Comparative Analysis of the Western Arctic Surface Climate among Observations and Model Simulations

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ABSTRACT: Accurate estimates of the spatial and temporal variation in terrestrial water and energy fluxes and mean states are important for simulating regional hydrology and biogeochemistry in high-latitude regions. Furthermore, it is necessary to develop high-resolution hydroclimatological datasets at finer spatial resolutions than are currently available from global analyses. This study uses a regional climate model (RCM) to develop a hydroclimatological dataset for hydrologic and ecological application in the Western Arctic. The fifth-generation Penn State–NCAR Mesoscale Model (MM5) forced by global reanalysis products at the boundaries is used to perform 12 yr of simulation (1990 through 2001) over the Western Arctic. An analysis that compares the RCM simulations with independent observationally derived data sources is conducted to evaluate the temporal and spatial distribution of the mean states, variability, and trends during the period of simulation. The RCM simulation of sea level pressure agrees well with the reanalysis in terms of mean states, seasonality, and interannual variability. The RCM also simulates major spatial patterns of the observed climatology of surface air temperature (SAT), but RCM SAT is generally colder in the summertime and warmer in the wintertime in comparison with other datasets. Although there are biases in the mean state of SAT, the RCM simulations of the seasonal and interannual variability of SAT are similar to variability in observationally derived datasets. The RCM also simulates general spatial patterns of observed rainfall, but the modeled mean state of precipitation is characterized by large biases relative to observationally derived datasets. In particular, the RCM tends to overestimate coastal region precipitation but underestimates precipitation in the interior of the Western Arctic. The Arctic terrestrial surface climate trends for the period of 1992 to 2001 of the RCM are similar to those derived from observations, with sea level pressure decreasing 0.15 hPa decade$^{-1}$, SAT increasing 0.10°C decade$^{-1}$, and precipitation decreasing slightly in the RCM simulations. In summary, the RCM dataset produced in this study represents an improvement over data currently available from large-scale global reanalysis and provides a consistent meteorological forcing dataset for hydrologic and ecological applications.

KEYWORDS: Regional climate modeling; Climate trend; Interannual variability

1. Introduction

Observational evidence indicates that the northern high-latitude continents have exhibited large climate change in the recent two decades relative to changes that have been occurring at the global scale (Jones and Moberg 2003; Moritz et al. 2002). These changes may be influencing hydrology and biogeochemistry in high-latitude regions in a way that may affect the global climate system (McGuire et al. 2006). To evaluate how hydrology and biogeochemistry is responding to changes requires credible data for regional hydrologic and ecological analyses. The Western Arctic Linkage Experiment (WALE) is designed to investigate regional water, energy, and carbon dioxide budgets in Alaska and western Canada through the comparison of modeling and observationally derived datasets (McGuire et al. 2007, manuscript submitted to Earth Interactions).

The availability of large-scale, long-term datasets of land surface water and energy budgets is essential for understanding the Arctic environmental system and
interactions among different components, especially in the face of potential climatic change. However, consistent observations of components of the terrestrial water budget are routinely unavailable. While some terms of the surface water balance are reasonably well observed [precipitation (PRC) and runoff in particular], other terms including evapotranspiration and soil moisture are generally not directly observed. Many of these variables are difficult to measure because of technical and environmental limitations. It has been suggested that an alternative to estimating terrestrial water and energy cycles is to use land surface models (LSMs; Bonan 2002) or regional climate models (RCMs; Wu and Lynch 2000; Wu et al. 2005). The models close the water and energy budget by design. Thus, if the large-scale forcing data, which drive LSMs and RCMs, are accurate, and if model biases are small, these modeled water and energy fluxes might be used in lieu of datasets derived from sparse data to provide a consistent picture of water and energy fluxes across a region. Nevertheless, while estimates of water and energy cycles obtained through an RCM are consistent, these estimates can be subject to large errors due to biases in the model and the forcing. In the absence of long-term, large-scale observations of components of the hydrologic cycle, a quality dataset for regional hydrologic and ecological application can be developed using a regional climate system model. This study attempts to produce a quality meteorological dataset in a consistent and coherent framework. We take the state-of-art fifth-generation Penn State–National Center for Atmospheric Research (NCAR) Mesoscale Model (MM5) as a regional model to simulate the climate in the WALE domain and to generate a comprehensive dataset. The regional climate simulation is then evaluated against global reanalysis, gridded observations, and direct measurements at selected weather stations. The study by Drobot et al. (Drobot et al. 2006) conducted a comprehensive intercomparison for precipitation and surface air temperature (SAT) among a number of data sources including the RCM simulation presented in this paper. Thus, the validation and intercomparison in this paper will focus on spatial patterns of mean states, variations, and corresponding seasonality. We also examine trends in the regional climate, with an emphasis on trends in the seasonality of surface climate.

