ABSTRACT

Reanalysis data have global coverage and faithfully render large-scale phenomena. On the other hand, regional and small-scale characteristics of atmospheric variability are poorly resolved. In an attempt to improve reanalysis data for regional use, a statistical downscaling strategy is developed based on cyclostationary empirical orthogonal function (CSEOF) analysis. The developed algorithm is applied to the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis data and to the European Centre for Medium-Range Weather Forecast (ECMWF) Interim Re-Analysis (ERA-Interim) data in order to produce winter temperatures at 60 Korea Meteorological Administration (KMA) stations over the Korean Peninsula. The developed downscaling algorithm is evaluated by predicting winter daily temperatures from 17 November to 16 March for 35 years (1979–2014). For validating the downscaling algorithm the jackknife method is used, in which winter daily temperature is predicted over a 1-yr period not used for training. This procedure is repeated for the entire data period. The mean and variance of the resulting downscaled temperatures match reasonably well with those of the KMA measurements. Validation based on correlation and error variance shows that the temperatures at 60 KMA stations are faithfully reproduced based on coarse reanalysis data. The utility of this technique for downscaling model predictions based on future scenarios is also addressed.

1. Introduction

General circulation models (GCMs) are a widespread means of understanding future climate and various aspects of climate changes (Hansen et al. 1988; Cox et al. 1999; Murphy et al. 2004; IPCC 2013). They also serve as a useful tool for seasonal forecasts and long-term predictions. Considerable effort to improve the performance of GCMs has been made for the past decades, and GCMs are capable of simulating large-scale climatological features and their changes in the atmosphere and the oceans. One important factor in improving GCMs is the temporal and spatial resolution of the model (IPCC 1996, 236–237; Sakamoto et al. 2004; Kimoto et al. 2005; IPCC 2007, 602–603). The interaction of climatological features across different scales should be simulated properly in order to make reliable long-term prediction of climates (Palmer et al. 2008; Shukla 2009; Hoskins 2013).

While the resolution of GCMs has significantly increased and is still increasing, the present generation of GCMs has not yet reached a level of resolution sufficient for simulating small regional features. The current computational power does not yet allow GCMs with, say, a 1-km resolution over the whole earth. To capture small regional features, a dynamical downscaling method has been used frequently, in which a high-resolution model with a smaller spatial domain is imbedded in a low-resolution GCM. This so-called nesting is often conducted a few times to accomplish model computations at a desirable resolution (Giorgi 1990; Ji and Vernekar 1997; Fennessy and Shukla 2000; Jones et al. 1995). The dynamical downscaling method has been applied to specific areas to address regional features (Giorgi 1990; Ji and Vernekar 1997; Fennessy and Shukla 2000; Misra et al. 2003; Coulibaly et al. 2005; Sun et al. 2006; Lim et al. 2007). While dynamical downscaling techniques have proven to be useful and have provided local conditions in greater detail, they also suffer from the difficulty of prescribing open boundary conditions (Giorgi 1990; Jones et al. 1995; Christensen et al. 1997; Marchesiello et al. 2001). A regional climate model (RCM) simulation is often inadvertently affected in a significant manner by the
natural variability in a GCM output introduced through open boundary conditions.

Statistical downscaling is also common and is a simple alternative to dynamical downscaling (Hewitson and Crane 1996; Wilby and Wigley 1997; Wilby et al. 1998; Wilks 1999; Huth and Kysely 2000; Huth 2002; Widmann et al. 2003; Robertson et al. 2004; Feddersen and Andersen 2005; Lim et al. 2007), or it serves as a means of improving dynamical downscaling (Fuentes and Heimann 2000). As the name implies, statistical downscaling delves into the statistical relationship between two variables—often between a large-scale feature, such as atmospheric pressure, and a local feature, such as wind speed at a specific location—in order to draw inference on a local feature based on a large-scale feature (Wilby et al. 2004; Lim et al. 2007). In this way, low-resolution GCM output can be used to obtain detailed local features. As such, the statistical downscaling method can bridge the gap between coarse GCM outputs and detailed regional outputs necessary for environmental assessment and decision-making (Wilby and Wigley 1997; Huth and Kysely 2000). Statistical downscaling is computationally much more efficient than dynamical downscaling.

