Effects of Spectral Nudging in WRF on Arctic Temperature and Precipitation Simulations

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ABSTRACT

Spectral (interior) nudging is a way of constraining a model to be more consistent with observed behavior. However, such control over model behavior raises concerns over how much nudging may affect unforced variability and extremes. Strong nudging may reduce or filter out extreme events since nudging pushes the model toward a relatively smooth, large-scale state. The question then becomes: what is the minimum spectral nudging needed to correct biases while not limiting the simulation of extreme events? To determine this, case studies were performed using a six-member ensemble of the Pan-Arctic Weather Research and Forecasting model (WRF) with varying spectral nudging strength, using WRF’s standard nudging as a reference point. Two periods were simulated, one in a cold season (January 2007) and one in a warm season (July 2007).

Precipitation and 2-m temperature were analyzed to determine how changing spectral nudging strength impacts temperature and precipitation extremes and selected percentiles. Results suggest that there is a marked lack of sensitivity to varying degrees of nudging. Moreover, given that nudging is an artificial forcing applied in the model, an outcome of this work is that nudging strength can be considerably smaller than the WRF standard strength and still produce climate simulations that are much better than using no nudging.

1. Introduction

Limited area models for climate simulation pose an issue of how to ingest time-varying lateral boundary conditions. Davies (1976) introduced the concept of a “sponge zone” as a means of reducing spurious features such as reflections at the lateral boundaries. These reflections would appear as transient waves and act to produce anomalous behavior within the domain. In the sponge zone the model solution is damped toward a specified external dataset, with the damping becoming progressively stronger as one moves toward the edge of the domain. However, substantial bias may still develop within the interior of the domain. Waldron et al. (1996) introduced the concept of spectral or interior nudging as a means of reducing anomalous behavior in regional simulations driven by global reanalyses. This additional damping toward the external dataset is weaker and focused on the interior of the domain. This forcing allows simulated large-scale fields advecting across the domain to remain consistent with the external dataset at the boundaries.

Miguez-Macho et al. (2004) provide greater detail on the interaction of regional model solutions with external boundaries. The most prevalent effect of this interaction is the alteration of the large-scale circulation. Circulation modification results from the incompatibility between the boundary conditions and model solution. This produces a domainwide interaction between the lateral boundaries and model dynamics. Miguez-Macho et al. also show that various domain sizes yield differing degrees of model drift as well as different precipitation values. Including spectral nudging effectively corrects the precipitation biases.

The internal forcing introduced by spectral nudging occurs by adding terms to certain model equations, such as horizontal momentum and thermodynamics equations (von Storch et al. 2000; Alexandru et al. 2009). These terms nudge model fields toward the externally specified driving fields. Since these are artificial terms...
added to the governing equations, care is needed to avoid introducing more error into the simulation. Also, the strength of the nudging can vary with height and field. Von Storch et al. suggests that, since the large scales tend to be rather deep, these nudging terms should be confined to levels away from the surface, allowing the smaller scales near the surface freedom to respond to local processes. Spectral nudging can also be limited by which wavelengths are nudged. This is determined in part by how well the boundary-conditions dataset can reliably resolve a given wavelength.

While there have been several studies on the subject of spectral nudging, there appears to be little analysis on the sensitivity of simulations to the strength of the nudging in regional climate simulation. Von Storch et al. (2000) did give some consideration to impacts of strength of the nudging in a one-month run but suggested that more comprehensive study is necessary. Various other studies have found that spectral nudging may improve precipitation simulations (Cha and Lee 2009; Tang et al. 2010; Colin et al. 2010; Song et al. 2011) or have a neutral effect (Yhang and Hong 2011). Bowden et al. (2012) suggests that directly nudging the moisture field in the Weather Research and Forecasting model (WRF) may be needed to produce improved precipitation simulations.