This paper is organized as follows. Section 2 describes the method for the comparative analysis, followed by intercomparison and validation in section 3. The discussion and conclusions are given in section 4.

2. Analysis methodology

2.1. Regional climate model

The MM5 (release 3.6) was used for this study. It has been widely used in a range of studies from short-term weather prediction to regional climate simulation (Mass and Kuo 1998; Wu et al. 2005). Model physics used in the present study includes the Grell deep convective parameterization (Grell et al. 1994), the Medium-Range Forecasting (MRF) planetary boundary layer scheme (Hong and Pan 1996), and the Reisner explicit cloud microphysics parameterization (Reisner et al. 1998). This latter parameterization predicts the mixing ratio of cloud water and ice crystals as well as the rain and snow water mixing ratios. The Rapid Radiative Transfer Model (RRTM; Mlawer et al. 1997) is chosen for longwave radiation, and
the delta-Eddington approximation (Briegleb 1992) is used for solar radiation in our study.

The horizontal domain of the model in this study covers the Western Arctic with a grid size of 50 km consisting of 50 north–south and 80 east–west grid points (Figure 1). It should be noted that the model buffer zone (five model grids on each side of the model domain) was excluded in all figures and all statistical computations. The initial and lateral boundary conditions are provided by the National Centers for Environmental Prediction (NCEP)–NCAR reanalysis (NNR; Kalnay et al. 1996). The lower boundary over the open oceans and sea ice are prescribed with the Hadley Centre sea surface temperature (SST) and sea ice dataset (HadSST1; Rayner et al. 2003). The 1° global monthly SST and sea ice data were first spatially interpolated into the RCM grids, then linearly interpolated into daily values for the RCM. We applied the RCM to simulate surface climate for 12 yr from 1 January 1990 through 31 December 2001. Because we consider the first 2 yr of the simulation to be model spinup, the analysis and comparison in this study were focused on the last 10 yr of the simulation. The model outputs all meteorological variables, including radiative fluxes, evapotranspiration, and runoff, that are necessary for estimating surface water and energy budgets and for driving hydrologic and ecological models over the Western Arctic. Output is produced at 3-h temporal resolution and 50-km spatial resolution.

### 2.2. Datasets

The datasets used for intercomparison include those derived from 1) large-scale global reanalysis: NCEP–NCAR reanalysis and 40-yr European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis (ERA-40); and 2) gridded observations: Willmott–Matsuura (WM) climatology, Global Precipitation Climatology Project (GPCP), and Xie–Arkin global precipitation. A global reanalysis is a retrospective global analysis of atmospheric and surface fields. Available observations are assimilated into a global model. The reanalysis data are model driven but provide self-consistent climatological mean states, fluxes, and variations. The reanalysis data used in this study have a horizontal resolution of T62 (~240 km). The gridded observations are generally based on a merging of remote sensing products with in situ observations in which quality control was applied before interpolating to regular grids (1° × 1° for GPCP and Xie–Arkin; 0.5° × 0.5° for WM). For intercomparison, we take the MM5 simulation (referred to as RCM hereafter) as the reference. In addition, a common grid must be used to facilitate direct comparison. Therefore, all data are bilinearly interpolated from their native resolution onto the MM5 grids. Table 1 summarizes the datasets used in this study and corresponding references and data sources. Because only monthly mean data in the gridded datasets are available, the comparative analysis of this study is based on monthly mean data.

### 2.3. Statistical techniques

Because of availability of meteorological variables in global reanalysis and observations, and limitation in temporal resolution, we select three representative fields: sea level pressure (SLP), SAT, and PRC, for intercomparison and valida-
Figure 1. Annual mean sea level pressure (1992–2001): (a) RCM simulation, (b) ERA-40, and (c) NCEP–NCAR reanalysis. The contour interval is 2 hPa.
tion based on monthly means. In our comparative analysis, spatial pattern and seasonal cycle for all three fields are examined. To quantify the similarity among the datasets, a Taylor diagram (Taylor 2001) is employed for objective comparison. The Taylor diagram, which integrates statistics on correlation and variance for multiple datasets and multiple fields into one diagram, can be used to identify the skill of a model and differences among datasets.