South Korea is located on the eastern coast of Asia and is strongly influenced by the East Asian winter monsoon (EAWM) during winter. A strong EAWM is characterized as strong low-level northwesterlies and the ensuing cold surface air temperatures over the northeastern part of East Asia, including northeastern China, South Korea, and Japan. Although South Korea occupies a small region, wintertime daily temperatures are highly variable due to its geographic location and topographic complexity. Thus, GCMs have difficulty resolving detailed regional features over the Korean Peninsula, and an accurate downscaling method proves to be useful. In this study, a statistical downscaling method is developed based on cyclostationary empirical orthogonal function (CSEOF) analysis (Kim et al. 1996; Kim and North 1997) for the purpose of improving GCM outputs to reflect regional details over the Korean Peninsula.

The paper is organized as follows: Section 2 provides information on the datasets used for this study. Section 3 addresses the concept of statistical downscaling technique based on CSEOF analysis. Then, the accuracy and utility of the developed downscaling method are discussed in section 4 in terms of various statistical measures. Finally, the summary and concluding remarks follow in section 5.

2. Data

This study uses winter 120-day (17 November–16 March) Korea Meteorological Administration (KMA) daily mean temperature measured at 60 stations (Fig. 1) for a 35-yr period (1979/80–2013/14; archived at http://www.kma.go.kr/weather/climate/past_table.jsp). One KMA station, Andong, was excluded from this study since it has an incomplete record for the 35-yr period. The KMA measurements have relatively high resolution, which is used as the target variable in this study.

Winter temperatures at the surface (2 m), and at 1000 and 850 hPa from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis dataset (Kalnay et al. 1996) have relatively low resolution: T62 Gaussian grid with 192 x 94 points for surface data and 2.5° x 2.5° resolution for pressure-level data. The dashed lines in Fig. 1 represent the latitude–longitude grids of the NCEP–NCAR reanalysis surface temperature. The four red dots denote the KMA stations closest to the NCEP–NCAR grid points. The 1.5° x 1.5° European Centre for Medium-Range Weather Forecasts (ECMWF) Interim Re-Analysis (ERA-Interim) daily temperatures at the surface (2 m), and at 1000 and 850 hPa are also used in this study (Dee et al. 2011). Both reanalysis...
data are for the same period of time of the KMA data and cover South Korea (31.4°–40.0°N, 124.5°–132.5°E). These lower-resolution temperatures serve as the predictor variables based on which a downscaling method will be developed to estimate the target variable (the KMA temperatures).

3. Method of analysis

a. CSEOF analysis

Given a space–time dataset, Data(r, t) CSEOF (Kim et al. 1996; Kim and North 1997) analysis decomposes them into
Data$(r, t) = \sum_n^{\infty} \text{CSLV}_n(r, t) \text{PC}_n(t), \quad t \in D, \quad (1)$

where CSLV$_n(r, t)$ are the $n$th cyclostationary loading vectors (CSLV), PC$_n(t)$ are the corresponding principal component (PC) time series, and $D$ is the record length of the data. Each CSLV is periodic in time with the nested period $d$, which is set to 120 days in the present study. Thus,
and each CSLV describes a deterministic evolution of temperature during winter. The corresponding PC time series represents a longer-term variation of the amplitude of the evolution depicted in the loading vector. Details of the CSEOF analysis are referenced to Kim et al. (1996), Kim and North (1997), and Kim and Wu (1999).

The KMA measurement (target variable) and the reanalysis temperature (predictor variable) can be written as

\[ CSLV_n(r, t) = CSLV_n(r, t + d), \quad (2) \]

and

\[ T(r, t) = \sum_n B_n(r, t)T_n(t), \quad t \in D, \quad (3) \]

where \( B_n(r, t) \) and \( C_n(r, t) \) are the CSLVs of the target and the predictor variables, respectively; and \( T_n(t) \) and \( P_n(t) \) are the corresponding PC time series.

\[ P(r, t) = \sum_n C_n(r, t)P_n(t), \quad t \in D, \quad (4) \]
b. Regression analysis in CSEOF space

