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Statistical downscaling of monthly mean temperature for Kazakhstan in Central Asia

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ABSTRACT: Very few studies on the impact of climate change have been carried out in Kazakhstan, which is located in Central Asia. It is the largest landlocked country in the world and has a sensitive natural environment and a human society that is vulnerable to climate change. In this study, we evaluated a statistical model for downscaling the monthly mean temperature in the Kazakhstan area built from a linear regression model combined with a principal component analysis (PCA) as the preprocessing method for predictors. The air temperature, geopotential height and both components of the wind were selected as predictor variables. The result shows that the linear regression model was able to simulate monthly mean temperature averaged over the Kazakhstan region as a whole reasonably well, although there are a few mismatches with observations for some stations and in some months. A further analysis of the results of downscaling also reveals that the monthly mean temperature in summer is downscaled more accurately by this model than that in winter, with the R^2 value of 0.8 for summer being larger than that for winter of 0.7. Moreover, this statistical downscaling model shows poor performance in complex terrain areas compared to flat terrain areas, with R^2 values for the southeastern mountain station and the station by the Caspian Sea being smaller than those for other stations in Kazakhstan.

KEY WORDS: Kazakhstan · Statistical downscaling · Linear regression · Monthly mean temperature

1. INTRODUCTION

Kazakhstan is located in Central Asia, and is surrounded by Russia, China, and 3 other Central Asian countries. With an area of 2.7×10^6 km^2—similar in size to Western Europe—Kazakhstan is the ninth largest country and the largest landlocked country in the world. It has a variety of natural environments, including the Caspian Lowland in the west; the world's largest dry steppe plain, the Kazakh Steppe, in the centre and occupying most of the country in the north; the Central Asian northern desert in the south; and the eastern mountainous region with some high, snow covered peaks reaching an elevation of approximately 7000 m.

As determined by its geographic characteristics, this region is sensitive and vulnerable to climatic and anthropogenic effects (de Beurs & Henebry 2004, Lioubimtseva & Henebry 2009) and was therefore identified as one of the 'hot-spots' for climate change by a range of change-detection approaches (Giorgi 2006). There are increasing numbers of studies showing concern about the impacts of climate change on a wide range of aspects in Kazakhstan with regards to both the natural environment and the human community (Wright et al. 2009, Qi et al. 2012, Eisfelder et al. 2014, Hu et al. 2014). For example, water in this region comes largely from melting mountain ice and snow; therefore, a slight fluctuation in annual mean temperature might result in a significant change in the volume of ice-melt water and cause either flooding and/or water shortages. The water resources in this region need to be better monitored, modelled, and managed in the context of climate change

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(Siegfried et al. 2012, Malsy et al. 2015, Xu et al. 2015). In addition, regional food security is affected by climate change, because changes in water and temperature conditions can have a significant effect on the productivity of crops (Sommer et al. 2013, Bobojonov & Aw-Hassan 2014). The number studies addressing these issues is increasing rapidly; however, the total number is still relatively small.

In climate change impact studies, temperature plays an important role. Obtaining future temperature projections simulated by general circulation models (GCMs) under various greenhouse gas emission scenarios is often the first step in a climate change impact study (Sommer et al. 2013, Bobojonov & Aw-Hassan 2014). However, GCMs are usually run at large scales, with spatial resolutions of about 100 km (Taylor et al. 2012). Currently, the representation of future temperature with a spatial resolution meeting the requirements of the impact assessment studies (like those mentioned above) cannot be achieved by most GCMs.

To address this limitation, downscaling techniques have been developed to transfer large-scale GCM outputs (predictors) to regional or local-scale climate variables (predictands). The downscaled climate projection has a finer spatial resolution and can be incorporated in the models for use in climate change research (Fowler et al. 2007). In the past few decades, a range of downscaling methods have been developed and applied in different regions. The latest IPCC report (Flato et al. 2013) provides a summary of recent developments in downscaling.