Alexandru et al. (2009) performed a series of experiments using the Canadian Regional Climate Model to determine benefits and drawbacks to altering degrees of freedom in regional climate simulation via spectral nudging. Three case studies involved changing the level at which the nudging was turned on. A fourth case doubled the nudging while making it constant throughout all levels. Their results indicated an inverse relationship between nudging strength and internal variability. Furthermore, a marked decrease in extreme precipitation occurred as nudging increased.

In this study, we use a polar-optimized version of the Weather Research and Forecasting (WRF) model to produce a six-member ensemble simulation for two case studies, January and July 2007, over a 50-km pan-Arctic domain. The use of interior nudging is especially important in our domain because it includes the circumpolar vortex. Because the circumpolar vortex is contained within the model, there is much less flow across lateral boundaries compared to midlatitude simulation, so the influence of the lateral boundary conditions inside this region is weaker.

The analysis focuses on four regions in our simulation domain to diagnose the effect of varying spectral nudging on mean and extreme 2-m temperature and daily precipitation fields. Of particular interest is determining a possible optimal nudging strength for minimizing large-scale, systematic circulation errors, while also minimizing errors in mean and extreme fields. The question then becomes: what is the minimum spectral nudging needed to correct the biases occurring within our simulation domain while not limiting the model’s ability to produce extreme events?

The paper is organized as follows. Section 2 describes the Pan-Arctic WRF model. Section 3 describes the simulation setup as well as the data used to force the model. Section 4 details the evaluation methodology for analysis. Section 5 presents the results of nudging strength on 2-m temperature and precipitation as a function of season and analysis region. Section 6 summarizes the results and gives our conclusions.

2. Pan-Arctic WRF

We use version 3.1.1 of the Advanced Research Weather Research and Forecasting model (ARW-WRF) (Skamarock et al. 2008). Selection of Arctic-appropriate physical parameterizations was an important consideration for our model simulations. This parameterization set is similar to the choices developed by Cassano et al. (2011) for Arctic simulation, with further modifications based on work by M. Seefeldt (2010, unpublished data).

We use the subgrid cumulus scheme developed in Grell and Devenyi (2002) and the Goddard Cumulus Ensemble (GCE) model (Tao and Simpson 1993) microphysical scheme, with three categories of ice phase. From Janjić (2001), we used the Mellor–Yamada–Janjić (MYJ) scheme for the planetary boundary layer (PBL), which is based on similarity theory from Monin and Obukhov (1954). Short and longwave radiation was parameterized by the National Center for Atmospheric Research Community Atmospheric Model (CAM 3.0) spectral-radiation scheme (Collins et al. 2004; Mlawer et al. 1997). A land surface model (LSM), modified to include important polar-specific processes, was also an important addition to our simulations; we used the four-layer Noah LSM (Chen and Dudhia 2001) as modified in Hines et al. (2011). Additionally, the sea ice albedo and emissivity were set at 0.80 and 0.98, respectively.

3. Simulations and data preparation

a. Pan-Arctic WRF simulations

Pan-Arctic WRF (PAW) was designed to produce simulations on a domain developed for the Regional Arctic Climate Model (RACM) project (Maslowski et al. 2013). This polar domain includes 205 (275) south-north (west-east) points with 50-km grid spacing (Fig. 1). The RACM domain contains all of the Northern Hemisphere sea ice cover as well as all of the Arctic river
drainage system. Moreover, it contains critical interocean exchange and transport features, such as horizontal advection of warm ocean water into and under sea ice cover from the Pacific and Atlantic (Stroeve and Maslowski 2007). Taken together, these processes are important for regional climate modeling. Vertical resolution uses 40 model levels with the model top at 50-hPa and the lowest level at 12.5 m AGL.

Initial long- and short-term simulations from the PAW showed a systematic, strong high pressure bias collocated with the North Pacific storm track (e.g., Fig. 1). The bias appeared in surface fields, including pressure and temperature (MSLP, 2m-\(T\)), and throughout the depth of the atmosphere in geopotential heights and level temperatures. The bias occurred throughout the year, despite different choices in forcing dataset, length of simulation, location of lateral boundaries, and changes in physical parameterizations (Cassano et al. 2011). The bias also followed a fairly simple annual cycle with spring and autumn representing the traditional transition seasons between winter and summer.

