity experiments performed using the Weather Research and Forecast model Advanced Research WRF (WRF-ARW) between different sea-ice treatments (fractional and binary) suggested that emergent differences were not the result of any clear forcing mechanism. However, longer simulations may be necessary to fully assess the impacts of sea-ice treatment differences on atmospheric circulation. Additionally, sea-ice treatment differences may need to be examined across the whole domain, however the largest sea-ice differences between fractional and binary simulations occurred in the Beaufort and Chukchi seas, so examining differences across the whole domain may not be meaningful. Of course, specified SSTs may impact the susceptibility of atmospheric circulation to differences in sea-ice treatment [Balmaseda et al., 2010], such that the physical meaningfulness of the differences would still be questionable.

References


Peng, P., A. Kumar, and W. Wang (2009), An analysis of seasonal predictability in coupled


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