Development of Regional Climate Scenarios Using a Downscaling Approach

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DEVELOPMENT OF REGIONAL CLIMATE SCENARIOS USING A DOWNSCALING APPROACH

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Abstract. As the debate on potential climate change continues, it is becoming increasingly clear that the main concerns to the general public are the potential impacts of a change in the climate on societal and biophysical systems. In order to address these concerns researchers need realistic, plausible scenarios of climate change suitable for use in impacts analysis. It is the purpose of this paper to present a downscaling method useful for developing these types of scenarios that are grounded in both General Circulation Model simulations of climate change, and *in situ* station data. Free atmosphere variables for four gridpoints over the Missouri, Iowa, Nebraska, Kansas (MINK) region from both control and transient simulations from the GFDL General Circulation Model were used with thirty years of nearby station data to generate surface maximum and minimum air temperatures and precipitation. The free atmosphere variables were first subject to a principal components analysis with the principal component (PC) scores used in a multiple regression to relate the upper-air variables to surface temperature and precipitation. Coefficients from the regression on station data were then used with PC scores from the model simulations to generate maximum and minimum temperature and precipitation. The statistical distributions of the downscaled temperatures and precipitation for the control run are compared with those from the observed station data. Results for the transient run are then examined. Lastly, annual time series of temperature for the downscaling results show less warming over the period of the transient simulation than the time series produced directly from the model.

1. Introduction

One of the major problems with using General Circulation Model (GCM) simulations for examining potential climate change is that it is difficult to extend the results of these coarse resolution models to local changes in climate. In particular, impacts researchers often need climate scenarios developed with a much finer spatial resolution than is currently available from GCMs. Furthermore, since a true change in the climate due to increasing greenhouse gases would be a transient change, it is desirable to have climate change scenarios in which the changes are transient. It is the purpose of this paper to present a methodology to develop transient regional scenarios of potential climate change that are grounded in the statistical distributions of observed station data but use information from a course resolution GCM simulation. In this paper the scenarios will deal specifically with temperature and precipitation, since these are the most widely observed and analyzed variables. However, scenarios for other climate variables may be developed if observations are available for use in the methodology.

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There are a number of approaches currently available to develop scenarios of potential climate change: (1) modification of observed station data, (2) the use of weather generators, (3) the direct use of climate model simulations, or (4) an approach that combines information from both observed station data and a model simulation (Robinson and Finkelstein, 1991). Each approach has potential strengths and weaknesses. In the first approach modification of observed station data can be done in a number of ways. The simplest approach is to add or subtract some specified offset to each observed value, with the offset value determined via climate change theory. However, the major problem with this approach is that it does not take into account changes in the higher statistical moments that are likely to be encountered in a true change of climate (Katz and Brown, 1992). Palecki et al. (1996) propose another approach to the modification of observed station data by using a calendar shift. Here again a target offset is determined (e.g., a warming of 3 °C), then the values for a particular day are shifted to a different date such that the average difference between the two dates is approximately equivalent to the desired offset. In both station modification approaches they have the advantage of being grounded in observed station data, yet have the disadvantage of a lack of modification to the higher statistical moments. Modification to the variance can be done by using a variance inflation factor. However the warmest parts of the year must be simulated in some way thereby mixing observations and simulated data.

Weather generators are useful for examining the effect of changes in the mean or variance when the generated values are used as input into impacts models (Mearns et al., 1996; Riha et al., 1996). However, like the modification of station data approach, changes in either the shape or scale parameters of the distribution must be determined either through general assessments of climate change (e.g., IPCC, 1996) or simply arbitrarily set.

The direct use of model output has the advantage of providing scenarios explicitly from climate change experiments. However, there are still many problems in the surface climate parameters generated via modeling, mainly due to problems in specifying the local surface climate. Furthermore, the most desirable method for using model output directly as climate scenarios is through the use of nested regional climate models (Giorgi et al., 1993), however this method is currently time-consuming and costly for developing long-term climate scenarios.

The last approach to providing climate scenarios is to perform a statistical downscaling using both observations and GCM simulations. In this approach statistical transfer functions are developed between observed free atmosphere variables and observed surface variables. These transfer functions are then used with free atmosphere variables from a GCM simulation to generate values for surface variables. Downscaling has the advantage of using information from both observed station data and model simulations of climate change, but may also have disadvantages, such as the variance inflation problem in which the downscaled values do not contained enough variance and must have the variance artificially increased in some manner.

Karl et al. (1990) introduced a downscaling approach, termed Climatological Projection by Model Statistics (CPMS), that uses a combination of rotated principal components analysis (RPCA), canonical correlation analysis (CCA), and inflated multiple regression (IMR). In this approach the RPCA is used with the free atmosphere variables, then the RPCA scores are used simultaneously with surface temperature and precipitation in the CCA. Finally, the CCA scores are used as predictors in the IMR to develop the regression equations. These regression equations are then used with the CCA scores derived using free atmosphere variables from a GCM simulation to generate surface temperature and precipitation values. This approach has its basis in model output statistics and perfect prog approaches to developing temperature and precipitation forecasts (Klein, 1982; Glahn, 1985) and has the potential for providing site specific climate change scenarios.

Other approaches to downscaling use different statistical methodologies but the basic idea of developing statistical transfer functions is the same. Matyasovszky and Bogardi (1995) use kernel techniques to estimate probability distributions for daily precipitation for one location using 500 hPa heights, and Hewitson (1995) and McGinnis (1997) use neural nets in place of regression, leaving out the RPCA and CCA steps to generate values for monthly precipitation and snowfall respectively.

For this paper an approach similar to that of Karl et al. (1990) is taken to generate regional climate scenarios monthly surface maximum and minimum air temperature for the Missouri, Iowa, Nebraska, Kansas (MINK, Easterling et al., 1993) region (Figure 1) using both the results of GCM simulations and observing station data. The MINK region was chosen because we intend to use this methodology to develop transient climate change scenarios for this region and assess the transient effect on agricultural production.

2. Methods

The methodology presented here is suitable for use with a transient GCM simulation and is performed for each individual observing station from a high-resolution network of stations resulting in a resolution comparable to the *in situ* observing network. The model simulation and observed data used for this study are monthly averaged values, since most GCM simulations are available only with monthly resolution, however, the method can be extended for use with daily simulations. Also, if daily values are needed for use in an impacts model, one approach would be to use a weather generator to simulate daily values based on the monthly output.