Spectral nudging emerged as a method to minimize the bias. However, concern arose that, for sufficiently strong nudging, weather extremes would be suppressed. Also, since spectral nudging introduces an artificial forcing into the model, minimizing such forcing is important. Hence, we explore here the sensitivity of mean and extreme model behavior to nudging strength.

b. Experimental design

In the simulations, the strength of the nudging varies about the default WRF value of 3.33 \( \times 10^{-4}\) s\(^{-1}\) (damping time scale of 50 min), ranging from 2 to 1/128 times the default. The various nudging coefficients and associated damping time scales appear in Table 1. The model applies nudging with equal strength to four fields: zonal and meridional wind components, temperature, and perturbation geopotential height according to a nudging equation from Miguez-Macho et al. (2004):

\[
\frac{dQ}{dt} = L(Q) - \sum_{|m|\leq N} \sum_{|n|\leq M} k_{mn} (Q_{mn} - Q_{omn}) e^{ikx} e^{iky},
\]

where \(Q\) represents the prognostic variable being nudged, \(L\) is the model operator, and \(Q_o\) is the driving field variable; \(Q_{mn}\) and \(Q_{omn}\) represent the spectral coefficients of \(Q\) and \(Q_o\). The nudging coefficient \(k_{mn}\) can vary with \(m\) and \(n\) (wavenumbers in the \(x\) and \(y\) direction, respectively) as well as height; \(k_m\) and \(k_n\) then represent the wave vector and are dependent on the domain size, \(D_x\) and \(D_y\), given by

\[
k_m = \frac{2\pi m}{D_x}; \quad k_n = \frac{2\pi n}{D_y}.
\]

Nudging is turned on at 500 hPa and linearly ramped up to full strength near the model top. We nudge the first two horizontal wavelengths.

Part of the analysis determines how the magnitude of nudging impacts daily average temperature and precipitation. In addition, we examine in each of our analysis regions the warmest and coolest 1% and 5% values of temperature and the highest 1% and 5% values of daily precipitation from among the ensemble members. We look at these extremes for four analysis regions within the domain. We also examine the difference between time means in each realization and observations to assess the sensitivity of mean fields to nudging.

c. Boundary conditions

Forcing data for PAW uses two input datasets. For initial and lateral boundary conditions, simulations use
the interim European Centre for Medium-Range Weather Forecasts Re-Analysis (ERA-Interim) data (Dee et al. 2011). The ERA-Interim output is available on a reduced Gaussian grid with a uniform, approximately 79-km horizontal grid spacing and 60 vertical levels up to 0.1 hPa. The ERA-Interim fields are available every 6 h starting from 1989 through 2012. The model also uses the bootstrap sea ice concentrations from Nimbus-7 Scanning Multichannel Microwave Radiometer (SMMR) and Defense Meteorological Satellite Program (DMSP) Special Sensor Microwave Imager (SSM/I) satellite sensors archived at the U.S. National Snow and Ice Data Center (NSIDC) (http://nsidc.org/data/ nsidc-0079.html). The native grid for the ice concentration data is the SSM/I polar stereographic grid with 25-km grid spacing.

d. Validation data

Model validation compares the output against two datasets. We use the National Climate Data Center (NCDC) global summary of the day (see http://ncdc.noaa.gov/records/GCMD_gov.noaa.ncdc.C00516.html), which provides both temperature and precipitation observations. Within the RACM domain there are nearly 150 stations with available observations, some of which date back to the 1940s. While NCDC does perform quality control on the station data, to ensure data continuity our analysis requires that an acceptable station have no more than four missing days in any month over its archival period.

The second dataset is the ERA-Interim reanalysis (Dee et al. 2011), which provides output for diagnosing atmospheric fields (e.g., MSLP, humidity, level temperatures, 500-hPa heights) and statistical analysis. We do not use ERA-Interim precipitation because it is a model product that is not constrained by precipitation observations.

