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Performance of a MIROC3.2-hires climate scenario in eastern Mongolian Steppe and its improvement by statistical downscaling

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Abstract

The spatial resolution of Global Circulation Models is too coarse to represent regional climate variations at the scales required for environmental impact assessments. Studies on downscaling over Mongolia were comparatively few, except dynamical downscaling studies, which have done by Kimura and Sato (2004), and Sato *et al.* (2007), especially on statistical downscaling. In this study, two climate variables (monthly mean temperature and monthly precipitation amount) of the output from MIROC3-2-hires climate model were downscaled and compared its performance with a bias correction method. Results showed that values from MIROC3-2-hires climate model overestimated the monthly accumulated precipitation and represented well the monthly mean temperature in eastern Mongolia during the control period from 1971 to 2000. The cumulative density function made it possible to compensate the difference by 36% for precipitation and by 16% for temperature.

Key words: Global Circulation Model, statistical downscaling, bias correction, Mongolia

1. Introduction

Global Climate Models (GCMs) provide spatial fields of the future climate condition with a resolution around 40,000 square kilometers even under the current technology. As a result, they can not be applied directly to the subject relating surface processes. Two kinds of the downscaling techniques have been developed that attempt to counter this deficiency: semi-empirical statistical downscaling of GCM outputs, and regional climate models (RCMs) nested within a GCM. A key strength of statistical downscaling is the low computational demand. There are many studies on evaluation (Benestad *et al.*, 2007) and comparison (Spak *et al.*, 2007; Schmidli *et al.* 2007; Robert *et al.*, 2000) of these two downscaling technique and the methods of statistical downscaling technique as well (Mohammad *et al.*, 2006).

Several studies on comparison (Spak *et al.*, 2007; Robert *et al.*, 2000) show that skills of the two technique at simulating past climate are comparable, even though their study areas are in dependent. Robert *et al.* (2000) concluded that the statistical downscaling required much greater skill for temperature estimation than for precipitation field. Multiple Linear Regression (Spak *et al.*, 2007; Robert *et al.*, 2000; Schmidli *et al.*, 2007; Gangopadhyay *et al.*, 2004), Bayesian Approach (Iizumi, 2009; Ceolho *et al.*, 2006), Cumulative Density Function (CDF) based statistical downscaling (Iizumi, 2009; Baigorria *et al.*, 2007) are most commonly used statistical downscaling methods.

In the present study, performance of the GCM, MIROC3-2-hires climate model is checked in eastern part of Mongolia, since accuracy of GCM outputs are differed from region to region. The most important property of the MIROC3-2-hires climate model is indicated by its finest graduation of the grid size. Then the performances of a statistical downscaling method based on CDF and a simple bias correction are compared. Here, an abbreviation of MIROC represents Model for Interdisciplinary Research on Climate.

2. Dataset and method

2.1. Model and method

In the present study, we used climate scenario projected by MIROC3-2-hires model, which is high resolution coupling atmosphere-ocean climate model with horizontal resolution of 1.125° (about 100km), which was developed by the joint research team of Center for Climate System Research of the University of Tokyo, the National Institute for Environmental Studies, and JAMSTEC's Frontier Research Center for Global Change. This climate scenario has one of the finest graduations and is provided by IPCC. Simulated data series named 20C3M which is used as a control data set from 1971 to 2000, and two inherent data series of 2011-2040 and 2071-2100 describing future climate conditions under SRES-A1B GHG emission scenario.

The surface meteorological data set, obtained from the Institute of Meteorology and Hydrology of Mongolia, contains monthly precipitation, and monthly mean temperature from 1971 to 2000 for 7 stations, which locate in eastern part of the country (Figure 1).

2.2. Cumulative density function and bias correction

Recently, Iizumi *et al.* (in press) used CDF-based

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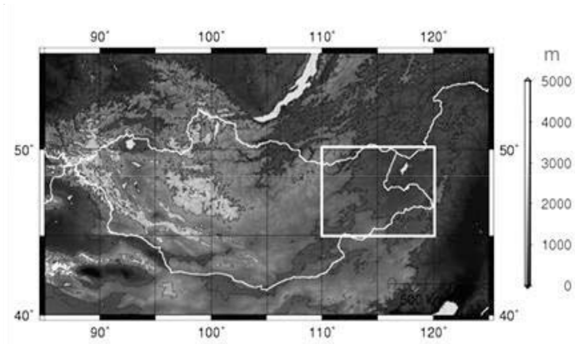