Figure 1 shows that each of the states in the MINK region except Iowa has a model gridpoint located within the state borders. The closest gridpoint to Iowa is in Illinois, hence the First-order station at Peoria, IL was also used. In other approaches to downscaling, results are usually presented for only one gridpoint-observing station pair where both the observed surface and free atmosphere obser-

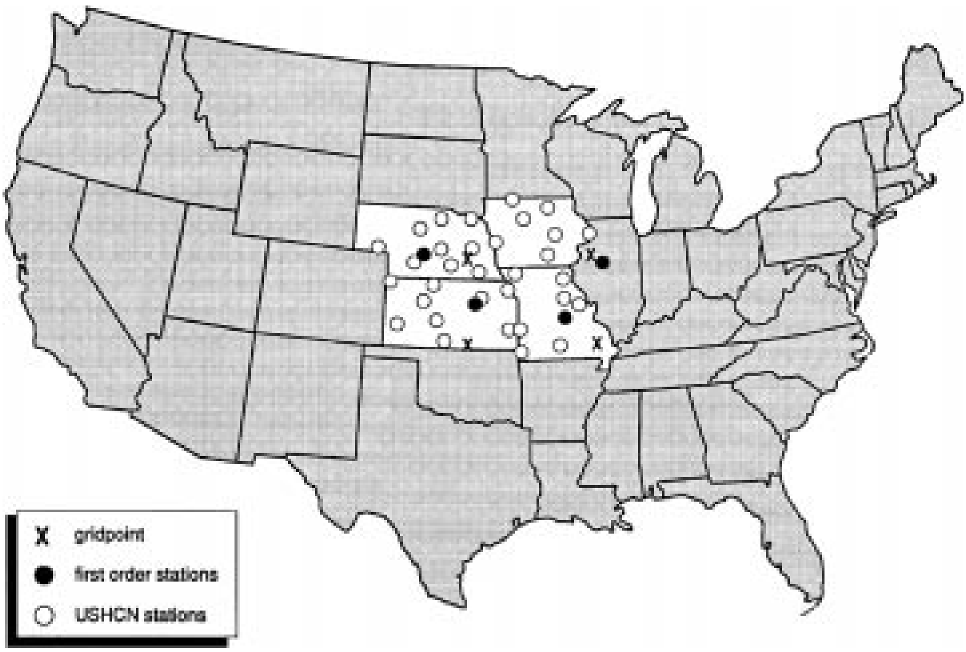

Figure 1. Location of the Missouri, Iowa, Nebraska, Kansas (MINK) region with stations and model gridpoints.

vations came from a single station (e.g., Karl et al., 1990) or for a region (McGinnis, 1997; Crane and Hewitson, 1998).

Here free-atmospheric data are taken from four GCM gridpoints, along with four nearby First-order stations within the study area (Table I). However, for the surface based observations (temperature and precipitation) a network of 32 stations from the United States Historical Climatology Network (USHCN, Easterling et al., 1996) were chosen along with the surface data at the four First-order observing stations (Figure 1). Hence, the spatial resolution is not constrained by the resolution of the model but by the resolution of the surface observing network. Lastly, it is shown here that this method can be used with a transient GCM simulation, where CO_2 and other time varying quantities, such as atmospheric aerosols, are changed over the period of the simulation.

The GCM simulations used for this study are from the Geophysical Fluid Dynamics Laboratory (GFDL) model as described in Manabe et al. (1991) and Manabe et al. (1992). This is a coupled ocean-atmosphere model with an approximate resolution in the atmospheric part of 5° by 7° latitude-longitude. Two simulations were used: a 97-year control simulation where atmospheric carbon dioxide was held constant at approximately 315 ppmv, and a 97-year transient simulation where carbon dioxide was started at 315 ppmv and increased 1% each year above the previous year's level. Only the last 97 years of the simulation were used, since the first two years were identical due to a spin-up problem (R. Stouffer, personal com-

TABLE I

Variables used in the downscaling procedure (monthly values). Predictor variables are taken from the four upper-air observing stations and the four GCM gridpoints, predictands are taken from the USHCN network of 32 stations

Predictors	Level
Geopotential height	850, 500 hPa
Temperature	500 hPa
Relative humidity	500 hPa
u and v wind components	500 hPa
Predictands	
Maximum, minimum temperature	Surface
Total precipitation	Surface

munication). Free atmosphere variables from both the model simulations and the four First-order observing stations were used (Table I). Temperature and relative humidity at 850 hPa were not used since the model gridpoints for two locations did not contain these variables due to their model elevation being above the 850 hPa level.

Data from the observing stations were used to develop the transfer functions between the free atmosphere variables and maximum and minimum air temperature and precipitation at each surface observing station for each month. The flow of the methodology is shown in Figure 2. The first step was to subject the free-atmosphere variables at all of the four First-order stations to one rotated principal components analysis (varimax rotation) for each month. This provided for more spatial correlation in the results. Screen test results indicated the first four PCs should be used, which typically accounted for approximately 90% of the variance in the input variables. The scores for the first 4 PCs were then used in a standard multiple regression procedure at each station to calculate the regression coefficients establishing the relationship between observed free atmosphere variables and the surface temperature and precipitation at each station for each month. The regression results (r^2) for each variable over all the stations and months ranged from 30–70% for maximum temperature, 30–78% for minimum temperature, and 10–60% for precipitation. The same free atmosphere variables for each gridpoint from the GCM simulations (both the control and transient) were also subjected to a RPCA retaining the first four components. The resulting PC scores were then used with the regression coefficients to generate the surface maximum and minimum temperature and precipitation at each of the 32 USHCN station locations