4. Evaluation methodology

a. Case study period

We are interested in how well PAW produces observationally consistent mean and extreme behavior in the Arctic as well as how both are affected by various degrees of spectral nudging. To determine sensitivity to nudging strength, and ultimately an optimum choice, we devised a standardized experimental design for two case studies: one winter month and one summer month. Each case study uses eight spectral nudging strengths, and each nudging strength in turn uses a six-member ensemble, thus producing six months of winter and six months of summer for each nudging coefficient. Overall, each seasonal case has 48 months of simulation.

Ensemble members for the winter case were initialized using a 24-h stagger start method from 13 to 18 December 2006 and run through 1 February 2007. The initial two weeks of the simulations were discarded, as they were used for model spinup. For summer, the same procedure was used; the ensembles were initialized from 13 to 18 June 2007 and run through 1 August 2007.

b. Analysis regions

To analyze the influence of nudging on mean and extreme behavior, we selected smaller regions within the domain for more detailed analysis. Of particular interest were regions in proximity to the northern Pacific bias region as well as the North American landmass contained in the RACM domain that was downstream from the strong bias. We focused on four regions.

1) Alaska: This region is downstream of the strong bias region and contains topographical features that interact with the large-scale flow.
2) North America: This is the largest of the analysis regions. Its importance here occurs because it contains a large portion of Arctic drainage basins. Also, it is downstream of the bias region and adjacent to the circumpolar vortex flow that potentially brings into the region heat and moisture from the bias region.
3) Oceana: This is the region where the largest model bias occurs when there is no nudging.
4) Siberia: This region is poleward and upstream of the bias region. This analysis region also contains important topographical features and Asian–Arctic drainage basins.

c. Differencing and statistical analysis

We show the effectiveness of spectral nudging in minimizing the northern Pacific bias using monthly domain-averaged bias plots for selected variables; these fields will aid in our understanding of how nudging affects the mean state. For all further analyses, there is no spatial averaging of data within an analysis region. We perform our analysis using PAW data, ERA-Interim reanalysis, and NCDC observations for the collection of grid points or observation sites in the individual analysis regions. We pool together the daily-averaged data from every grid point/site within each of the four analysis regions. The pooled data thus contains all scales resolved by the input datasets and is not spatially smoothed otherwise. Another important analysis is the relationship between simulations using different nudging coefficients. This is necessary to determine how the mean and extreme behaviors are modified via nudging and which coefficient(s) is the optimum for retaining observationally valid model behavior. More important, we ask...
the question: how sensitive are temperature and precipitation extremes to nudging strength, and can some ranges of nudging produce similar results (suggesting model insensitivity, for example)?

Our analysis involves a number of steps. We calculate ensemble means and percentiles for each nudging strength and compute the sensitivity of model behavior to changes in the nudging strength using the Tukey “honestly significant difference” test (HSD) (Ott and Longnecker 2001). The Tukey test also includes an analysis of variance (ANOVA) for assessing the significance of changes as the strength of the nudging is changed.

The power of the Tukey HSD is that it compares the means of all possible pairs from the group pool. Here, the pool is the output from the eight nudging coefficients plus the applicable observations. The formula for the Tukey HSD is

$$\text{HSD} = \frac{Y_{\text{max}} - Y_{\text{min}}}{\text{SE}}, \quad (3)$$

where $Y_{\text{max}}$ ($Y_{\text{min}}$) is the largest (smallest) of the pairwise means being compared and SE is the standard error of the group pool. The Tukey procedure assumes that all tested samples are independent and have equal variation across observations—a condition known as homoscedasticity. Tukey HSD calculates how large the mean difference among group members must be for any two individual members to be significantly related. The result of the HSD analysis is a ranking of all group members, as well as information stating when the ordering among some pool members is statistically indeterminate (i.e., they are significantly related).