Two sets of CSEOFs derived from the target and predictor variables do not exhibit one-to-one correspondence. Namely, two PC time series for each mode number \( n \) are not maximally correlated. The two corresponding loading vectors, as a result, do not necessarily have identical amplitude variation. To make two sets of CSEOFs physically consistent, regression analysis is conducted in CSEOF space. As the first step, a regression relationship is built between the PC time series of the target variable and those of the predictor variable; that is,

\[
T_n(t) = \sum_{m=1}^{M} a_m^{(n)} P_m(t) + \epsilon^{(n)}(t), \quad n = 1, 2, \ldots, \tag{5}
\]

where \( \{a_m^{(n)}\} \) are the regression coefficients, \( \epsilon^{(n)}(t) \) is the regression error time series for the \( n \)th target PC time series, and \( M \) is the number of predictor PC time series used for regression. In this study, \( M = 30 \) was used; this value was chosen to keep the regression error variance less than 5% for each of the first 20 CSEOF modes. The second step of the procedure is written as

\[
D_n(r, t) = \sum_{m=1}^{M} a_m^{(n)} C_m(r, t), \quad n = 1, 2, \ldots, \tag{6}
\]

where \( \{D_n(r, t)\} \) are regressed loading vectors for the predictor variable. As a result of the regression analysis in CSEOF space, the predictor variable can be written as (Seo and Kim 2003; Yeo and Kim 2014)

\[
P(r, t) = \sum_{n=1}^{N} D_n(r, t) T_n(t). \tag{7}
\]

Then the evolution of the target variable, \( B_n(r, t) \), and that of the predictor variable, \( D_n(r, t) \), share identical
PC (amplitude) time series and are said to be physically consistent.

c. Statistical downscaling

After the regression analysis in CSEOF space, the target and predictor variables are written as

\[ \{T(r, t), P(r, t)\} = \sum_n \{B_n(r, t), D_n(r, t)\} T_n(t), \quad t \in D, \quad (8) \]

where \( \{B_n(r, t), D_n(r, t)\} \) are essentially the mapping function between the target and the predictor variables. The accuracy of this mapping function depends on the \( R^2 \) value of the regression in (5). If we have a longer predictor variable, then we can write

\[ P(r, t) = \sum_n D_n(r, t) \hat{T}_n(t), \quad t \in D + R, \quad (9) \]

where \( R \) is the extended period of time. The tilde symbol signifies that the PC time series are estimates from the predictor variable, not the target variable. Then, the target variable can be extended by using the estimated PC time series \( \hat{T}_n(t) \)—that is,

\[ \hat{T}(r, t) = \sum_n B_n(r, t) \hat{T}_n(t), \quad t \in D + R. \quad (10) \]

Again, the tilde symbol implies that \( \hat{T}(r, t) \) is an estimate by using the PC time series derived from the predictor variable.

The procedure described in (8)–(10) can be used for statistical downscaling. If \( P(r, t) \) denotes a dataset with a coarse resolution and \( T(r, t) \) represents a dataset with a high resolution, then coarse-resolution data can be translated into high-resolution data by using (8)–(10). The physical relationship between the two datasets in (8) can be determined by using the data over the training period \( D \). Then, high-resolution data in the prediction period \( R \) can be found from the predictor variable by using (9) and (10). The accuracy of downscaling depends on how accurately the estimated PC time series are, which, in turn, depend on the accuracy of the physical relationship in (8).

d. Verification method

To validate the new downscaling approach, the jackknife method is used. From the target data, one year in the data record \( D \) is removed and is designated as the prediction year \( R \). Then, the physical relationship between the target and predictor variables, (8), is established by using the data in \( D - R \). Then, the target variable is constructed in \( R \) by using the downscaling method, (9) and (10). This procedure is repeated for every year in the data record \( D \). The resulting downscaled data \( \hat{T}(r, t) \) are then compared with the raw data \( T(r, t) \) by measuring the correlation and the relative root-mean-square error (RMSE) defined by

\[ \rho = \frac{\sum_r T'(r, t) \hat{T}'(r, t)}{\sqrt{\sum_r [T'(r, t)]^2 \sum_r [\hat{T}'(r, t)]^2}} \quad (11) \]

and

\[ \text{RMSE} = \sqrt{\sum_r [T'(r, t) - \hat{T}'(r, t)]^2 / \sum_r [T'(r, t)]^2}, \quad (12) \]

respectively, where the prime denotes that the mean is removed from the time series.

4. Results

a. Comparison of the KMA and reanalysis winter temperatures

South Korea shows an intricate temperature distribution in winter although it has a small territory. Reanalysis data at their current resolutions cannot faithfully depict
the detailed characteristics of winter temperatures. Figure 2 shows the mean and variance of winter surface temperatures from the NCEP–NCAR reanalysis data and those derived from the 60 KMA stations. With this resolution, the NCEP–NCAR dataset has only four grid points over the Korean Peninsula. As seen in Fig. 2, the NCEP–NCAR dataset is not capable of depicting the detailed features of winter temperatures in Korea, such as the lower mean temperature and stronger temperature variability in the mountainous interior regions, although it captures the general meridional structure of the mean and variance. Without the seasonal cycle, the spatial pattern of variance remains similar although the magnitude decreases significantly. Other variables including the NCEP–NCAR lower-tropospheric temperatures and the ECMWF surface and lower-tropospheric temperatures show similar patterns of mean and variance to those of the NCEP–NCAR surface temperature.