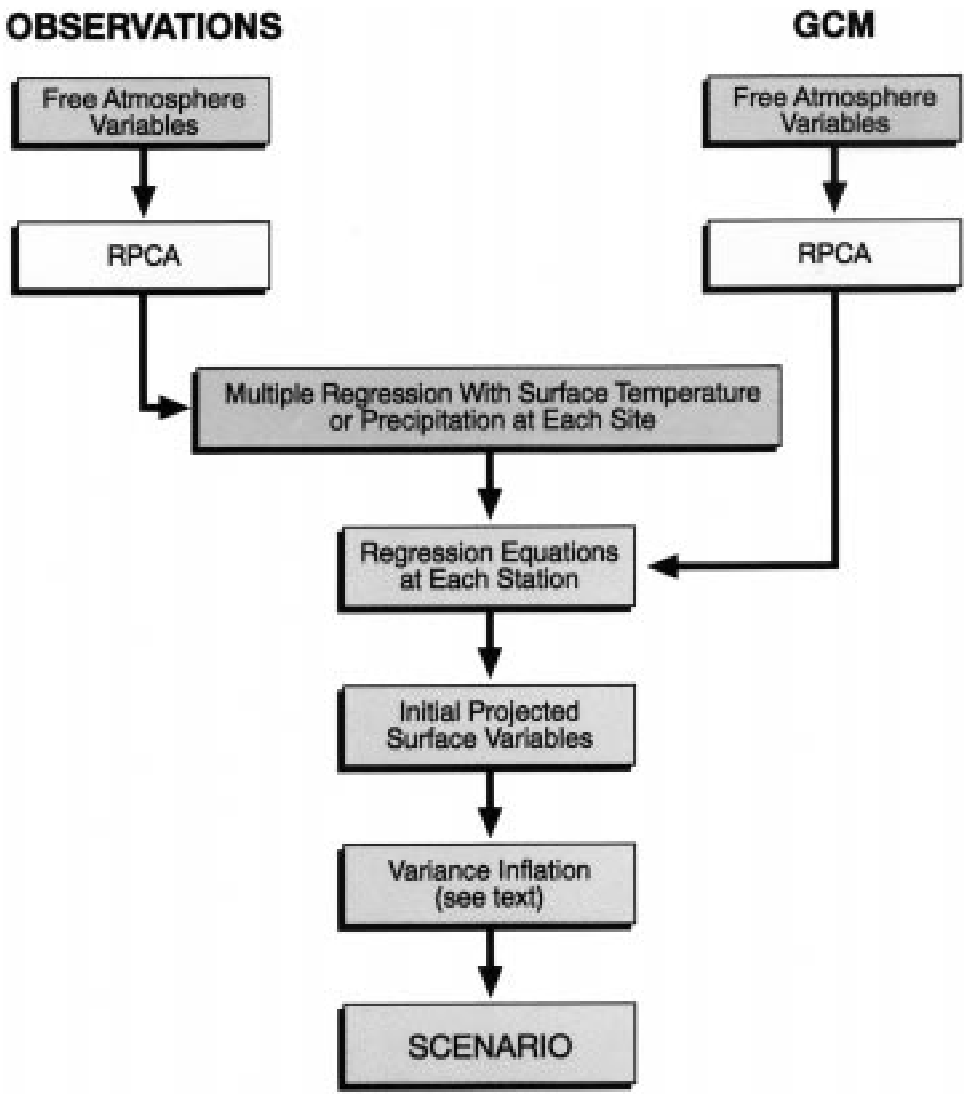

Figure 2. General flow of the downscaling methodology.

and the four upper-air observing stations. Inspection of the rotated factor pattern for both the RPCA on the observed and on the GCM free atmosphere variables indicated that the first rotated component (RC) was temperature and geopotential height related, the second was most strongly related to the U wind component, the third most related to the V wind component, and the fourth RC was the humidity component.

It is well known that regression estimates typically underestimate variance, in particular extreme values, hence the use of a variance inflation factor to realistically simulate the observed statistical distributions is required (Klein et al., 1959). Karl et al. (1990) showed that for a control simulation of the Oregon State University GCM, with no time varying greenhouse forcing, the use of inflated regression (Klein et al., 1959) could reproduce almost exactly the mean and variance in surface climate parameters using their downscaling approach. However, inflated regression was not appropriate for use in this methodology since the model simulation is a transient run and any trend present in the downscaled surface variables would be affected by the use of inflated regression. This is because the inflation process involves subtracting the mean value from each element of the time series, then dividing the result by the multiple correlation coefficient, then adding back the mean. Therefore, with a monotonic trend present, the trend is enhanced by division of each residual from the mean by a value less than 1.

Since the objective here, as it is with any climate scenario generation scheme, is to develop *plausible* scenarios, the following procedure was used to inflate the variance of each time series:

1. each of the monthly time series at each of the 32 stations were first detrended using simple linear regression;
2. each detrended time series was converted to z-scores, then re-formed back into either temperature or precipitation time series using the standard deviations calculated using the observations at that station for that month;
3. the simple linear trend was added back to each time series.

Since some form of variance inflation is required, this method was devised to provide, at least for the control simulation, variance that is similar to that found in the observations. Extending this to the transient simulation requires the assumption that the transient response in the temperature and precipitation variables from the simulation will contain some form of trend and that variance must be added around this trend. However, if there is no trend in the downscaled values from the transient simulation then the detrending exercise is just one additional step, which neither adds, nor subtracts anything from the downscaled values.

This raises additional questions regarding variance inflation, such as the potential for changes in the variance under transient conditions, and even the application of this approach to a transient simulation where there is intentional climate change due to time-varying greenhouse gas concentrations. One of the major assumptions of this approach and any statistical downscaling approach is often called the ‘invariability’ assumption. This assumption maintains that there are certain physical relationships underlying the statistical relationships developed here, and that these physical relationships (e.g., lowering geopotential heights, coupled with increasing relative humidity, etc. increases the potential for precipitation) hold regardless of whether the model simulation is a control or transient. While it is likely true that major features, such as the El Niño-Southern Oscillation (ENSO) or the Pacific-North America (PNA) pattern will change under a changed climate, it is highly unlikely that the basic physical relationships, such as that described above, will change.

3. Results

In order to provide some measure of the robustness of the methodology, the regression equations were used to predict temperature and precipitation values for each month, at each station for the period of record of the observations. Comparisons were then made between the predicted and observed values at each station. Correlations between the predicted and observed values were typically on the order of 0.8 to 0.9 for maximum temperature, 0.7 to 0.8 for minimum temperature and 0.4 to 0.7 for precipitation. The results for precipitation varied the most seasonally, with summer usually showing the least correlation, and winter the most. Comparison of mean values of the predictands for each month at each station showed that, in general the method reproduced well the observed means, and variances, with no obvious tendency to over- or under-predict values for any of the three predictands.

In previous studies comparisons were made between the statistical distributions of observed data and the statistical distributions of the parameters from the downscaling performed with a control simulation. For example, Karl et al. (1990) showed that the downscaling results for their CPMS approach almost exactly reproduced the means and variances for daily surface temperature and precipitation at each of five station-gridpoint pairs. The station-gridpoint pairs were chosen such that each represented a different climate to illustrate the robustness of the methodology across different climatic regimes. Secondly, since the CPMS methodology is regression-based it is not surprising that it would reproduce the means in the absence of a trend. The reproduction of the variance is a more encouraging result, particularly in the context of producing realistic scenarios of potential climate change.

In addition to assessing the downscaling results at one point in space, it is equally important that the methodology is able to realistically reproduce the spatial variation of the observed climate across the study region. First the downscaling results from the control simulation are compared with the observed values for the region in order to assess how well the statistical downscaling process reproduces the observed statistical distribution of temperature and precipitation over the region and by extension the observed local climate. Then the time series results are presented for the downscaled surface quantities at each of the upper-air observing stations.

The results for the annual values of maximum, minimum and mean temperature and precipitation for the observed data, downscaled control, and the modeled control averaged over the MINK region are shown in Table II. It is clear from this table that the statistical distributions of the results from the downscaling and the observed data are very similar. The biggest difference is in the precipitation, but even here the results are very similar. However, the results for the model simulation averaged over the four gridpoints show that the direct output does not compare well, with the mean temperature being very close to the minimum in the observed values, and the annual average precipitation being almost 25% too high.