There are 2 main categories of downscaling techniques: the dynamical (e.g. Laprise 2008, Orskaug et al. 2011, Mannig et al. 2013, Sales & Xue 2013) and the statistical (e.g. Hanssen-Bauer et al. 2005, Wetterhall et al. 2009, Goyal & Ojha 2011). Dynamic downscaling is usually performed by running a regional climate model (RCM) nested into a GCM as its boundary conditions. Since the RCM is based on the complex physics of atmospheric processes, the dynamical downscaling requires intensive computing. In addition, the performance of the dynamical downscaling depends on model parameterization and the boundary conditions provided by the GCMs and reanalysis (Sachindra et al. 2014). Statistical downscaling, in contrast, involves a statistical model instead of a process model based on complex atmospheric physics, and therefore entails less computational cost. For this reason, statistical downscaling is often preferred to dynamical downscaling, especially in studies that respond to the need for rapid assessments of the impacts of climate change. Moreover, statistical downscaling is usually easier to apply and has the ability to provide local or site-scale information, which is not provided by dynamical downscaling techniques (Wilby & Wigley 1997, Wilby et al. 2002). On the other hand, the major weakness of statistical downscaling is that the empirical relationships between predictors and predictands may not hold in a future climate (Giorgi et al. 2001).

The fundamental idea of statistical downscaling is to establish empirical relationships between large-scale predictors and local predictands and then apply the relationships to the simulation of the local-scale future climate. In general, statistical downscaling methods are classified into regression models, weather typing schemes, and weather generators, with many different methods in each group (Fowler et al. 2007). Regression model methods, or so called 'transfer functions', are the most widely used kind of statistical downscaling technique due to their simplicity and straightforwardness (Wilby et al. 2004, Nasseri et al. 2013). As the first step in statistical downscaling using a simple regression method, a set of large-scale predictors such as pressure fields or geopotential height are extracted from the GCMs or reanalysis data. Then, together with predictands, such as a surface temperature series at a single point from historical observations, selected suitable predictors are used to estimate the parameters of the regression model. Finally, this regression model with estimated coefficients is applied to predict (in this example) the future temperature series based on values of predictors extracted from GCM outputs under different greenhouse gas emission scenarios (e.g. RCP2.6, RCP8.5) over the study period.

In different regions, the performance of one statistical downscaling method may vary significantly (Fowler et al. 2007), so that application of the method in different areas can contribute to the development of the technique. A great many studies using statistical downscaling have been carried out in highly developed European countries (Miro Perez et al. 2015). Studies are also underway in developing countries, such as China (Simon et al. 2013, Zhang & Yan 2015), India (Goyal & Ojha 2012), and Pakistan (Kazmi et al. 2015), among others. However, to our knowledge, no literature on statistical downscaling in Kazakhstan can be found.

In the present study, we downscaled climate data from the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis and employed a linear regression model combined with principal component analysis (PCA) to predict monthly mean tempera-

Fig. 1. Selected Global Historical Climatology Network (GHCN) stations in Kazakhstan

tures at 11 meteorological stations in Kazakhstan over the period 1960–2009. The objective of this study was to explore the capability and efficiency of statistical downscaling to predict monthly mean temperatures in Kazakhstan.

2. DATA AND METHODS

2.1. Predictand

To obtain a reliable observational series of monthly mean temperatures over the Kazakhstan region, we used the Global Historical Climatology Network (GHCN)-Monthly database (Peterson & Vose 1997; www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/global-historical-climatology-network-ghcn). The monthly mean temperature is derived from the GHCN-Daily database, which is a composite of climate records from multiple sources. Missing days and consecutive missing days in the aggregating process of each month are also given by GHCN, and we used these data to select stations with complete series. Eleven sites broadly scattered throughout Kazakhstan were selected based on the completeness of their temperature series throughout the entire period 1960–2009 and their credibility measured by the number of non-missing days in each month. The locations and summary information for the 11 stations selected are shown in Fig. 1 and Table 1, respectively.