3. Intercomparison and validation

As noted in the introduction, our focus is on the three most important surface climate variables: sea level pressure, surface air temperature, and precipitation. The three fields are key driving forcing to regional- and local-scale process models. The climatological mean states (average over 1992 through 2001), seasonality, interannual variability, and the trends are analyzed. All the figures and computation are for land grids only, as oceanic grids were excluded from the analysis.

3.1. Sea level pressure

Sea level pressure is an important indicator for the atmospheric circulation. Figure 1 shows the annual mean sea level pressure (1992 to 2001) from the RCM simulation, ERA-40, and NCEP–NCAR large-scale reanalysis. All three SLPs exhibit a similar spatial pattern that is largely controlled by the Aleutian low pressure system. The two global-scale reanalyses are slightly different in the northeastern part of the domain with higher pressure in the ERA-40 dataset. The RCM-simulated SLP presents some mesoscale features, and also higher pressure in the eastern part of the domain relative to ERA-40.

One effective statistical tool for evaluating similarity among the RCM simulation and the global reanalyses is the Taylor diagram (Taylor 2001), which shows correlation ($R$), variance [standard deviation (SDEV)], and root-mean-square difference (RMSD) in one single diagram for multiple fields and multiple datasets. Figure 2 is the Taylor diagram for three fields (SLP, SAT, and PRC) of the RCM simulation and the other datasets to which the RCM is being compared. We set the RCM simulation as a reference dataset in the Taylor diagram, and SDEV and

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Variables</th>
<th>Reference and source</th>
</tr>
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<tbody>
<tr>
<td>MM5 (RCM)</td>
<td>SLP, SAT, PRC</td>
<td>Wu et al. (2005) <a href="http://wale.unh.edu">http://wale.unh.edu</a></td>
</tr>
<tr>
<td>ERA-40</td>
<td>SLP, SAT</td>
<td>Uppala et al. (2005) <a href="http://www.ecmwf.int/research/era">http://www.ecmwf.int/research/era</a></td>
</tr>
<tr>
<td>NNR</td>
<td>SLP, SAT</td>
<td>Kalnay et al. (1996) <a href="http://www.cdc.noaa.gov">http://www.cdc.noaa.gov</a></td>
</tr>
<tr>
<td>GPCP</td>
<td>PRC</td>
<td>Adler et al. (2003) <a href="http://www.cgd.ucar.edu/cas">http://www.cgd.ucar.edu/cas</a></td>
</tr>
<tr>
<td>Xie–Arkin global precipitation</td>
<td>PRC</td>
<td>Xie and Arkin (1998) <a href="http://www.cgd.ucar.edu/cas">http://www.cgd.ucar.edu/cas</a></td>
</tr>
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</table>
RMSD are normalized to the RCM SDEV. Thus, for the RCM reference dataset, all variables (or fields) have their standard deviation as one. The radial distance from the origin is the normalized standard deviation of a dataset. The centered RMSD between a dataset and the reference fields is their distance apart. The correlation between a dataset and the reference field is given by the azimuthal position of the dataset.

Figure 2. Taylor diagram for displaying resemble statistics between the RCM simulation, large-scale reanalysis (ERA-40 and NNR) and observations (WM, GPCP, and Xie–Arkin) for SLP (blue), SAT (red), and PRC (green). The RCM simulation is considered as the reference. Standard deviation and RMSD are normalized by the reference standard deviation. The radial distance from the origin is the normalized standard deviation of a dataset. The centered RMSD between a dataset and the reference is their distance apart. The correlation between a dataset and the reference is given by the azimuthal position of the dataset.

RMSD are normalized to the RCM SDEV. Thus, for the RCM reference dataset, all variables (or fields) have their standard deviation as one. The radial distance from the origin is the normalized standard deviation of a dataset. The centered RMSD between a dataset and the reference fields is their distance apart. The correlation between a dataset and the reference field is given by the azimuthal position of the dataset. In Figure 2, colors represent different variables (blue: SLP, red: SAT, and green: PRC) and markers represent different datasets. The correlation in SLP between the RCM and the ERA-40 and NNR datasets is 0.94 and 0.92, respectively. The RCM shows the largest spatial variability (expressed by standard deviation) among the three. The RMSD between the ERA-40 and RCM datasets is relatively smaller than that between the NNR and RCM datasets. From
the diagram, we also can see the difference between the two large-scale reanalyses from their position relative to the reference.