TABLE II

Annual mean maximum and minimum temperature (°C), and precipitation (mm) for the observations and the downscaling performed with the control simulation averaged over the MINK area. Also shown are the model produced mean temperature and precipitation averaged over the MINK region. Included are the means, standard deviations and extreme values for each variable

	Mean	Std. dev.	Minimum	Maximum
Downscaled				
Maximum temperature	17.32	0.75	15.91	19.36
Mean temperature	10.58	0.67	9.12	12.30
Minimum temperature	3.84	0.63	2.32	5.36
Precipitation	780	113	442	1055
Observed				
Maximum temperature	17.32	0.85	15.71	19.19
Mean temperature	10.56	0.67	9.20	12.10
Minimum temperature	3.80	0.58	2.64	4.96
Precipitation	761	125	524	1051
Modeled				
Mean temperature	5.34	0.76	3.2	7.25
Precipitation	1021	114	762	1300

The root mean squared difference between the anomalies of annual mean temperature, defined as (max + min)/2, from the downscaling for the control simulation, and the anomalies of the model simulated temperature for the control is 0.70 °C, and the correlation between the two time series is 0.50. This indicates, that on an annual basis, the factors influencing temperature in the model simulation, and the statistical transfer function developed using the observed data work in similar ways, but often disagree.

The maps shown in Figures 3–11 provide the means to compare the spatial relationship between the mean maximum, and minimum temperature and average precipitation for the downscaled and observed values at each USHCN station both

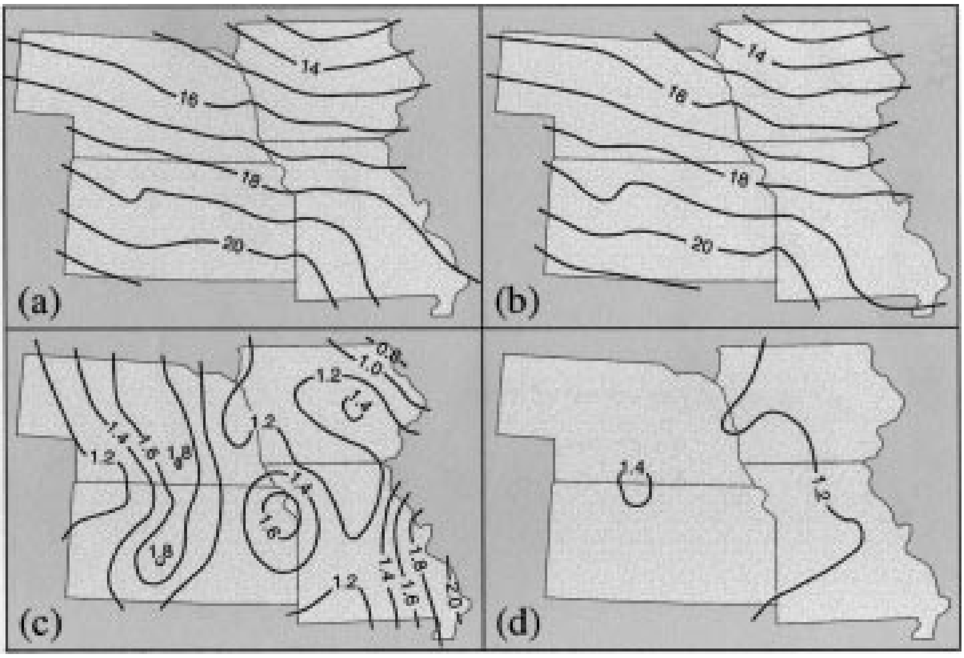

Figure 3. Maps of the annual mean maximum temperature (°C) for, (a) observations and, (b) downscaled using the control simulation, and standard deviation for, (c) observations and, (d), downscaled using the control simulation.

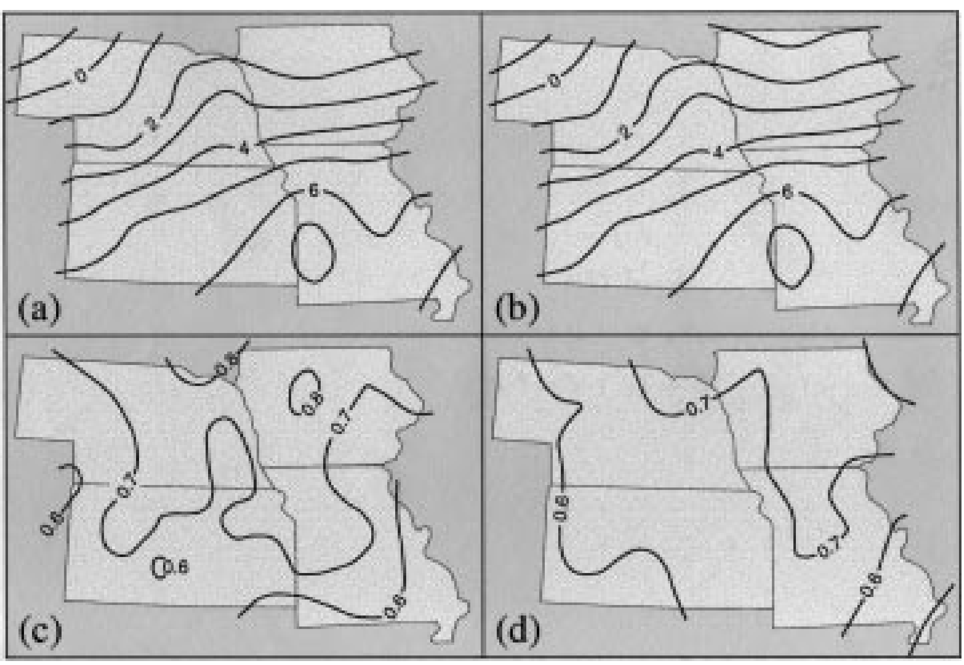

Figure 4. Same as Figure 3 except for annual mean minimum temperature.

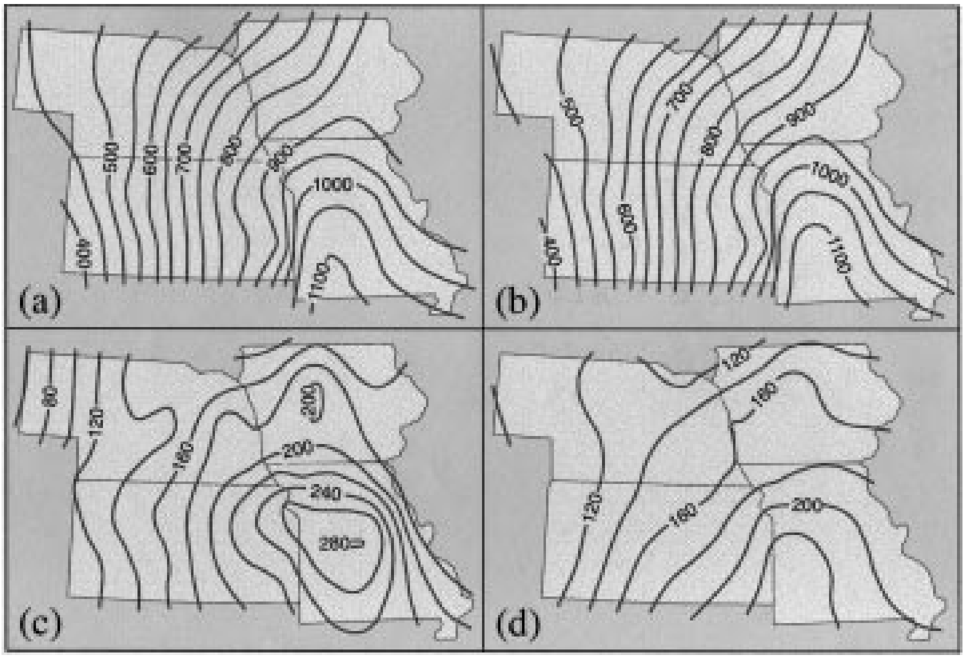

Figure 5. Same as Figure 4 except for the annual average precipitation (mm).