Table 1. Summary information for the selected Global Historical Climatology Network (GHCN) stations in Kazakhstan

Station name	Elevation (m)	Latitude (°N)	Longitude (°E)	Mean temperature in Jan. (°C)	Mean temperature in July (°C)
Aktobe	219	50.28	57.15	–13.39	22.62
Aralskoe More	62	46.78	61.67	–11.44	26.86
Uralsk	36	51.25	51.40	–11.55	22.63
Atyrau	–22	47.12	51.92	–7.30	26.42
Atbasar	304	51.82	68.37	–16.99	20.21
Balhash	350	46.80	75.08	–13.80	23.96
Semej	196	50.42	80.30	–14.83	21.71
Irtyshsk	94	53.35	75.45	–17.00	20.99
Petropavlovsk	142	54.83	69.15	–16.72	19.55
Zharkent	645	44.17	80.07	–6.90	24.43
Uil	128	49.07	54.68	–11.50	24.78

2.2. Predictors

The NCEP/NCAR monthly mean reanalysis (Kalnay et al. 1996; www.esrl.noaa.gov/psd/data/gridded/reanalysis/) was used to extract predictors. The NCEP/NCAR reanalysis was simulated with an atmospheric model with a resolution of 2.5° × 2.5° in the horizontal and 17 vertical levels.

To correspond with the observational data we obtained, the whole period of NCEP/NCAR data was trimmed to 1960–2009. The 9 nearest NCEP/NCAR grid boxes to each of the 11 sites were selected as the corresponding predictor domain. For illustrative purposes, we show the boundary of the predictor domain for Aktobe station in Fig. 2.

Referring to previous statistical downscaling studies for monthly mean temperature in other locations, 12 candidate predictor variables were initially selected from the NCEP/NCAR data: the air temperatures (Ta) at 925, 500 and 200 hPa (Ta925, Ta500, Ta200), and the geopotential height (Zg) and zonal (Ua) and meridional (Va) wind velocities at the same levels.

Each of the variables for each month was standardized separately by removing the mean and dividing by the standard deviation, with the baseline taken as the period 1960–1989. This standardization procedure is widely used in the development of statistical models.

2.3. Selection of predictors

For each site, there were 4 predictor variables with a domain of 9 grids on 3 levels. The feature (predictor) vector of 118 = 4 × 9 × 3 dimensions could be used

Fig. 2. Example of the use of NCEP/NCAR grid boxes as the predictor domain for a statistical downscaling model, as applied to the Aktobe weather station in Kazakhstan

in the multiple regression model, which however would be sensitive to multicollinearity (high correlation between features). Several approaches have been developed to solve the problem, such as the lasso and ridge regression models. Here, we used a principal component analysis (PCA) to reduce not only the multi-dimensionality but also the computational demand (Benestad et al. 2015).

The PCA was carried out separately on each variable and each level for each month. The first principal component (PC) series that in most cases explained >95% of the original predictor's variance was extracted from the transformed NCEP variables by the PCA procedure. These PCs then formed the potential feature vectors which would be used to train and validate the regression model. As the 9 closest grid values were represented by 1 PC, the dimensionality of the potential predictor was decreased dramatically to 12 = 4 (variables) × 1 (PC) × 3 (levels). The details of these potential features and a comprehensive evaluation of them are as follows.

The predictors were chosen using criteria such as that the predictors would have significant correlation with the predictands but that they would not strongly correlate with each other (Hewitson & Crane 1996). The degree to which the candidate predictors met those requirements provided a clear instruction for the subsequent selection of predictors for use in the downscaling model. Thus, the evaluation process examined the candidate predictors with respect to (1) correlations with predictands and (2) correlations with each other. The Pearson's correlation coefficient (Pearson 1896) was able to measure the correlations, with values closer to 1 or −1 indicating a higher correlation between the variables. We squared the correlation coefficients to get the explained variances, so that a higher value indicates a stronger correlation. We use a heat map to illustrate the explained variances between the predictors and predictands, as well as those between the predictors (see figure Fig. 3 below), in order to assist with the choice between the candidate predictors.

2.4. Downscaling model

Before building the downscaling model, the predictors and predictands were first partitioned into a 30-yr training set from 1960 to 1989 and a test set of 20-yr data from 1990 to 2009 for validation. In this study, we chose linear regression analysis for the statistical model of downscaling. Linear regression is a simple and widely-used statistical model. The basic form, given n observations, is:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_2 + \ldots + \beta_p x_p + \varepsilon_i \text{ for } i = 1, 2, \ldots n \quad (1)$$

where y_i is the response variable, β_p is the pth coefficient to be estimated, ε_i is the residual, and x_p is the pth dimension of the feature vector (i.e. in this case the selected PCs from the NCEP/NCAR variables after PCA).