Figure 3 shows the mean bias, relative RMSE, and correlation of the NCEP–NCAR surface temperatures.
in comparison with the KMA temperatures. These maps were produced from the difference in temperatures between each of the 60 KMA stations and the closest NCEP–NCAR grid point. The mean bias is, in general, fairly high except for a few stations in the midwestern and the southern part of the peninsula; the mean bias generally exceeds 2 K over much of the peninsula with particularly strong bias on the mountainous eastern side of the peninsula (Fig. 3a). The relative RMSE is also high (>0.6) on the eastern and southern parts of the Korean Peninsula. This means that the standard deviation of the difference between the KMA temperature and NCEP–NCAR temperature is greater than 60% of the standard deviation of the KMA temperature. The correlation between the KMA and NCEP–NCAR temperature is high on the western part of the peninsula but is lower between the western and eastern coasts. Reasonably high correlations over the Korean Peninsula indicate that the long-term variability in the NCEP–NCAR surface temperature is similar to that in the KMA temperature. Figure 3 implies that a statistical downscaling method may be useful if it can alleviate the

![Figure 7. Comparison of the 20-mode downscaled NCEP surface temperature (red) and the raw KMA temperature at the four stations closest to the NCEP grids (blue).](image-url)
regional differences between the reanalysis and KMA temperatures as depicted in the figure. Without the seasonal cycle, the mean bias is nearly zero since the bias is primarily in the seasonal cycle. The correlation is slightly degraded and the RMSE increased slightly as should be expected.

Figure 4 shows the winter temperatures at the four KMA stations (red dots) in Fig. 1 and at the nearest grid points of the NCEP–NCAR surface dataset. For easier comparison, time series are plotted from year 2000. It appears that the NCEP–NCAR temperatures are reasonably similar to the KMA data with an average correlation of 0.85 (0.87, 0.81) at the surface (1000, 850 hPa) level. While the correlations are fairly reasonable, the NCEP–NCAR reanalysis products fall short of reality in terms of their ability to reproduce the spatial peculiarity in the KMA measurements. Similarly, the ECMWF reanalysis temperature exhibits an average correlation of 0.85 (0.89, 0.79) at the surface (1000, 850 hPa) level.

b. Test results

By using the jackknife method, the first 20 CSEOF PC time series were generated as shown in Fig. 5; the first 20 CSEOF modes explain about 90% of the total variability of winter temperatures measured at 60 KMA stations. The black curve in each panel represents the estimated PC time series from the predictor variable, which is the NCEP–NCAR surface temperature. Except for mode 20, the correlations between the PC time series of the KMA data and those estimated from the NCEP–NCAR data are fairly high ($\rho \approx 0.59$). Table 1 provides the correlations for the first 10 PC time series of all predictor variables tested in this study. Since the performance of the downscaling method is similar for all six variables tested here, the results based on the NCEP surface temperatures will be shown below.

Figure 6 shows the downscaled temperatures based on the 20 PC time series estimated from the NCEP–NCAR surface data against the 20-mode reconstruction of the KMA temperatures at the four stations closest to the four NCEP–NCAR grid points. Although the downscaled temperatures occasionally underestimate the peaks in the KMA reconstruction data, the evolution of the wintertime temperatures in the 35-yr KMA record is reasonably captured by the developed downscaling method. Correlation between the 20-mode reconstruction of the KMA data and the downscaled temperatures based on the NCEP–NCAR surface data are close to 0.93 at all four stations. A comparison of the downscaled temperature and the raw KMA data is shown in Fig. 7. Correlations decrease slightly from those in Fig. 6, since the first 20 modes explain only about 90% of the total variability of the KMA data; this decrease is obviously due to the neglect of the remaining variability in the KMA data. Nonetheless, the downscaled temperatures are quite comparable in accuracy to the original reanalysis surface temperatures.