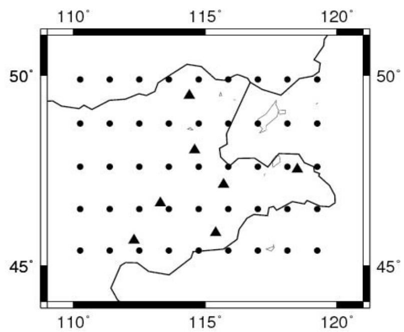


Fig.1 Study area, eastern Mongolia (white countered area in the top figure) and location of meteorological stations and model grid (bottom figure)
(Black dots: location of the gridpoints, Black triangles: location of meteorological stations)

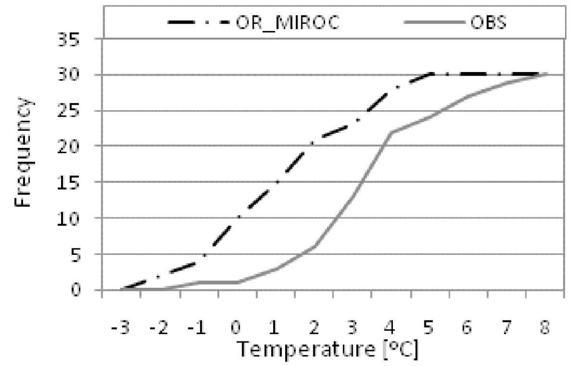


Fig.2 Experimental CDF of observed and simulated temperature of April
(OR_MIROC indicates uncorrected original MIROC data and OBS – observed value)

downscaling method in model data, which is used in crop modeling. The method relies on changing of CDF of modeled data. We applied the method separately for temperature and precipitation in each month. Experimental CDF of observed and modeled variables was constructed in control period (1971-2000) for each month and for each variable. For example, CDFs of observed and simulated monthly mean temperature in April are shown in Figure 2. Firstly, observed and simulated variables are sorted in ascending order and associated the probabilities accordingly. Next, difference between observed and simulated value with same probability is calculated. In order to modify the simulated data, the difference is added to simulated value.

By sorting the modified value in chronological order, we get downscaled value. If the value of modified precipitation after downscaling was negative, we assumed it as zero. If we construct the CDF of simulated variables after downscaling, we will get exactly same CDF with observed variable. We applied this modification to future projection data in order to obtain the modified time series of temperature and precipitation in future. The main assumption here was that the bias is the same for the same probability both in the training period and in the future projection of the same model.

For bias correction method, it was easy to find the difference between the observation and model simulation data for the control period (1971-2000), because the bias appeared apparently. After finding the mean difference, it was applied to the future climate projection data. If the value is less than 0 after correcting, we replaced by 0.0. The bias correction applied to monthly mean values of each 12 months.

2.3. Distribution of grid point and observatory

Gangopadhyay *et al.* (2004) studied that effect of spatial and temporal aggregation on accuracy on statistical downscaling and concluded that spatial and temporal averaging increased the skill of downscaled precipitation estimates. Therefore, in the study comparison of observed and model variables was done only for regional averages in eastern Mongolia. Regional average for model data was average of the grid data within 45°N - 50°N and 110° N - 120°E. As a regional average of observed variables, an average data of 7 observation stations, which locate within model data coverage, was considered (Figure 1).

3. Result and Discussion

3.1. Model performance

In order to measure performance of the bias correction, we used the mean bias error (MBE), root mean squared error (RMSE), and standard deviation (SDV) for the model simulated data and bias corrected data. We also adopted these definitions as indications of the spatial difference between simulated data coverage and observed data coverage.

The ability of climate model to capture the realistic seasonal cycles of temperature and precipitation is critical for a discussion on the future climate conditions. Therefore, we compared the simulated and observed monthly climatology for a period of 1971-2000.

The climate model data overestimated the precipitation

Table.1 Statistics of annual precipitation and annual mean temperature

	Precipitation (mm)			Temperature (°C)		
Data	Mean	SDV	RMSE	Mean	SDV	RMSE
Observed	249.3	71.81	-	1.2	0.71	-
Climate model	423.1	53.82	190.2	1.5	0.60	0.77
Downscaled	249.3	51.86	76.7	1.2	0.69	0.77
Bias corrected	249.3	53.82	77.2	1.2	0.60	0.72