Our analysis of the seasonal and spatial variation in SLP focuses on the comparison between the RCM simulation and ERA-40. The RCM-simulated climatological SLPs for winter, spring, summer, and fall from 1992 to 2001 are shown in Figure 3, and the corresponding ERA-40 climatology for the same period is displayed in Figure 4. A visual comparison indicates that the two climates datasets have similar seasonal and spatial patterns. As in Figure 1, the Aleutian low has dominant control on circulation in the region in all seasons except summer, in which circulation is quite uniform. In comparison with the large-scale reanalysis, the RCM not only simulates large-scale patterns, but also produces mesoscale patterns that are not found in datasets produced by global reanalyses, especially in the cold season. Because our analysis is based on a 10-yr average of seasonal means, we expect that most (if not all) weather “noise” has been removed. The RCM simulates lower SLP relative to ERA-40 in the winter and fall, but higher SLP in spring and summer. The mean annual SLP simulated by RCM is 0.44 hPa greater than that of the ERA-40 dataset.

We use standard deviation to evaluate interannual variability in the RCM and the reanalysis. Figures 5 and 6 are the SLP spatial distribution of the standard deviations for the period of 1992 to 2001 from the RCM simulation and ERA-40. Clearly, the interannual variability in SLP exhibits strong seasonality. The interannual variability is as high as 7 hPa in winter, but only 1.5 hPa in the summer.

Figure 3. RCM-simulated sea level pressure: climatology. (a) January, (b) April, (c) July, and (d) October.
Figure 4. Same as in Figure 3, but for ERA-40.

Figure 5. RCM-simulated sea level pressure: interannual variability. (a) January, (b) April, (c) July, and (d) October.
The transition seasons are about 3–4 hPa. Similar to the climatology, the RCM and ERA-40 are in good accordance in the interannual variability in terms of its seasonal cycle and spatial patterns. Overall, the RCM simulation exhibits relatively larger variations (2.90 hPa) than ERA-40 (2.63 hPa).

Arctic climate has been characterized by substantial changes in recent decades. The SLP trends for each month from 1992 to 2001 are shown in Figure 7 based on the RCM simulation and the large-scale reanalysis. The trends in SLP have seasonal variation, and the trends simulated by the RCM are similar to the trends derived from the reanalyses. The trends in SLP are negative throughout most of the year except June, November, and December when positive trends occur. The largest trend occurs in February (~−0.9 hPa decade⁻¹), with other months between January and September having trends of about −0.2 hPa decade⁻¹. The annual trends in SLP are −0.15, −0.18, and −0.18 hPa decade⁻¹ for the RCM, ERA-40, and NNR, respectively. These trends are consistent with the analysis of Walsh et al. (Walsh et al. 1998).

### 3.2. Surface air temperature

Surface air temperature is another key surface climate indicator. Figure 8 is the annual mean surface air temperature climatology from the RCM, ERA-40, NNR, and WM datasets. While the RCM is capable of simulating large-scale spatial patterns in the reanalysis and in the observationally derived datasets, the RCM simulation is colder than the other datasets. The area-averaged annual temperature is −7.49°, −4.24°, −4.85°, and −5.62°C for the RCM, ERA-40, NNR, and WM,
respectively. The RCM also produces some mesoscale features that are also present in the gridded observation dataset (WM). From Figure 2 (SAT is indicated in red), the correlation between the RCM and the ERA-40, NNR, and WM datasets is 0.96, 0.93, and 0.85, respectively. The spatial variability of SAT in all four datasets is quite similar, with the NNR dataset having relatively weaker variation. The RMSD between RCM and the other datasets is between 0.25 (RCM versus ERA-40) and 0.50 (RCM versus WM).