After segregating the PAW output into the analysis regions, we used the ranking process for percentiles of daily temperature and precipitation. The ranking and degree to which pool members are significantly related thus gives us an understanding of model sensitivity to changes in nudging. The ranking procedure followed these steps:

1) Perform Tukey analysis on each RACM analysis region separately for mean temperature and precipitation

   (i) Daily precipitation includes eight SN coefficients and NCDC observations ($N = 9$ available values)

   (ii) Daily temperature includes eight SN coefficients, ERA-Interim, and NCDC observations ($N = 10$ available values)

2) Create an $N \times N$ grid, with $x$ axis = rank order, $y$ axis = nudging strength

3) Follow same procedure for each percentile

   (i) Daily precipitation: 50th, 95th, and 99th

   (ii) Daily temperature: 1st, 5th, 50th, 95th, and 99th

For case studies, we created rank matrices for each analysis region. Each cell in the rank matrix was then subdivided so that each set of percentiles could be plotted together. Since precipitation contains only three percentiles, their rank matrices used grayscale shading for the extreme percentiles and black for the median. For temperature, the rank matrices for the cold (warm) percentiles used blue (red) symbols, with the 50th percentile plotted as purple.

More important, the patterns among the percentiles show how the median and extreme behaviors are related. Comparing ranking matrices for different fields and percentiles can reveal common patterns of nudging sensitivity. While this ranking procedure is important in determining an optimal nudging strength, the magnitude of change among the nudging coefficients complements the ranking analysis. We plot individual percentile values for the nudging coefficients and observations to show the magnitude spread among the group members. Specifically, a measure of the magnitude of change (within a percentile) as nudging strength changes will give us an idea of the behavior of a region over and above the statistical ranking. Thus we supplement the matrix presentation with information showing the sensitivity of results to nudging strength.

5. Results

a. PAW: ERA-Interim time-average bias

We analyzed monthly spatial mean fields of MSLP, 2-m temperature, 500-hPa geopotential heights, and level temperatures for the full RACM domain so as to determine the pre- and post-nudging PAW biases versus ERA-Interim output. Table 2 shows biases in these fields for each of our target regions with no nudging and with the WRF standard nudging strength. As mentioned in section 3, the initial simulation on the RACM domain produced large, time-average bias within the North Pacific storm track. In our analysis regions, the largest biases occurred in Oceana followed by the Alaska analysis region. Spectral nudging substantially reduced the bias for nearly all fields shown in Table 2. The exception was 2-m temperature over the ocean, which would already have relatively small bias because the model uses specified sea surface temperature. There also appears to be a seasonal pattern in that the January case produces much higher biases than the July case.

Spectral nudging is beneficial in minimizing the biases in all of the state and diagnostic fields for both case
months. We find an interesting feature when intercomparing each set of monthly mean field plots (not shown) corresponding to the nudging coefficients. While minor differences occur, in general, the amount of correction for any given nudging coefficient is not substantially different from any other coefficient. This suggests that for monthly spatial means, spectral nudging at any strength aids in minimizing bias. In other words, Pan-Arctic WRF appears to be insensitive to the amount of prescribed nudging.

b. Magnitude spread among spectral nudging coefficients within a percentile

The mean behavior for all analysis regions and in both case study months produces the smallest spread among the nudging coefficients while the highest extremes in rainfall produce the largest spread (Fig. 2). Alaska and Oceania have the largest spreads, especially in July, while Siberia and North America show the smallest. The NCDC observations do not appear in the precipitation plots, as they are appreciably larger than the model output (i.e., the model has a negative precipitation bias at all percentiles).

Figure 3 shows the sensitivity of daily temperature percentiles to nudging strength for observations, the reanalysis, and the model. For the land regions, we find relatively small difference in the spread among all percentiles, averaging on the order of 5°C. Oceana shows little, if any, spread as the specified sea surface temperatures modulate the air temperature above the surface. The observation-based fields are generally warmer in all analysis regions, with the exception of Oceana.