Table.2 RMSE values of climate model, downscaled and corrected monthly variables

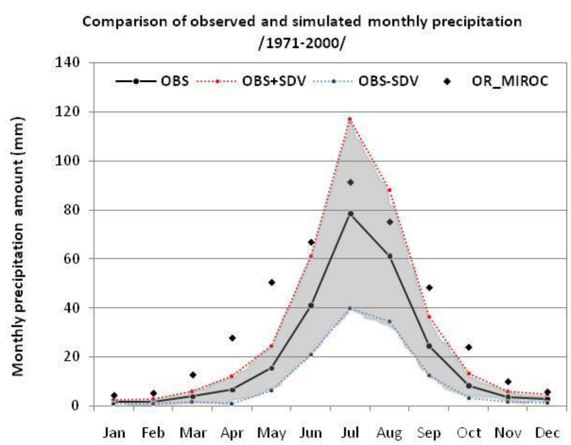
Data	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Ave.
						Precipitation (mm)							
Climate model	3.4	4.0	10.3	23.2	45.5	41.4	39.2	37.2	29.7	17.8	7.5	6.0	**22.1**
Downscaled	1.1	1.4	2.7	8.2	14.3	28.8	46.8	35.9	16.7	6.8	3.0	4.2	**14.1**
Bias corrected	1.8	1.8	4.8	9.2	23.8	32.4	37.1	34.5	17.6	8.2	3.9	2.6	**14.8**
						Temperature (°C)							
Climate model	2.8	3.3	3.5	3.4	1.8	3.6	3.4	2.5	1.5	2.3	3.4	2.5	**2.8**
Downscaled	2.7	3.3	3.9	2.6	1.7	2.1	1.4	1.4	1.3	2.4	3.6	2.4	**2.4**
Bias corrected	2.7	2.8	3.4	2.6	1.7	1.9	1.4	1.4	1.2	2.1	3.1	2.5	**2.2**

for all months, e.g. by 116% (for July) and 427% (for April), besides the annual precipitation overestimated by about 170%, e.g. 249.3mm for observed and 423.1 mm for climate model data (Table 1). Only in July and August, precipitation laid in their values within each standard deviation.

In contrast, the temperature was well represented by the model. Difference between observed and simulated annual mean temperature was 0.27°C (Table 1) that was very close to the HadCM3 model's performance, which was provided by Hadley Centre for Climate Prediction and Research, UK, and selected as the best performed GCM in Mongolia (Dagvadorj *et al.*, 2009). On monthly base, it shows that most cases of months' mean temperature were within a unit of the SDV, except in June, July and August.

The model had a bit warmer bias during the warm season, e.g. from May to September, and the temperatures in the rest of months, except January, were simulated a bit colder than observed temperature (Figure 3, bottom). The RMSE of monthly mean temperature varies from 1.5°C to 3.6°C (Table 2). This result was consistent with several other studies' results on comparison IPCC-AR4 GCMs' performance (Maxino *et al.*, 2008). They show that MIROC-hires had better performance for temperature, especially for maximum temperature.

Inter-annual variability is also an essential element for model validation. Figure 4 displays comparison of inter-annual variability of observed and simulated variables of the annual mean temperature and annual total precipitation. The inter-annual variation of the annual mean temperature was relatively well correspond with observed variation whereas magnitude of simulated annual mean temperature was reasonable. For the annual total precipitation, the graph clearly shows that there was not



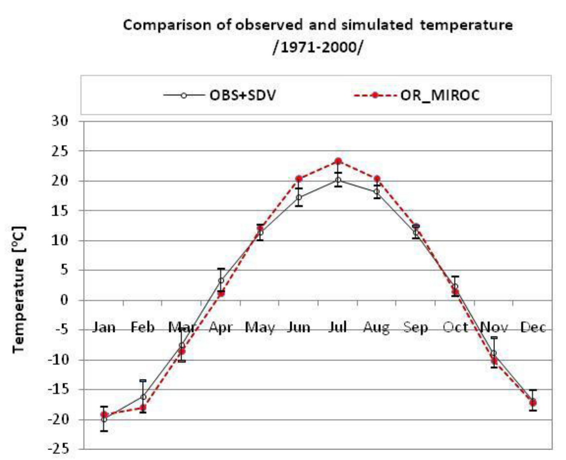


Fig.3 Comparison of observed and simulated monthly precipitation (top) and monthly mean temperature (bottom) (OBS: observed value, OR_MIROC: uncorrected original output of MIROC. Gray shaded area indicates the area within OBS+SDV)

well agreement between observed and simulated values, which behave steady large amount of bias.

3.2. Analysis of downscaling

After downscaling and correcting, the MBEs were removed for each month for both temperature and precipitation (Table 1). The SDV values of bias corrected annual means were in same order as of model annual means, because the present method does not influence the variability of the series of data. The SDV of CDF-based downscaled temperature was closer to the observed temperature variation and the values were lying in the lowest level.