From both SLP and SAT statistics in Figure 2, we can see that there are biases between global reanalysis and gridded observations like the WM dataset. To further validate the RCM simulation, we selected four weather stations (station latitudes and longitudes are labeled in Figures 9 and 15) within our model region to directly compare the station observations to the datasets. Figure 9 displays monthly mean surface air temperature for Bethel, McGrath, Fairbanks, and Bettles, Alaska. All datasets have a seasonal cycle that is similar to the station observations, but the RCM displays a relatively small amplitude. Also, the biases between

Figure 7. Monthly sea level pressure trend between 1992 and 2001 in the RCM, and large-scale reanalysis (ERA-40 and NNR).
the datasets and the station observations are generally similar for all four stations, which suggests the possibility of a systematic error in the regional datasets. All datasets, including the RCM, show warm biases (~5°C) in the winter. While both the WM and ERA-40 datasets are in good agreement with the station observations in the summer, the NNR and the RCM exhibit cold biases in the summer. The biases in RCM may be partially attributed to biases in the large-scale forcing of the NCEP–NCAR reanalysis at the boundaries of the WALE region.

Our analysis of the spatial and seasonal variation focuses on comparisons between the RCM and ERA-40 datasets. Figures 10 and 11 are the SAT seasonal climatology from the RCM and ERA-40. Overall, the RCM simulates large-scale spatial patterns similar to those that are in the ERA-40 dataset but also produces some mesoscale features. As in Figure 9, the RCM climate is warmer in the wintertime, but colder in the summertime. The SAT differences are relatively small in transition seasons. Further analysis indicates that the simulated summertime SAT is much closer to the WM climatology (not shown), as demonstrated in a recent study (Wu et al. 2005). As illustrated in Drobot et al. (Drobot et al. 2006), the SATs from different data sources exhibit significant uncertainty and may be as high as 10°C. Such large uncertainty might partially be attributed to a sparse observational network and a very difficult observational environment (Walsh et al. 2002; Jones and Moberg 2003).

The SAT interannual variability is displayed in Figures 12 and 13 for the RCM and ERA-40, respectively. Both the RCM simulation and ERA-40 have similar spatial patterns and seasonality. The SAT has strongest interannual variability in
the winter (4°–6.0°C) and weakest interannual variability in summer (about 1.0°C in July). Over the WALE region, the interannual variability in the RCM and ERA-40 datasets is similar (4.50° and 4.38°C).

The monthly SAT trends from 1992 to 2001 are shown in Figure 14 for all four datasets. All four datasets exhibit similar trends throughout the year. The largest positive trends occur in February (~0.5°C decade⁻¹) and September (~0.35°C decade⁻¹), and a negative trend occurs in May (~0.15°C decade⁻¹). In comparison to the other datasets, the RCM simulation has weaker trends from March through August, a stronger trend in November, and almost no trend in December. The trends in mean annual SAT across the WALE region are 0.10, 0.06, 0.07, and 0.11 for the RCM, ERA-40, NNR and WM, respectively. Both the trends in annual and monthly SAT are consistent with other analyses for recent decades (Walsh et al. 1998) using longer records. The patterns of SAT variability and trends are closely associated with the changes in sea level pressure. The association of decreasing SLP and increasing SAT over Arctic continental landmass has also been shown in recent studies (Moritz et al. 2002; Thompson and Wallace 1998).
Figure 10. RCM-simulated surface air temperature: climatology. (a) Winter, (b) spring, (c) summer, and (d) fall.

Figure 11. Same as in Figure 10, except for ERA-40.
Figure 12. RCM-simulated surface air temperature: interannual variability. (a) Winter, (b) spring, (c) summer, and (d) fall.

Figure 13. Same as in Figure 12, but for ERA-40.
3.3. Precipitation

Precipitation is one of the most problematic atmospheric variables in both observations and modeling, especially for the Arctic. Inadequate coverage of observational stations and measurement errors due to difficult conditions may cause significant inaccuracy in precipitation estimates, and biases can be as high as 50% of precipitation estimates based on observations (Bogdanova et al. 2002). While numerical models like MM5 can estimate precipitation at fine spatial and temporal resolution, they have difficulties in accurately describing precipitation-related processes like convective activities and cloud–radiation feedback. Thus, comparisons of precipitation estimates between simulations and observations are challenging because of substantial uncertainties in measurements and models. The study by Drobot et al. (Drobot et al. 2006) identified substantial differences in precipitation estimates among different datasets. In addition to the datasets analyzed by Drobot et al. (Drobot et al. 2006), we used two other observationally based precipitation
datasets in this study, the GPCP and Xie–Arkin global precipitation (Xie and Arkin 1998) datasets. The overall qualitative comparison among the four datasets can be seen in the Taylor diagram of Figure 2 (green indicates precipitation). The correlation coefficients between the RCM and each of the other datasets are 0.83, 0.83, and 0.66 for GPCP, Xie–Arkin, and WM, respectively. The three datasets have smaller spatial variation than the RCM. From the Taylor diagram, the GPCP and Xie–Arkin are very close to each other, and their RMSDs are about 0.75, while the WM has its RMSD at about 0.51.