An important point to consider when assessing “optimum” choices for spectral nudging coefficients is how the magnitude of spread for a given percentile is related to its rank matrix. If the amount of spread is negligible, then the ranking results are not as important. Such results indicate that the model is insensitive to nudging strength. On the other hand, if a large degree of spread occurs, the rank matrix gives a better indication of the coefficient (or range of coefficients) that produces the most realistic results.

c. Daily precipitation Tukey analysis—January 2007

When analyzing the Tukey HSD output with respect to the most extreme values of daily precipitation over the four analysis regions, a noticeable diagonal pattern emerges (Fig. 4). As the nudging strength decreases in PAW, the extreme values also decrease in rank—the stronger the nudging, the larger the extreme values. This pattern is somewhat more pronounced when considering the 50th percentile behaviors. In comparison with the NCDC station data, the higher values of nudging coefficients show closest agreement with the observations. When considering only PAW output plotted in Fig. 4, the standard and half coefficients yield the most extreme daily precipitation values. The Siberian analysis region exhibits a reverse behavior from the other regions. When the nudging strength is increased, the extreme values decrease.

The NCDC observations yield the largest values across all percentiles (50th, 95th, and 99th) for the land analysis regions. For the Alaska and North America regions, the largest values produced by our simulations result from two of the strongest spectral coefficients, full and half. Thus, the general behavior indicates that a decrease in nudging strength from the default WRF value produces a decrease in each percentile’s values. Similar behavior occurs for Oceana, although there are no station-based observations for comparison.

Siberia again exhibits a reversal in behavior compared to the other land regions. When we compare the slope of the Tukey ranks, an intersection point occurs between results for Siberia (positive rank slope) and for the other land analysis regions (negative rank slope) around the 1/8th and 1/16th coefficients. The behavior suggests that a smaller nudging strength than the default value may be an appropriate compromise for obtaining the best results. Although the Alaska region shows the greatest sensitivity to nudging strength (Fig. 2) and so might merit greater weight in this consideration, the sensitivity

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TABLE 2. Selected diagnostic field biases pre and post nudging over the RACM domain. The left column under each month represents the bias between the nonnudged model [Pan-Arctic WRF (PAW)] and observations [ERA-Interim (EI)]. The right column under each month represents the bias between the nudged model and observations. The rightmost column represents the analysis region. All biases were found to be positive.
to nudging strength in the other regions is not much smaller.

d. Daily precipitation Tukey analysis—July 2007

When we analyze the July percentiles, the general behavior for Alaska is reversed from what occurs in January (Fig. 5). As the nudging increases, the percentile values of precipitation decrease. However, as in the January case, the NCDC observations have the highest percentile values in the Alaska region. The Oceana region’s behavior in July is similar to January’s, although again there are no station-based observations to indicate which values are more accurate. For North America and Siberia multiple coefficients are significantly related. Thus, no discernible behavior can be extrapolated from the Tukey analysis. When compared with North America and Siberia magnitude plots (Fig. 2), we find that a lack of sensitivity to changes in nudging strength is consistent with the small spread among percentile values in Fig. 2.

For July, indications of an optimum nudging strength are less clear. However, the model shows greater sensitivity to nudging strength in January (Fig. 2), suggesting that results for January should have greater weight in determining an optimum value.
e. Daily 2-m temperature Tukey analysis—January 2007

For all land regions in January, the warmest temperatures in each percentile tend to occur in the ERA-Interim output and NCDC data (Figs. 6 and 7). For the 1st and 5th percentiles, results for different coefficient values tend to be less significantly related than for 95th and 99th percentiles, thus indicating greater sensitivity to nudging strength for the lower percentiles (cold temperature extremes). However, for all model percentiles, the smallest coefficients produce values closest to the observation-based data, suggesting that an
Optimum nudging strength is smaller than the default value.

Oceana exhibits noisier behavior than the other regions (Figs. 6 and 7). Results for different coefficient strengths are often significantly related. This behavior is consistent with the small spread of results in Fig. 3. Taken together, these results show that Oceana temperatures are the least sensitive to changes in nudging strength.