The linear regression method estimated the coefficients by minimizing the residual sum of squares between predictands in the training set and the values predicted by the linear approximation. The regression model with the estimated coefficients was then fitted to the test dataset, and its performance indicated whether the model was able predict the unknown data, i.e. the future temperature in this case. In this study, we built a statistical model for each month separately, so there were 12 different models, 1 for each calendar month.

To evaluate the quality of the predictions of the model, 3 statistical parameters (metrics) were used as measures of the statistical agreement between the predicted values and observed data, including the root mean square error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2). They were calculated for all 12 models.

3. RESULTS

3.1. Evaluation of predictors

The Pearson's correlation coefficients (CC) and plots of squared CC values (Fig. 3) contributed to the identification and selection of the most valuable predictors for developing the downscaling model.

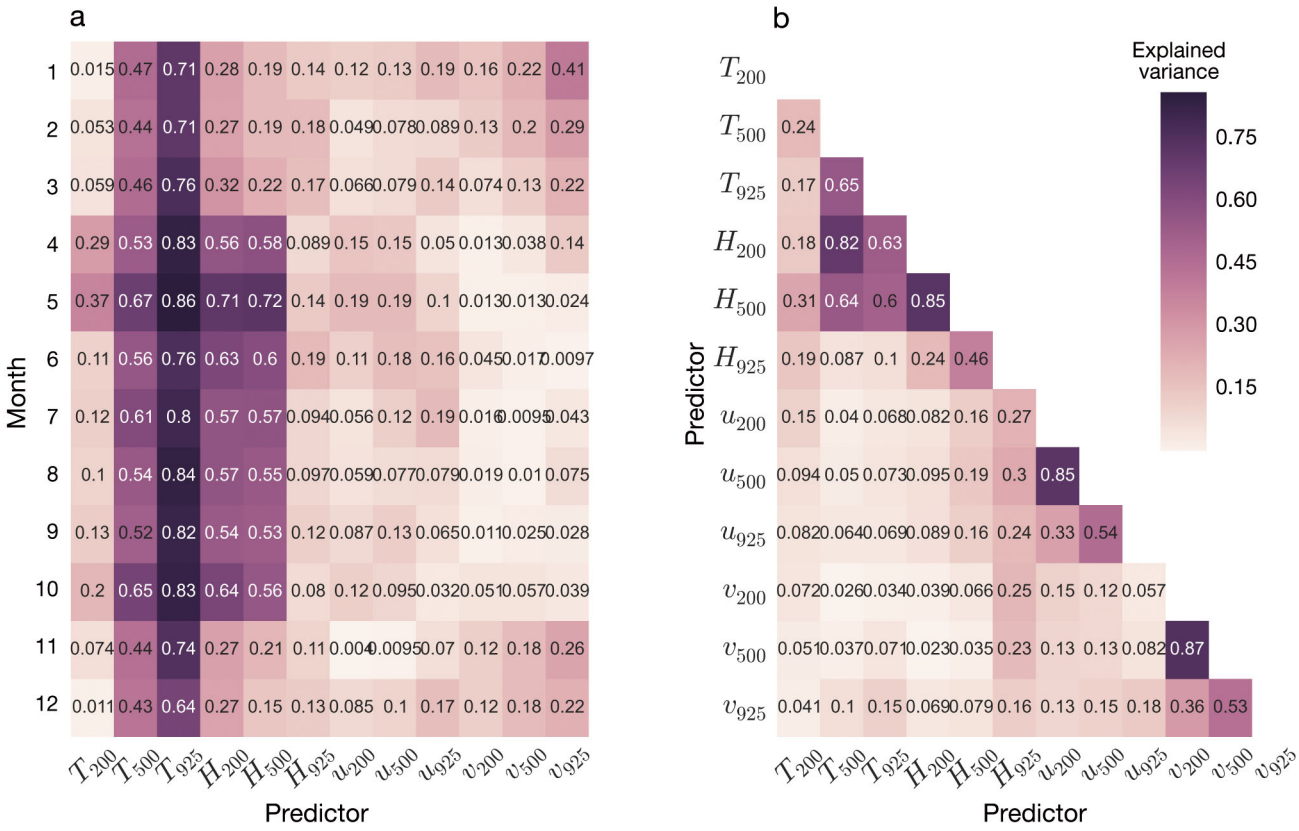

Fig. 3. (a) Explained variances between candidate predictors of monthly mean temperatures (predictand) over the Kazakhstan region. Values are Pearson's correlation coefficients (CC) averaged over 11 weather stations (Table 1). Months are shown as 1 (January) to 12 (December). (b) Mean CC values between pairs of candidate predictors. The predictors considered were the air temperatures at 925, 500 and 200 hPa (Ta925, Ta500, Ta200), and the geopotential height and zonal (Ua) and meridional (Va) wind velocities at the same levels