Magnitude of the RMSE reduction in the precipitation was larger (~60%) than that of the temperature (~6%). The results of CDF-based downscaling method were slightly improved in the RMSE of precipitation compared with the bias correction method. Magnitude of the RMSE in temperature was not significantly improved by both methods. As shown in Table 2, the RMSEs were significantly reduced by 33%-36% for monthly precipitation and 16%-21% for monthly mean temperature.

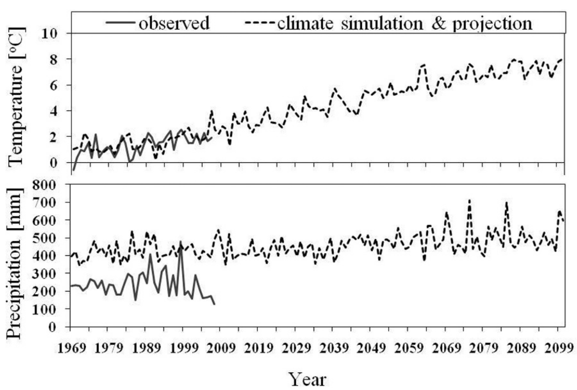


Fig.4 Comparison of inter-annual variation of observed and modeled climate variables, 1969-2100
(Top: annual mean temperature, Bottom: annual precipitation)

The CDF-based downscaling had better performance in precipitation compared to bias correction method, although it made worse in July for precipitation. Reduction of error varies by months and the biggest reduction observed in precipitation of March. Summer precipitation, especially for July and August, was not improved much. However, for example, overestimation of precipitation in July was reduced to 12% by bias correction method. This is accordance with Kimura and Sato (2004), which downscaled a precipitation over Mongolia using regional climate model with 10%-20% underestimation.

The RMSE of climate model temperature was not as high as RMSE of precipitation. In May and September, it was the lowest value. The RMSE was higher in March, July and November. Generally, bias correction method showed improvement in the RMSE. Since summer, e.g. through June to August, temperature had comparatively higher warm-side bias, the RMSE of those month's temperature was significantly improved.

In general, the both methods showed comparable performance in improving GCM during the control period. Since the CDF-based downscaling method demonstrated slightly better skill in precipitation, it was recommended for a suitable modification in future projection data. The precipitation in July and August was not modified, because the MBE was in the level of a unit of the SDV (Figure 3, top) and the CDF-based downscaling did not improved July precipitation.

Table.3 Simulated (1971-2000) and projected (2011-2040 and 2071-2100) climate

	1971-2000	2011-2040	2071-2100
Precipitation [mm]	249.3	280.5*	350.7**
Temperature [°C]	1.2	3.2**	6.7**

* Statistical significance $p<0.05$
** Statistical significance $p<0.01$
Note: This statistical significance indicates that the values for 2011-2040 and 2071-2100 significantly, e.g 95% and 99%, different from values for 1971-2000.

Table.4 Future change of seasonal precipitation [%], compared to control period (1971-2000)

Periods	Precipitation change [%]			
	Summer	Winter	Spring	Autumn
2011-2040	13.2	38.5	-18.8	26.4
2071-2100	30.6	193.7	59.9	50.7
	Temperature change [°C]			
2011-2040	1.8	3.1	1.0	2.3
2071-2100	5.3	6.8	3.8	6.0

4. Future climate condition

Modified future projection showed that annual mean temperature was projected to be 3.2˚C ($p<0.01$) by 2011 to 2040 and 6.7˚C ($p<0.01$) by end of the century (Table 3). Annual precipitation was projected to be 280.5mm ($p<0.05$) in 2011-2040 and 350.7mm ($p<0.01$) in 2071-2100. The projected increase in precipitation in eastern Mongolia was also revealed by Batima *et al.*'s (2005) study. In terms of seasonal precipitation, winter precipitation increase was expected to be higher in both periods (38.5%-193.7%), while summer precipitation increase was projected to be lower (13.2%-30.6%), compared to other season's precipitation (Table 4). These increases were higher than that in projection of Batima *et al.* (2005). Their projection showed 12.6%-119.4% increase in winter precipitation and 2.5%-11.3% increase in summer precipitation by 2020, 2050 and 2080. In addition, spring precipitation was projected to decrease in present study by 2011-2040. For temperature, winter temperature increase was projected to vary from 3.1˚C to 6.8˚C, which is the highest among seasons, whereas summer temperature increase was projected to be 1.8 ˚C -5.3˚C (Table 4). These increases in temperature were a bit lower than that in Batima *et al.*'s projection. It is important to note that spring temperature increase was the lowest among temperatures in seasons.