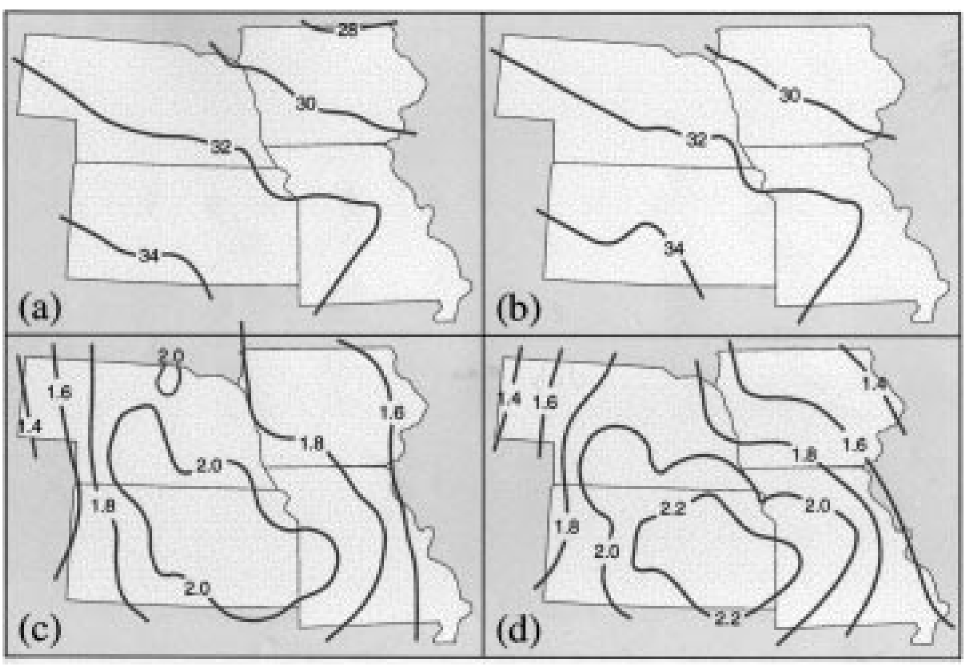

Figure 6. Same as Figure 2 except for July average maximum temperature.

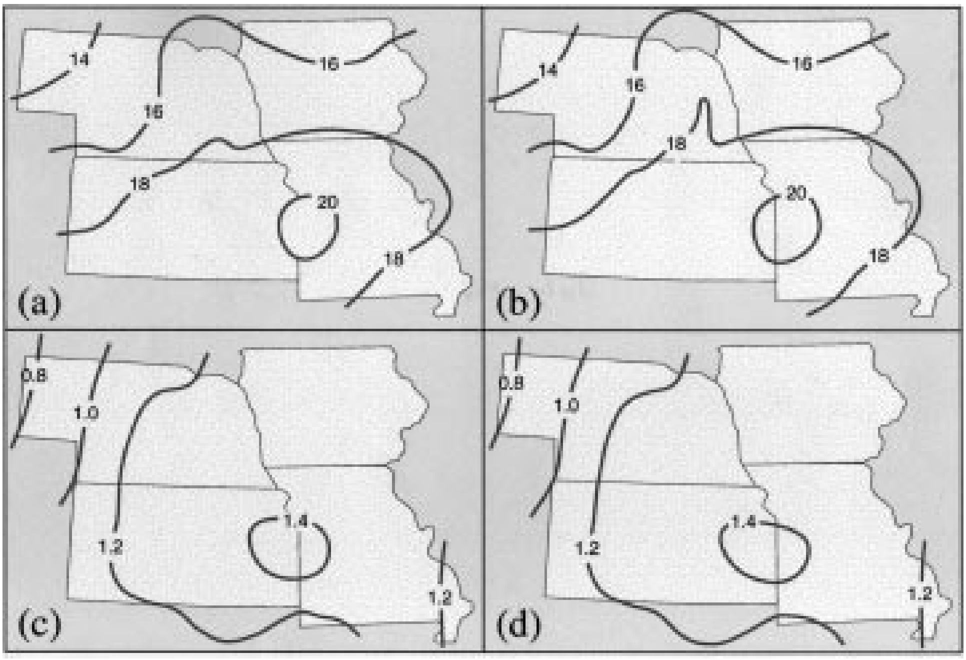

Figure 7. Same as Figure 2 except for July average minimum temperature.

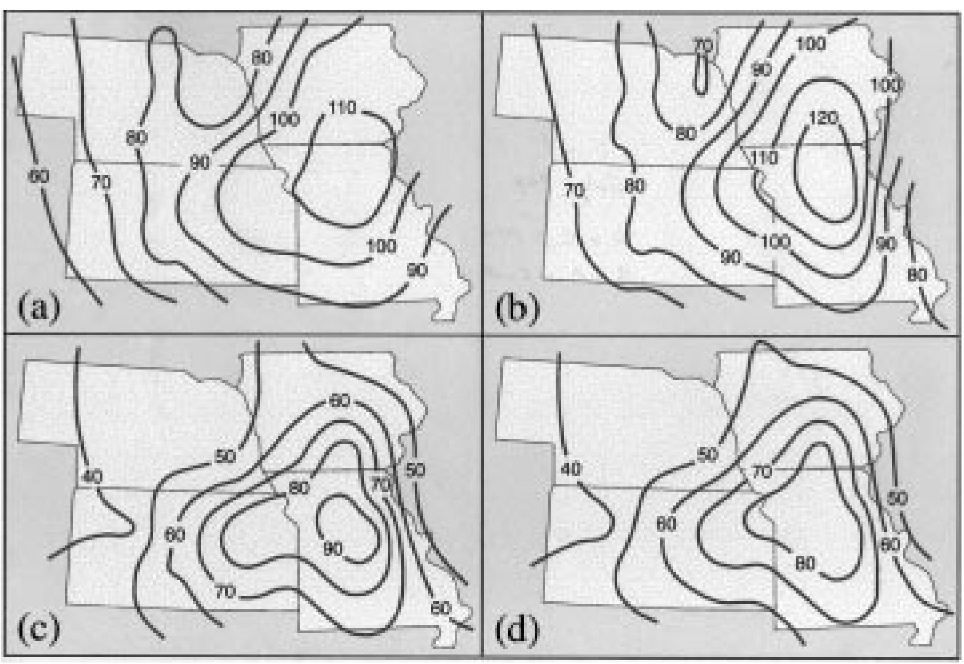

Figure 8. Same as Figure 5 except for July average precipitation.