Fig. 3(a) shows the mean CCs between the 12 candidate predictors (i.e. the PC series of NCEP variables after the PCA process) and the predictands (i.e. the monthly mean temperature series during the training period) for each month over all 11 stations in our study region, and Fig. 3(b) shows the correlations of the candidate predictors with each other.

It is obvious in Fig. 3(a) that the best predictor is air temperature at 925 hPa (Ta925), with the explained variance >0.6 in every month, indicating that the predictor and predictand have a strong correlation with each other. The geopotential heights are also correlated quite closely with the predictands, with the explained variances in certain months higher than 0.5 and reaching a high of 0.72. The other circulation variables, such as the zonal and meridional wind fields (Ua and Va, respectively), show lower explained variance, with values <0.1 in many of the boxes in Fig. 3(a). However, we chose to retain both of these variables in the list of predictors because their explained variances of the predictands varied in different months. For example, Ua had relatively high values in the warmer months (from May to September) but lower values in the colder months (from October to April).

The correlations between the predictors and predictand can be explained in a physical way. (1) The upper air temperature obviously has direct connection to the surface air temperature, so the explained variances are higher than for other predictors. (2) The geopotential height is also strongly connected to the predictand, because variation in geopotential height reflects variation in air pressure, which in turn is affected by surface temperature through vertical energy transfer and air movement. (3) The surface temperature in the Kazakhstan region has correlation to wind velocity, and the degree of this correlation depends on the direction of wind and the season. In the winter, the Siberian high moves air from Siberia to Kazakhstan in a north to south direction, and it is captured by the Va component of wind (north/south direction). Similarly, in the summer, moist air is transferred from the Caspian Sea to inner Kazakhstan in a west to east direction

and influences the local temperature, so that the Ua wind (west/east direction) becomes the most informative indicator.

Variables at a lower level (925 hPa) are correlated closer than other levels except for the variable of geopotential height, as can easily be appreciated from the dark shaded columns in Fig. 3(a). In addition, from the locations of the dark shaded boxes in Fig. 3(b), it appears that predictors of the same variable but at different levels often have a high correlation with each other; therefore, there is no need to choose multiple levels of one variable.

Therefore, the PCs of Ta925, Zg200, Ua925, and Va925 were selected as the predictors based on the analysis described above. In terms of physical mechanism, Ta925 is an indicator of the radiative property of the atmosphere, while Zg200 represents upper air condition. In this inland region, especially in cold seasons, cold fronts from Siberia have a marked effect on temperatures. Thus, Ua925 and Va925 were selected as circulation predictors to capture the variability of circulation.

3.2. Evaluation of prediction

The errors in each month from January to December between predicted and observed monthly mean temperature at the 11 weather stations over the 20-yr test period 1990–2009 are shown in Fig. 4. The errors for each month between prediction and observation at the 11 stations are shown as an individual subplots, since the models were calibrated separately. The error was calculated by subtracting the observed temperature from the predicted temperature, so a positive value means that the predicted mean temperature was higher than the observed mean temperature.

In general, the results demonstrate the abilities of those statistical downscaling models to reproduce monthly mean temperature. The errors are not significant, all within a range of ±1.5°C and, in most cases, within range of ±0.5°C. Comparison of errors among models for different months, in overall terms, shows no fixed distribution. Both overestimation (positive error) and underestimation (negative error) can be observed in every month. However, patterns of differences among months can be identified, even though models were calibrated separately for each month. Strong errors are more likely to occur in cold months, such as January and February, while weaker errors are more likely to be observed in warm months, such as July and August. Seasonal difference among errors are analysed in the following section. In addition, some stations stand out as having larger errors than the rest. For instance, in Atyrau and Zharkent, strong underestimations can be observed in nearly all months.