**f. Daily 2-m temperature Tukey analysis—July 2007**

The coldest percentiles for the land regions in July occur in the ERA-Interim output and NCDC data. Compared to January, results in a percentile for different nudging strengths more often tend to be significantly related (Figs. 8 and 9). The behavior suggests less sensitivity in July to nudging strength, consistent with the July precipitation results.
6. Discussion and conclusions

Spectral nudging can constrain a model to be more consistent with the observations. However, since nudging is an added artificial forcing on model behavior, inappropriate nudging can smooth extreme events even while yielding realistic mean behavior. Thus, this study analyzes how changing the strength of the interior nudging affects median and extreme behavior. Daily 2-m temperature and total precipitation percentiles were analyzed during two periods, January 2007 (cold season case) and July 2007 (warm season case) for eight spectral nudging strengths.

A table of monthly biases for several diagnostic variables from the four analysis regions showed the extent to which nudging minimized bias. The biases were insensitive to the nudging strengths tested. This suggests that the mean behavior as produced by PAW is not sensitive to changes in nudging, although the use of any nudging appreciably decreases the bias relative to non-nudged simulations.

Results from the eight nudging strengths were compared against each other and observation-based data, using Tukey “honestly significant difference” (HSD) for each analysis region and case month. Ranking the percentiles

![Figure 5](image-url)
together in matrix format revealed how specific nudging strengths affect individual analysis regions.

Precipitation ranking indicated that in both January and July cases the NCDC station observations ranked first in all percentiles. When comparing the nudging coefficients in January, we found that a decrease in nudging leads to a decrease in the median and extreme precipitation in our North America and Alaska regions.

FIG. 6. January 2007 daily 2-m temperature Tukey rank matrix for (a) North America, (b) Alaska, (c) Siberia, and (d) Oceana. The vertical table axis represents the spectral nudging strength and observations for ranking. The horizontal axis represents the rank of the daily temperature value. The 1st, 5th, and 50th percentiles are represented by light blue, dark blue, and purple symbols, respectively. Coefficients significantly related via the Tukey test are connected with a box.
Siberia showed the opposite behavior with decreased nudging strength yielding increased precipitation in all percentiles. For January, Oceana exhibited a pattern consistent with North America and Alaska.

In July the pattern of percentile ranking reversed from January in all three land regions. As nudging decreased, we found a general increase in values for each percentile. In contrast, for Oceana, the general behavior of all percentile rankings was a decrease as nudging strength decreased. The implications of these results are clarified further when coupled with the change of magnitude plots (Fig. 2). The spread among the nudging coefficients

**Fig. 7.** As in Fig. 6 but for the January 50th, 95th, and 99th percentiles, represented by purple, light red, and dark red symbols, respectively.
indicates the degree of sensitivity in the model behavior to nudging. The results overall show that, for precipitation in our pan-Arctic simulation domain, nudging less than the WRF default produces model output more consistent with observations.

NCDC observations and the ERA-Interim reanalysis were used in the temperature analysis and almost always had the highest rank in all percentiles; that is, their extremes were warmer. For January 2007 in the land regions, when nudging increased, all percentile values tended to decrease (became less cold), although the colder percentiles were more sensitive to nudging strength than the warmer percentiles. The results imply that optimum nudging is less than the WRF default value. Oceana rankings were noisier
with multiple groups of significantly related nudging coefficients, implying insensitivity of surface air temperature in this region to nudging. The July analysis for all regions showed greater insensitivity to nudging than found in January.

Focusing on the regions and fields showing greatest sensitivity to nudging strength, Tukey HSD analysis indicates that an optimum nudging coefficient for our pan-Arctic WRF domain is somewhat smaller than the default value, perhaps as much as an order of magnitude smaller. Of course, the ultimate goal of climate simulations should be to improve the modeling sufficiently that nudging is no longer necessary for producing observationally realistic output.

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