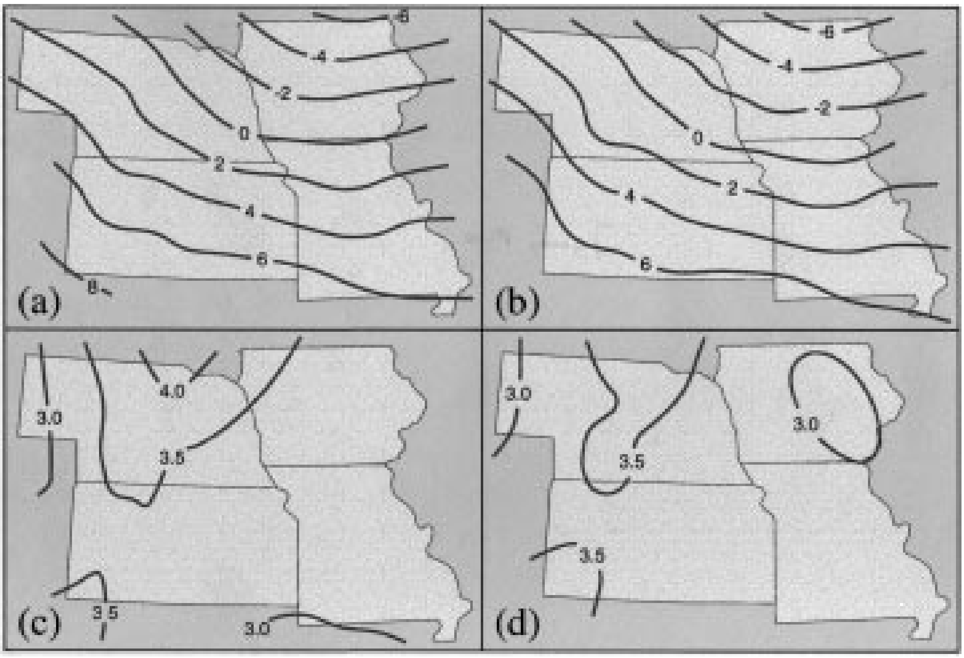

Figure 9. Same as Figure 2 except for January average maximum temperature.

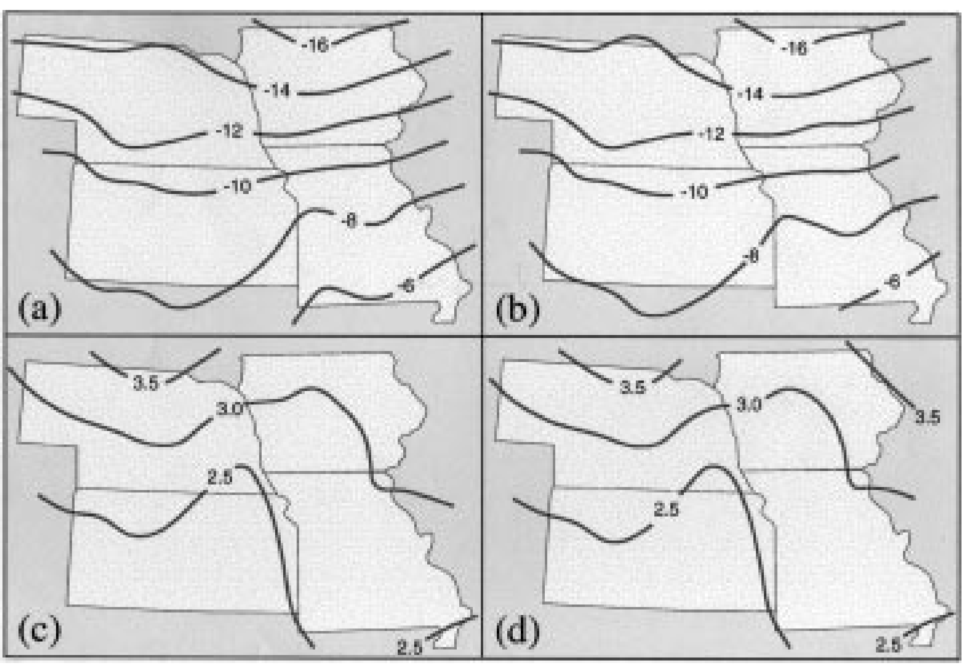

Figure 10. Same as Figure 2 except for January average minimum temperature.

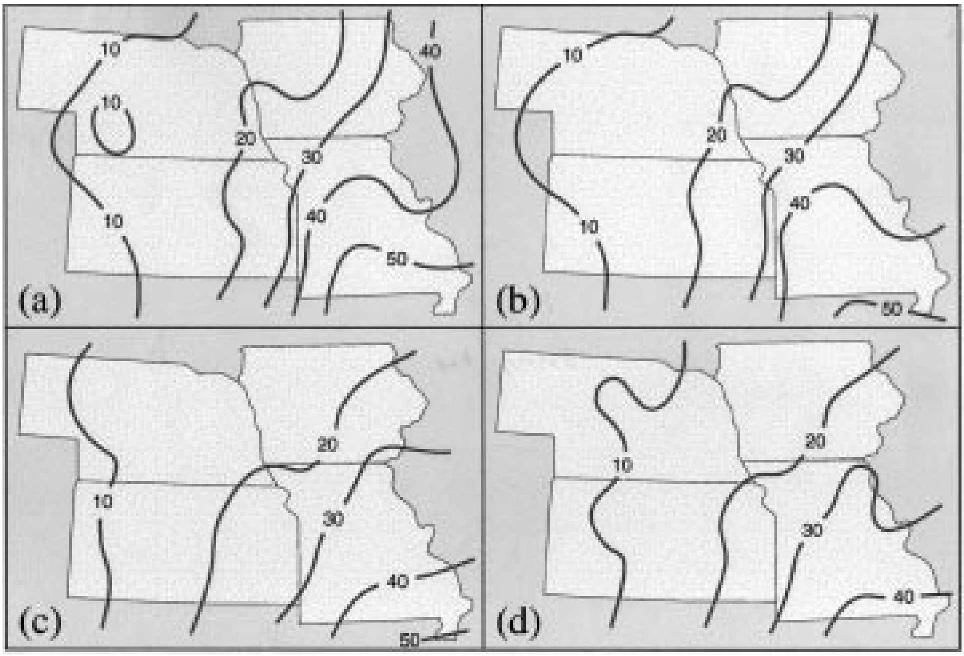

Figure 11. Same as Figure 5 except for January average precipitation.

on an annual, and monthly basis. The important point is to insure that the downscaling procedure is able to capture realistically the spatial variation of both of the mean values, and the variance. The maps showing the mean annual maximum and minimum temperature and precipitation that the procedure captures the spatial variation of each of the parameters well. However, for the variance the procedure is somewhat conservative in the estimation, even with the variance inflation procedure described earlier. It performs reasonably well for the spatial distribution of the variance for precipitation and minimum temperature, however it is more problematic for the maximum temperature variance.