Correlations of the 20- and 10-mode downscaled temperatures from the NCEP–NCAR surface data with the original KMA data are shown in Table 2. Correlations are calculated with and without the seasonal cycle at four stations. The averaged correlation between the 20-mode (10 modes) downscaled temperature and the KMA temperature is $\sim 0.88$ ($\sim 0.82$) with the seasonal cycle and is $\sim 0.82$ ($\sim 0.73$) without the seasonal cycle. The correlation decreases slightly by removing the seasonal cycle, which is a major component of the variability in the data. Correlations of the 20-mode (10 modes) downscaled temperature with the 20-mode (10 modes)
KMA reconstruction temperature is \( \sim 0.93 \) (\( \sim 0.97 \)) with the seasonal cycle and is \( \sim 0.89 \) (\( \sim 0.95 \)) without the seasonal cycle. The correlation increases by using the same number of modes for the KMA temperatures.

Figure 8 shows the difference between the downscaled temperature and the raw KMA temperature together with the difference between the reanalysis and the KMA temperatures. Downscaling reduces the mean bias in the reanalysis surface temperatures. The mean bias ranges from 0.93 K at Uljin station to 1.93 K at Suncheon station in the NCEP–NCAR surface temperatures, which was reduced to \( \sim 0.008 \)–\( 0.04 \) K after downscaling. The variance of the error time series is reduced at two stations (Suncheon and Icheon) but is slightly increased at the other stations. The purpose of downscaling is to reproduce temperatures accurately away from the reanalysis grid points.

Figure 9 summarizes the accuracy of the downscaled temperatures against the raw KMA temperatures. In the presence of the seasonal cycle, the correlation is greater...
than 0.87 all over the peninsula and the relative RMSE is less than 50%. Even in the absence of the seasonal cycle, the correlation is reasonably high (≥0.80) and the relative RMSE is less than 62%. It should be noted that both the correlation and the RMSE values are fairly uniform over the peninsula. A comparison between Figs. 3 and 9 reveals that specific regional characteristics of the KMA temperature have been reasonably reproduced by the downscaling method. Tables 3 and 4 show the range of RMSE and correlation values for different datasets. As can be seen in the tables, the performance of the developed downscaling method is not overly sensitive to the choice of a predictor variable. For six different variables, the range of relative RMSE is (0.462, 0.551) and that of correlation is (0.841, 0.900) at the 60 KMA stations.

<table>
<thead>
<tr>
<th>Data station</th>
<th>NCEP–NCAR</th>
<th>ECMWF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Surface</td>
<td>1000 hPa</td>
</tr>
<tr>
<td>1st</td>
<td>0.474</td>
<td>0.479</td>
</tr>
<tr>
<td>2nd</td>
<td>0.474</td>
<td>0.480</td>
</tr>
<tr>
<td>3rd</td>
<td>0.474</td>
<td>0.480</td>
</tr>
<tr>
<td>58th</td>
<td>0.514</td>
<td>0.521</td>
</tr>
<tr>
<td>59th</td>
<td>0.516</td>
<td>0.525</td>
</tr>
<tr>
<td>60th</td>
<td>0.517</td>
<td>0.527</td>
</tr>
</tbody>
</table>
Figure 10 shows the mean and standard deviation of the raw KMA temperature over the peninsula and the 20-mode downscaled temperature based on the NCEP–NCAR surface data. The patterns of the standard deviation are similar between the two, although the downscaled temperature underestimates the standard deviation by ~10%–20%. It is clear that the statistical downscaling method cannot reproduce all the variability in the KMA winter temperatures. Nonetheless, the details of the distribution of the temperature variability over the peninsula are faithfully captured by the downscaling method. The patterns of the mean are nearly identical; the mean bias in the reanalysis data has been removed almost completely.

### Table 4. The lowest three and the highest three correlation values of the 20-mode downscaled NCEP–NCAR and ECMWF temperatures with those at the 60 KMA stations.