Figure 15 depicts the seasonal cycle of precipitation of the four datasets (RCM, GPCP, Xie–Arkin, and WM) for four observational stations in Alaska. It is apparent that all datasets capture the annual maximum precipitation in August. The station observations generally indicate that the annual minimum precipitation occurs in the winter. However, the ERA, NNR, and WM datasets indicate annual minimum precipitation in the spring, and the minimum does not occur in the RCM dataset until June. The RCM tends to overestimate winter precipitation, particularly for Bettles, and tends to underestimate summer precipitation, except for Bettles. There are large differences among all of the datasets in winter.

Because the seasonality of precipitation in the GPCP and Xie–Arkin datasets is
quite similar, we focus our evaluation on comparing precipitation estimates between the RCM and GPCP datasets. The estimated annual precipitation over the WALE region is 1.52 and 1.36 mm day$^{-1}$ for the RCM and GPCP, respectively. The spatial distribution of RCM-derived monthly precipitation (in units of mm month$^{-1}$) and corresponding GPCP climatology are illustrated in Figures 16 and 17. The RCM and GPCP precipitation datasets have similar spatial patterns across the WALE region, but the RCM dataset has finer-scale variation. In comparison to the GPCP dataset, the RCM overestimates the observed coastal rainfall near the Gulf of Alaska, particularly in summertime, but underestimates summer precipitation in the interior Alaska. This dry bias in the interior is consistent with the cold bias in surface air temperature identified in Figures 10 and 11.

The interannual variability of precipitation is illustrated in Figures 18 and 19 for the RCM simulation and the GPCP climatology. The spatial pattern of interannual variability is similar between the two datasets, with large variability in coastal areas and small variability in the interior. The trends in precipitation estimates are shown in Figure 20 for the four precipitation datasets (RCM, GPCP, Xie–Arkin, and WM). Unlike SLP and SAT, there are substantial differences in precipitation trends among the datasets, except between the GPCP and Xie–Arkin datasets. The WM dataset has negative trends throughout the year, and has an annual trend of $-0.03$ mm day$^{-1}$ decade$^{-1}$. The GPCP and Xie–Arkin datasets have large positive trends in July, and negative trends for most of the rest year, with an annual trend of about $-0.02$ mm day$^{-1}$ decade$^{-1}$. The RCM simulates the trend extremes of the

![Figure 16. RCM-simulated precipitation: climatology. (a) Winter, (b) spring, (c) summer, and (d) fall.](image-url)
Figure 17. Same as in Figure 11, but for GPCP precipitation.

Figure 18. RCM-simulated precipitation: interannual variability. (a) Winter, (b) spring, (c) summer, and (d) fall.
other datasets, with the largest positive trend in July (\( \sim 2.0 \text{ mm day}^{-1} \text{ decade}^{-1} \)) and
the largest negative trend in November (\( \sim -2.0 \text{ mm day}^{-1} \text{ decade}^{-1} \)), but has
almost no trend on an annual basis.

4. Discussion and conclusions

It is important to understand the variability of the climate system in the Arctic in order to determine the vulnerability of terrestrial hydrology and ecology to future changes in regional climate. Because the availability of near-surface meteorological observations is sparse in the Arctic, it is challenging to estimate climatic variables at the spatial and temporal resolutions that are required for regional applications of hydrologic and ecosystem models. A regional climate model can potentially provide a comprehensive dataset for such applications. This study makes an attempt to generate a complete meteorological dataset with the Penn State–NCAR MM5, and this paper documents the RCM dataset and conducts a comparative analysis with a variety of data sources in terms of mean state, seasonality, and interannual variability of the surface climate.