The monthly maps show similar results. However, for July the downscaling results show slightly higher variance than the observations in the area with the highest variance, however these differences are slight. The July minimum temperature maps are nearly identical, and for precipitation the downscaling shows slightly higher means, but slightly reduced variance. In January, the variance for the maximum temperature appears to be reversed from July in that the downscaling produces a slightly less variance than observed. Yet, for the minimum temperature and precipitation in January the downscaling nearly exactly reproduces the spatial distribution of the observed mean and variance.

Another way of examining the validity of the downscaling procedure for generating spatial climate scenarios is to examine the spatial correlation function for each parameter. This is shown by plotting all correlations between each station

TABLE III

100 year linear trends (°C) for the downscaled annual maximum and minimum temperatures at each First-order station and matching gridpoint downscaled using the transient model simulation, and slopes for the annual surface air temperature directly from the model simulation

Station/gridpoint	Downscaled max (slope/100 yrs)	Downscaled min (slope/100 yrs)	Model air temp. (slope/100 yrs)
N Platte, NE	4.26	2.61	4.7
Topeka, KS	3.64	2.86	4.8
Peoria, IL	3.73	3.5	5.2
Columbia, MO	1.42	2.0	5.1

pair as a function of distance, then fitting an exponential curve (Groisman and Easterling, 1994). The results for annual maximum and minimum temperature and annual precipitation for the downscaled values for both the control and transient simulation are shown in Figures 12 and 13, with the observed values also plotted on each graph. The comparison between the downscaled values for the control simulation and the observed values is perhaps the most meaningful. Here the correlation functions for the annual maximum temperature for both the downscaled control simulation and observations are shown by the smoothed, fitted lines which indicate that the downscaled values have a correlation about 0.1 higher than the observed values.

The same plot for the minimum temperatures however, show a much larger difference between the downscaled control simulation and the observations. This is likely due to microclimatic differences that tend to affect minimum temperatures more than maximums, and are not captured well by the large-scale features (free-atmosphere variables) used in the downscaling procedure. The results for annual precipitation also indicate that the downscaling procedure provides somewhat too much spatial coherence, with the difference on the order of 0.1 to 0.2 between the observed and downscaled correlations. It is clear from Figure 14 that the transient simulation downscaling produces even stronger spatial correlation than the control simulation results, with the biggest correlation difference (0.2–0.3) occurring with the minimum temperatures.

Table III includes the 100-year slopes for both the downscaled maximum and minimum temperatures, and the model calculated surface air temperature all using the transient simulation. This shows that the slope for both the maximum and minimum temperatures generated by the downscaling procedure are each less than the slope for the air temperature from the lowest level of the model.

One area of interest was whether the downscaled maximum and minimum temperatures from the transient simulation would show a decrease in the diurnal tem-

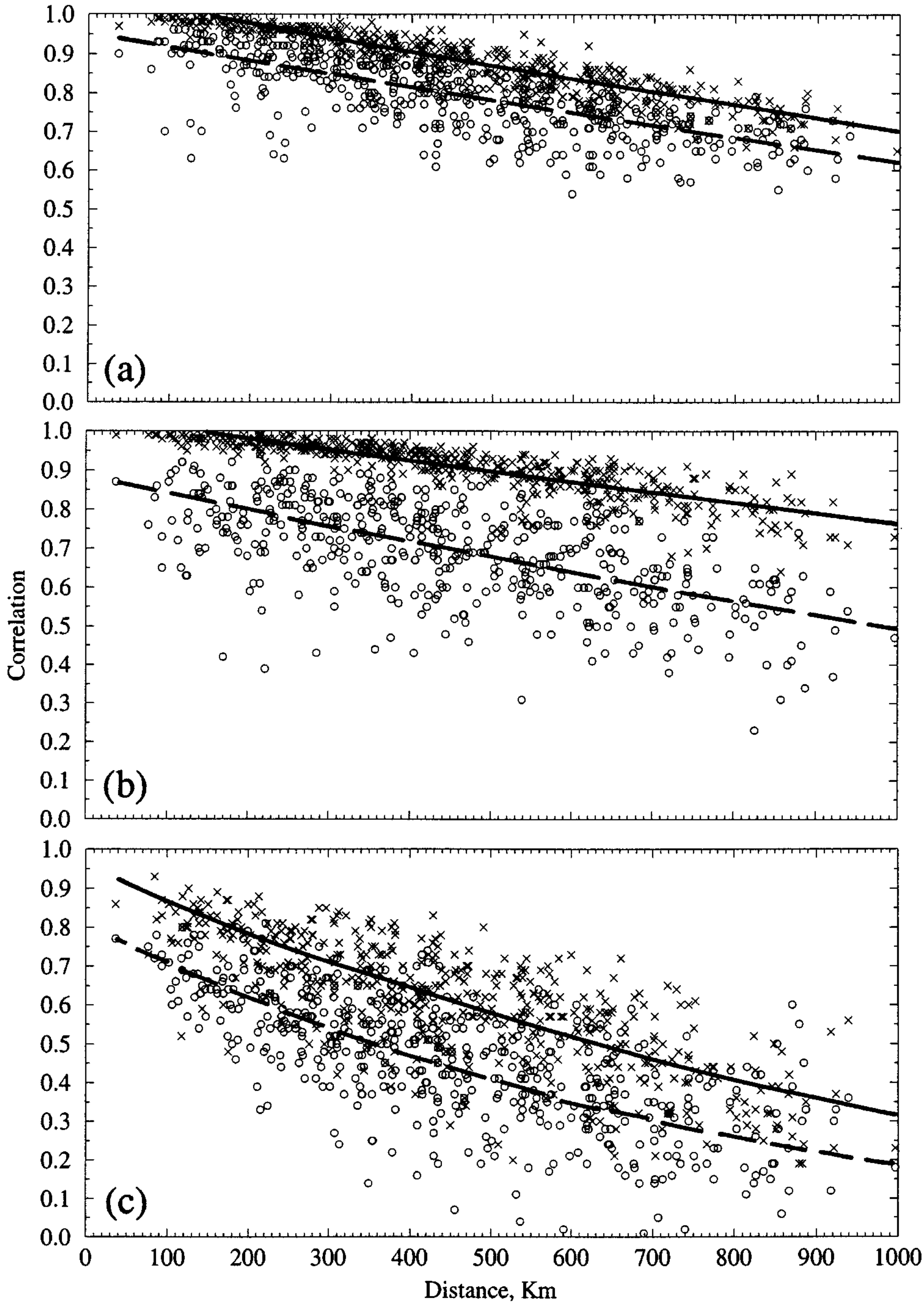

Figure 12. Spatial correlation of average annual maximum (a) and minimum (b) temperature and precipitation (c) for the downscaled control simulation (×'s and solid line), and observations (○'s and dashed line).