<table>
<thead>
<tr>
<th>Data station</th>
<th>NCEP–NCAR</th>
<th></th>
<th></th>
<th>ECMWF</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Surface</td>
<td>1000 hPa</td>
<td>850 hPa</td>
<td>Surface</td>
<td>1000 hPa</td>
<td>850 hPa</td>
</tr>
<tr>
<td>1st</td>
<td>0.891</td>
<td>0.887</td>
<td>0.871</td>
<td>0.894</td>
<td>0.900</td>
<td>0.872</td>
</tr>
<tr>
<td>2nd</td>
<td>0.890</td>
<td>0.886</td>
<td>0.870</td>
<td>0.893</td>
<td>0.900</td>
<td>0.872</td>
</tr>
<tr>
<td>3rd</td>
<td>0.890</td>
<td>0.885</td>
<td>0.869</td>
<td>0.892</td>
<td>0.900</td>
<td>0.871</td>
</tr>
<tr>
<td>58th</td>
<td>0.869</td>
<td>0.864</td>
<td>0.842</td>
<td>0.869</td>
<td>0.873</td>
<td>0.847</td>
</tr>
<tr>
<td>59th</td>
<td>0.867</td>
<td>0.860</td>
<td>0.841</td>
<td>0.867</td>
<td>0.873</td>
<td>0.844</td>
</tr>
<tr>
<td>60th</td>
<td>0.867</td>
<td>0.860</td>
<td>0.841</td>
<td>0.862</td>
<td>0.866</td>
<td>0.844</td>
</tr>
</tbody>
</table>

**Fig. 10.** (top) Standard deviation and (bottom) mean of the (left) raw KMA temperature and (right) 20-mode downscaled temperature from the NCEP surface data.
c. Implications of the test results

GCMs are frequently used for seasonal predictions. GCMs at the present resolutions, however, have limitations in rendering small-scale climate variability. The utility of GCM seasonal predictions can be enhanced by using the statistical downscaling method developed in the present study. For example, Fig. 11 shows the regressed PC time series over the 5-yr prediction interval (2009/10–2013/14) based on the NCEP–NCAR and ECMWF surface temperatures over the training period (1979/80–2008/09). This is a stringent test since daily winter temperatures are predicted for five consecutive years based on 30-yr training data. As seen in the figure, the amplitudes of the first 10 modes were reasonably predicted with some underestimation for modes 6 and 8. Figure 12 shows the correlation map of daily and monthly winter temperatures predicted over the peninsula. It is clear that the predicted temperatures reflect both regional accuracy and details.

An added advantage of the CSEOF-based downscaling method here is that regional patterns of other variables can also be obtained by carrying out regression analysis in CSEOF space. Upon regression of two KMA variables in CSEOF space, we have

\[ \{T(r, t), S(r, t)\} = \sum_n \{B_n(r, t), A_n(r, t)\} T_n(t), \]  

where \( \{B_n(r, t), A_n(r, t)\} \) are two matching evolutions in two different variables \( \{T(r, t), S(r, t)\} \). By estimating the PC time series of \( T(r, t) \) (target variable: KMA temperature) from a predictor variable (e.g., NCEP–NCAR surface temperature), we can also generate the detailed spatial pattern of other KMA variables based on (13). The accuracy of the regression procedure depends on the accuracy of the regression between two KMA variables. Nonetheless, this idea is intriguing considering the reasonable performance of the developed downscaling method as applied to surface temperatures.

5. Summary and conclusions

A statistical downscaling method based on CSEOFs was developed in this study. The resulting downscaling method was tested in the construction of winter temperatures at 60 KMA stations over South Korea by using the NCEP–NCAR and ECMWF reanalysis datasets. The essence of the technique is to identify mapping relationships (matching evolutions) in CSEOF space between a target variable (KMA temperatures) and a predictor variable (NCEP–NCAR or ECMWF winter temperatures). Then, the evolution in a predictor variable is translated into the matching evolution in a target variable. This strategy should work if a predictor...
variable is reasonably accurate in depicting the long-term evolution in a target variable.

To validate the downscaling method, winter temperatures at the 60 KMA stations were constructed by using the jackknife method. The performance of the downscaling method was assessed in terms of mean bias, relative RMSE, and correlation at each station. The downscaled temperatures improve the reanalysis temperatures, and they exhibit little mean bias, smaller relative RMSE, and higher correlation at most KMA stations. The downscaling method reproduces the regional characteristics of temperature in a faithful manner and is not very sensitive to the choice of the predictor variable tested in this study. In practice the accuracy of downscaling depends not only on the method but also on the predictor field itself.

In the present resolutions, the utility of GCM predictions is very limited. As demonstrated in Figs. 11 and 12, GCM predictions can be enhanced in terms of systematic bias and spatial details by using the developed statistical downscaling method. It should be noted that the temporal resolutions of GCM predictions could also be improved by using the CSEOF-based downscaling method. This can be accomplished by reproducing the PC time series of the temporally dense target variables (say, daily observations) from the PC time series of temporally coarse predictor variables (say, monthly GCM outputs).

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