The RCM produces many features of observed circulation and surface air temperature. The Taylor diagram demonstrates the similarity of patterns in terms of correlation, variance, and root-mean-square difference. The Taylor diagram also identifies uncertainty among different data sources (e.g., ERA-40, NCEP–NCAR reanalysis, and gridded observations). The simulated SLP agrees well with the reanalysis SLP in terms of mean state, seasonality, interannual variability, and

![Figure 19. Same as in Figure 13, but for GPCP precipitation.](image-url)
trends over the period from 1992 to 2001. In comparison with station measurements, all datasets including the RCM simulation exhibit warm bias in the winter (∼5°C). The ERA-40 and WM agree well with the station data in the summertime while the NNR and RCM display cold biases. Wu et al. (Wu et al. 2005) have demonstrated the sensitivity of the RCM solution to the lateral boundary forcing. Because the RCM is driven at its lateral boundary by the NNR data, the bias in the RCM may be partially attributed to biases that exist in the NNR forcing data.

Interannual variability in regional-scale climate has not been extensively explored, especially the seasonal cycle of the interannual variability. The simulation with the regional climate model provides an opportunity to investigate interannual and seasonal variability in the regional-scale climate. This study identifies that both the SLP and SAT have substantial interannual variation, with large interannual variation in the wintertime and small interannual variation in the summertime. Interannual variability is also spatially variable within the WALE region, with coastal areas having large interannual variability and interior Alaska having small
variability. Such a spatial pattern in interannual variability may relate to sea surface temperature and sea ice variability during the analysis period (Rayner et al. 2003).

Many studies have indicated that precipitation estimates in the Arctic are problematic whether they are derived from observations or models. The four observational precipitation datasets used in this study are substantially different. The uncertainty in the observations poses difficulty in validating simulated precipitation by the RCM, particularly in the wintertime when most precipitation is in the form of snow. Although the RCM produces general spatial patterns of rainfall that are seen in the observationally derived datasets, substantial differences exist in the mean state. In comparison with other datasets, the RCM tends to underestimate precipitation in the interior of Alaska, particularly in the summer, but tends to overestimate coastal rainfall.

Besides analyzing the mean state and variability, we have evaluated annual and seasonal surface climate trends in this study. Across all datasets used in this study, annual mean sea level pressure decreases (~0.15 hPa) and surface air temperature increases (~0.10°C) from 1992 to 2001. Precipitation slightly decreases by only about 0.02 mm day\(^{-1}\) during the same period. All the trends in SLP, SAT, and precipitation are seasonally variable.

The RCM dataset evaluated in this study provides a complete meteorological forcing that has high temporal and spatial resolution and is consistent in time and space. In this respect, the RCM dataset may represent an improvement over datasets developed from global reanalyses and gridded observations derived from sparse observational networks. A validation of the RCM dataset against reanalysis data and independent data sources has been conducted to quantify possible errors and biases. The intended application of the RCM dataset is for regional hydrologic and ecological applications, where the focus of interest is on the variation of the land surface over seasonal and annual time scales. It is important to establish that the dynamics represented in the RCM dataset are credible. The dataset can be further evaluated by forcing a hydrologic process model (e.g., Rawlins et al. 2006) and by comparing the resultant water and energy fluxes with observations.

Murphy (Murphy 1999) assessed the downscaling skills of statistical and dynamical techniques including global and regional modeling for climate, and concluded that 1) RCMs capture mesoscale detail present in observations, and 2) simulated variability of RCMs is much more realistic than in global models because the finer grid reduces the amount of spatial smoothing. Additionally, in a recent study based on an MM5 simulation, Liang et al. (Liang et al. 2006) demonstrated that 1) the RCM can significantly reduce biases in global model simulations, and 2) the RCM results are sensitive to the parameterization of cloud physics. Nevertheless, the studies of Murphy (Murphy 1999), Wu et al. (Wu et al. 2005), and Liang et al. (Liang et al. 2006) along with this present study have each recognized the limitations of an RCM in downscaling regional or local climate (e.g., biases that might be associated with forcing data used at the lateral boundary). In light of biases in the regional climate modeling, one computationally intense approach to reduce biases is to employ the four-dimensional data assimilation of the MM5 modeling system, which allows the RCM to ingest in situ and remote sensing data into a time- and space-discretized representation of the atmosphere and land surface in the Arctic. Finally, the use of improved large-scale
driving data to force the RCM at the regional boundaries may lead to improvements in the RCM simulations of regional climate.

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