3.3. Error and performance

The error measures RMSE, MAE and R^2 were used to evaluate the downscaling model. Specifically, RMSE and MAE indicated the difference between the predicted temperatures and the observations, while R^2 indicated how well the temperatures are likely to be predicted by the downscaling model in this study. Figs. 5 & 6 show the results for sites and seasons, respectively.

It can be observed from the subplots of RMSE and MAE in Fig. 5 that errors were small at all stations. The maximum error occurred at Aktobe, with a RMSE of 1.5 and a MAE of 1.1. A higher coefficient of determination (R^2), up to a maximum of 1.0, denotes a better performance of the model for prediction. The R^2 in a majority of the stations was as high as 0.8, and R^2 values at poorly performing ones were still higher than 0.5. The only exception was Zharkent, which had a very low R^2 score of 0.12.

Fig. 6 shows the error results by season. The results for both RMSE and MAE reveal a clear seasonal pattern, with minimum values in the summer months (JJA) and a maximum in the winter months (DJF); while there was no significant difference between spring (MAM) and autumn (SON). By contrast R^2 showed no clear seasonal variation. The medians of R^2 for each season were all in the range of 0.7 to 0.8, and the spread among the seasons was quite small.

4. DISCUSSION AND CONCLUSIONS

This study explored the ability of the linear regression model for the downscaling of the monthly mean temperature in the Kazakhstan region, where the environment and human society are sensitive and vulnerable to climate change, but in-depth studies and reliable data are relatively scarce. The results for the validation period indicated that the process of selecting the potential predictors combined with the linear regression model simulated monthly mean temperature averaged over the Kazakhstan region as a whole reasonably well. However, there are a few mismatches between predictions and observations at some stations and in some months. We find that the