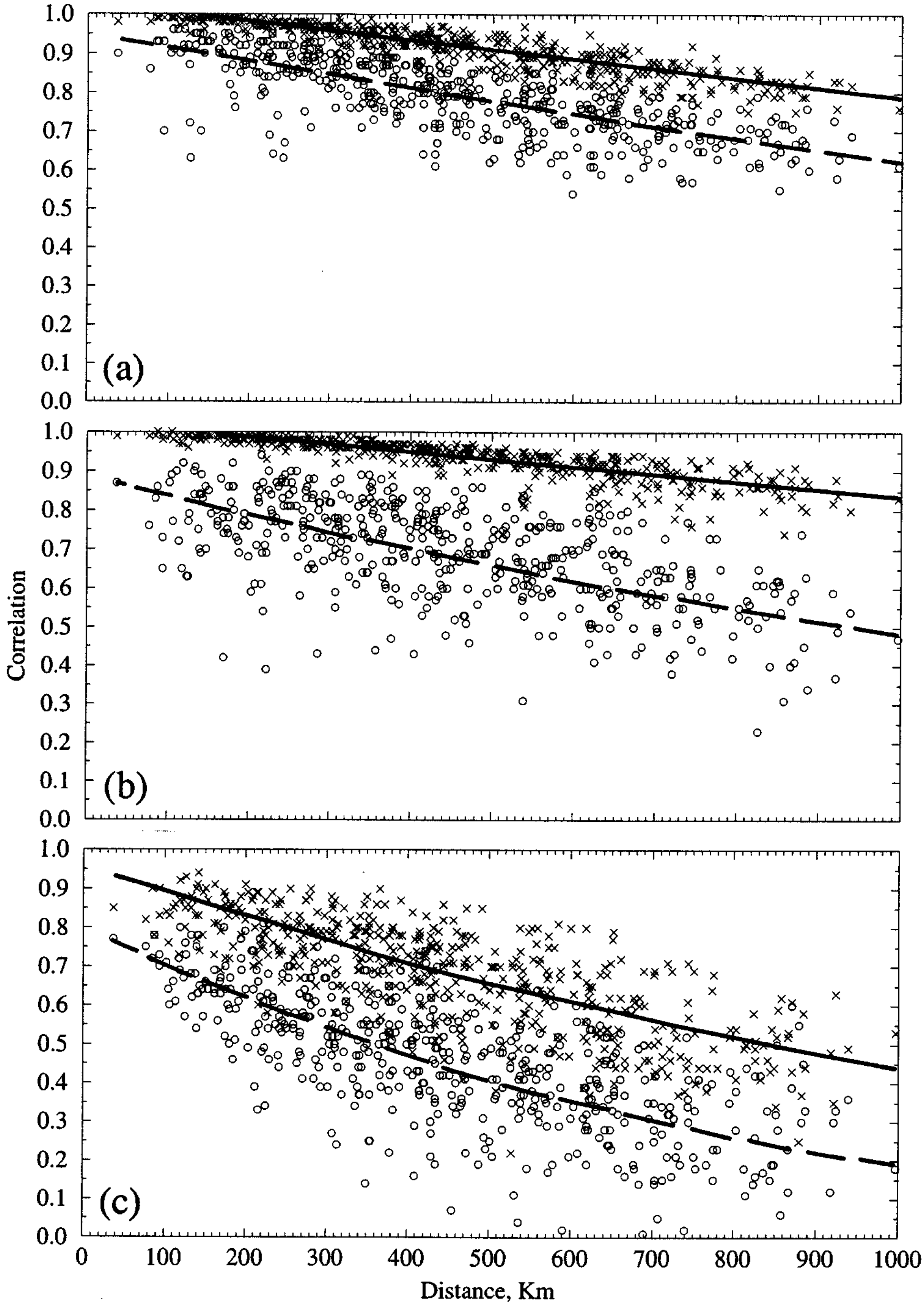

Figure 13. Same as in Figure 12 except the downscaling was performed using the transient simulation.

perature range (DTR, defined as the maximum-minimum temperature) similar to what has been found by researchers in many parts of the world (e.g., Karl et al., 1993; Easterling et al., 1997). However, the slopes for the generated maximum and minimum temperatures at each First-order station shows that at only one location, Columbia, does the diurnal temperature range decrease. Recent analysis of trends in the DTR at individual stations in the region indicate that changes are small and that the region as a whole appears to be a transition zone with adjacent stations showing small slopes of opposite sign.

4. Conclusions

A downscaling procedure has been presented that has promise for the generation of regional climate scenarios for use in climate impacts work. The procedure is developed specifically for use in transient GCM simulations where greenhouse gases and other radiatively active quantities are gradually changed over the period of the model simulation. The results of the downscaling procedure outlined here show that the downscaled climatologies of temperature and precipitation developed using the control GCM simulation closely resemble those of observed climatologies using the same network of stations. Furthermore, based on comparison with observed data, these results are clearly more realistic than that produced from the model simulation itself. This fact is not surprising, however, given the results of Karl et al. (1990), and keeping in mind both that the regression methodology tends to regress predicted values toward the mean (in the absence of a trend the intercept value is approximately equal to the mean), and the variance inflation method employed.

Comparison of downscaled and model simulated time series for temperature averaged over the region for the transient simulation shows that the downscaling procedure produces less warming over the nearly 100-year simulation that is produced by the model. The results of Manabe et al. (1992) indicate that much of the temperature increase in the simulation was due to a soil moisture-temperature feedback, with increased drying of soil during the summer leading to a greater sensible heat flux and warmer temperatures. Therefore it is possible that this surface warming increase did not as strongly affect the free-atmosphere, and only using the free-atmosphere variables to project the downscaled surface temperatures, results in less warming. However, there also remains the possibility that some of the difference in trends may be a statistical artefact.

Spatial correlation functions for each parameter show that, in general, the downscaling procedure produces somewhat too much spatial correlation, particularly for minimum temperature. These problems may be overcome with the use of GCM simulations with a daily rather than monthly resolution, which will allow the use of a number of additional free-atmosphere variables (e.g., day-to-day changes or thermodynamic parameters such as the K-index) that will likely lead to more spatial variation on a daily basis.

Lastly, the results of this procedure should prove useful for climate impacts researchers who desire both transient changes and better spatial detail in regional climate scenarios. However, one problem from an impacts standpoint is that the output from this example is on a monthly resolution, and agricultural impacts models, usually need information on a daily basis. Lacking a GCM with daily resolution, this problem may be overcome through the use of a weather generator designed to take monthly values and simulate daily values consistent with the monthly average of temperature or total precipitation.

Acknowledgements

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