Seasonal distribution of the annual precipitation was probable to change. Figure 5 shows that winter precipitation ratio in annual precipitation was expected to gradually increase. Slightly small increase will appear in summer precipitation ratio in annual precipitation by 2011-2040. By end of the century, summer precipitation ratio in annual precipitation was projected to decrease from 73% to 67%. The similar trend is expected to be observed in autumn precipitation. In contrast, spring precipitation ratio in annual precipitation was expected to decrease by about 3% by 2011-2040 and then it was projected to increase by about 5% by 2071-2100.

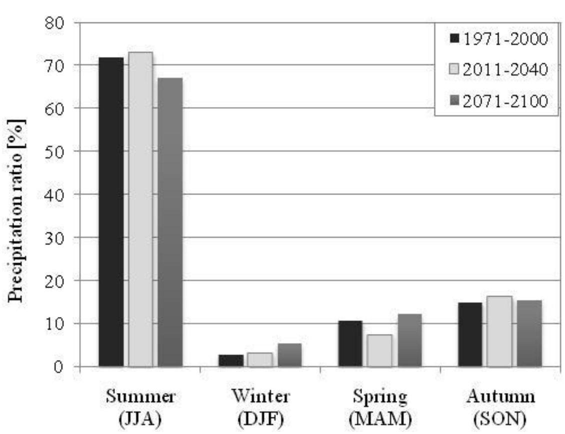


Fig.5 Change of seasonal precipitation ratio in annual precipitation

Future monthly precipitation and mean temperature change relative to 1971-2000 were different with months (not shown). For monthly precipitation, precipitation in all months, except in May and July, was expected to increase by 3% to 64% in 2011-2040, compared to that in 1971-2000, and this increase was projected to extend to 19% and 24% by end of century. Precipitation in May and June was expected to decrease by 46% and 1% in 2011-2040, respectively. Projected precipitation in January and February in 2071-2100 was higher than observed precipitation in March in 1971-2100. Although January precipitation change projected to be the highest not only in 2011-2040 but also in 2071-2100, projected amount was still less than 6mm. Although projected precipitation in July in 2071-2100 was 93.6mm, the increasing rate was the lowest. Precipitation in May was expected to decrease by about 45% in 2011-2040. Those are unfavorable condition for pasture growth. Projected precipitation in August was almost similar to projected precipitation in July by end of century.

For monthly mean temperature, all months' mean temperature, except March, were expected to increase by 1.3˚C to 4.0˚C in 2011-2040 and all months' mean temperature were expected to increase by 2.5˚C to 7.3˚C in 2071-2100, compared to monthly mean temperatures in 1971-2000. In addition, by end of century, temperature in January and December were projected to be warmer than that is in February of 1971-2000. Temperature warming projected to be stronger in 2071-2100. Inter-annual variation of temperature in April and January shows gradual increase in both temperatures.

Generally, summer precipitation change projected to be the lowest in selected two periods, in contrast, winter precipitation increase projected to be highest in 2071-2100.

In conclusion, climate in eastern part of Mongolia was projected to be warm and normal in 2011-2040 and warm and wet in 2071-2100, compared to climate in 1971-2000. Summer expected to be warm and dry and winter was projected to be warm and wet. Warming more pronounced in autumn compared to spring. Spring likely to be wetter in 2071-2100. July precipitation, which is important factor for pasture growth, was expected to hardly change, whereas January temperature warming was obvious.

5. Conclusion

Since there was a lack of the studies on GCM performance and its correction and downscaling over Mongolia, the present study would be contribution to this field.

The examination of performance of MIROC3_2_hires showed that the model overestimated the precipitation for all months by 116% to 427%. The temperature was well represented by the model; annual mean temperature in control period was simulated 0.27°C warmer than observed temperature. Inter-annual variability was relatively reasonable, especially for temperature. This analysis shows that over Mongolia, MIROC3-2-hires performance could be comparable with other GCMs's performances, which were used in Dagvadorj *et al.*'s report (2009). However, MIROC3-2-hires simulation still has certain error and in order to use for future impacts models, we need to correct the error or downscale them to regional scale.

In present study, the comparison between CDF-based downscaling method and bias correction method was done. The comparison indicates that the performance of both methods were comparable. However, due to its performance on precipitation, CDF-based statistical downscaling was selected and used for modification for future projection.

Modified future projection projected the climate over eastern part of the country as warm and normal by 2011 to 2040 and warm and wet by end of the century compared to control period.

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