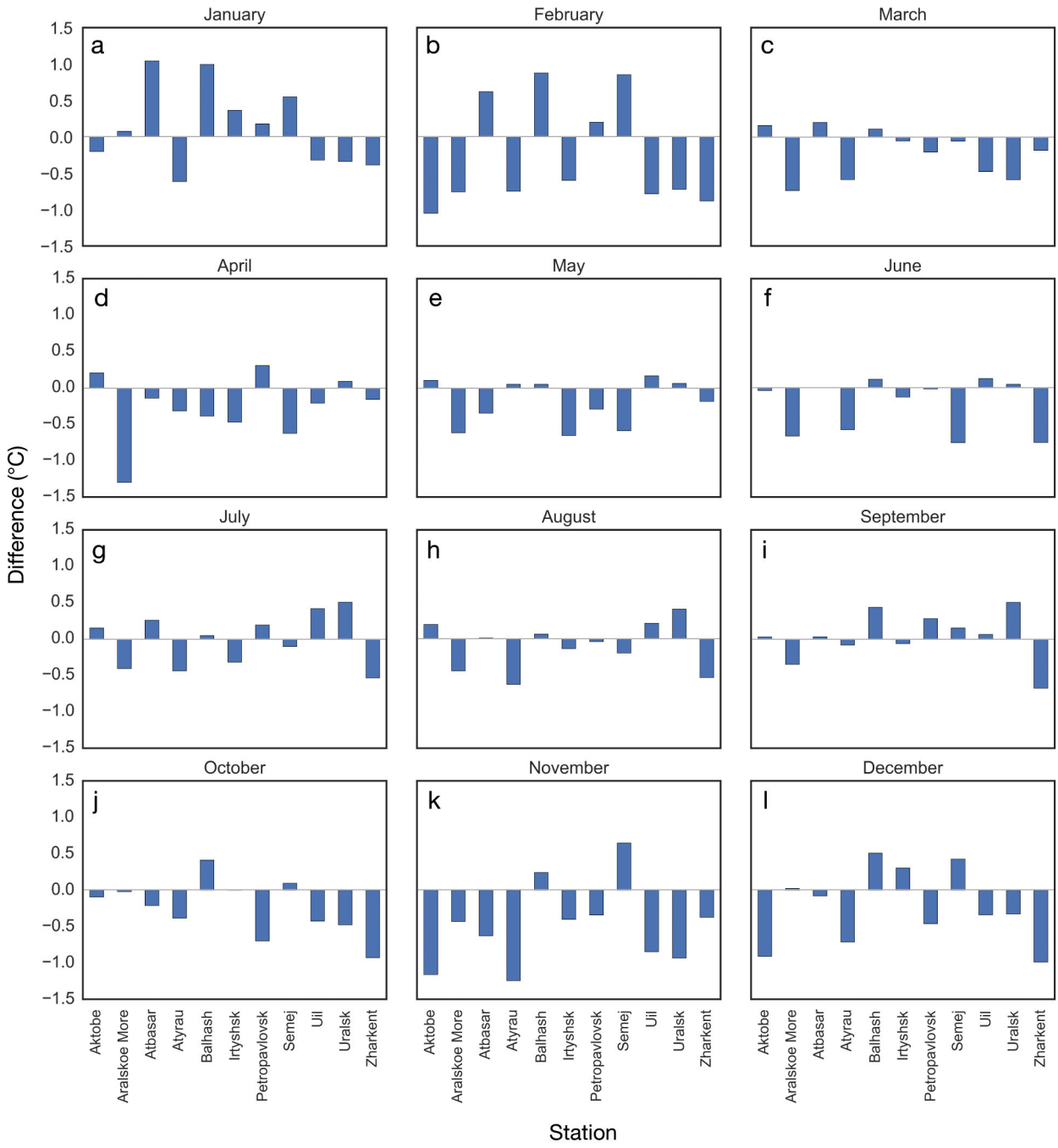

Fig. 4. Differences between predicted and observed monthly mean temperature during 1990–2009 for January to December at 11 weather stations in Kazakhstan. Errors were calculated by subtracting the observed temperature from the predicted temperature, so a positive value means that the predicted mean temperature was higher than the observed mean temperature

statistical downscaling model shows poor performance in complex terrain areas compared to flat terrain areas, since the R^2 of the models applied in the southeastern mountain station and the station by the Caspian Sea are smaller than for other stations in Kazakhstan. It is also clear that the performance of the statistical downscaling model applied in this study is better in the summer than in the winter for the Kazakhstan region. The observed year-to-year variability of monthly mean temperature in the summer is less than in the winter. However, linear regression models with small numbers of predictors, as employed in this study, have difficulty in predicting complex variability. Therefore, a more sophisticated

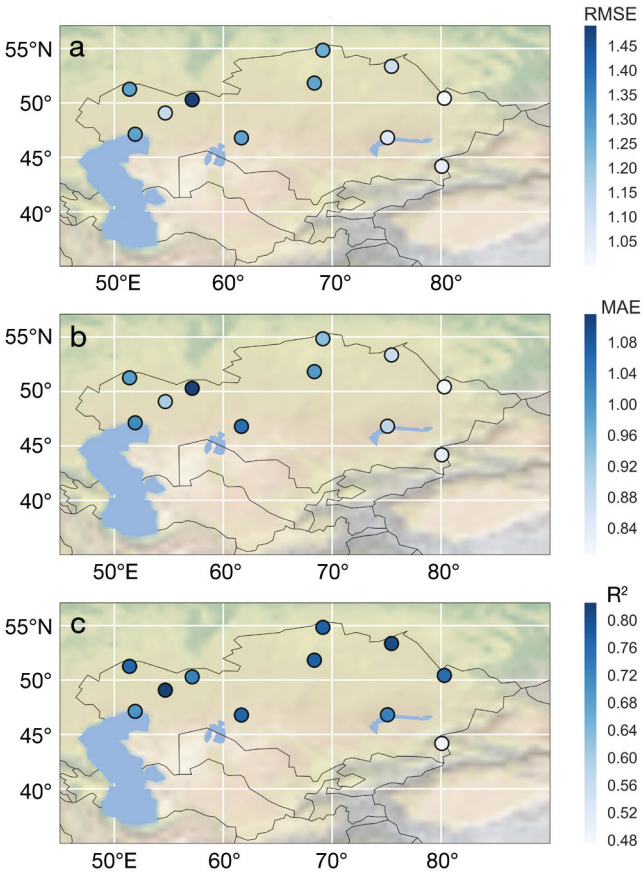

Fig. 5. Spatial distributions of model performance statistics (a) RMSE, (b) MAE and (c) R^2 for the downscaled projection of mean monthly temperatures during 1990–2009 at 11 weather stations in Kazakhstan

statistical model should be developed in further studies to improve the performance of downscaling in the winter over the Kazakhstan region.

The factors that could result in failures and the inaccuracies in downscaling large-scale atmosphere fields at some Kazakhstan sites include, but are not limited to, the selection of inappropriate predictors and/or statistical models. In the first stage of this study, predictors were selected by a method based on a principal component analysis performed on a 9-grid NCEP domain for each station. However, according to Wetterhall et al. (2006), the domain where the PCA is performed can exert influence on the resulting correlation between the predictands and the transformed series. Therefore, experiments and innovative methodologies for the selection of predictor domains (e.g. Zhang & Yan 2015) should be evaluated in future studies for the Kazakhstan region. In the second stage, a linear regression model was employed as the statistical model; the efficiencies of other more sophisticated models utilized recently for statistical downscaling (e.g. Goyal et al. 2012, Lu & Qin 2014, Zhang & Yan 2015) are still unknown for Kazakhstan.

Finally, the challenge in a statistical downscaling study is, we believe, not only related to the unsatisfactory performance of some methods, but also, more importantly, to the absence of a downscaled climate projection for the vast areas where long periods of observed climate data are lacking or nonexistent. There are places that need finer scale future climate

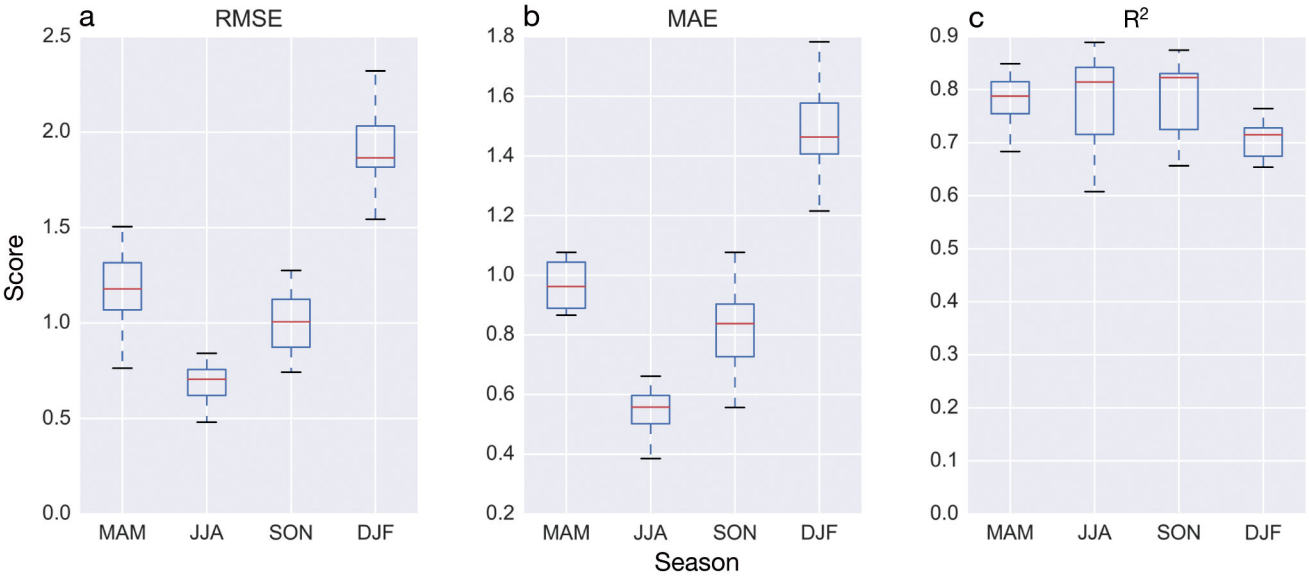

Fig. 6. Seasonal variation in model performance statistics (a) RMSE, (b) MAE and (c) R^2 for the downscaled projection of mean monthly temperatures at 11 weather stations in Kazakhstan. Red lines show medians, the boxes represent the range between first and third quartiles, and the whiskers indicate minimum and maximum values of all data

projections but suffer from the lack of quality observations, similar to Kazakhstan, all over the world. We look forward to further studies on application of statistical downscaling methods that can be used for places without observations in order to contribute to efforts by those countries and communities to tackle climate change.

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