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Statistically Downscaled Climate Change Projections for the Animas River Basin, Colorado, USA

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Mountain river basins provide the majority of western North America with snowmelt runoff water resources throughout the late spring–early summer snowmelt season. However, this snowmelt water resource is

extremely vulnerable to any changes in air temperature and precipitation. Studies of larger mountain river basins have projected potentially warmer and drier climates in the future, but the resolution of these studies is often incompatible with smaller basins and subsequent water resources planning. The purpose of this study was to test the potential of increasing the resolution of future climate projections by combining a series of surface and upper-level atmospheric

datasets using a statistical downscaling technique and to then project how the future climate could change for a typical small snowmelt fed mountain basin in western North America, the Animas River Basin, Colorado, over the course of the 21st century. Results indicated that, in general, a warmer and drier climate may occur, with this technique more effectively capturing changes in air temperature over precipitation. With this kind of data at hand, increasing levels of sustainable water resource planning for a range of future climate scenarios may be achieved for mountain river basins of a similar scale.

Keywords: Statistical downscaling; climate change; mountain river basins; general circulation model (GCM); snowmelt; USA.

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Introduction

Snowmelt is an important source of water for many mountain river basins across the western United States. The coverage of snowpack in upper river basins strongly controls the availability of water for the proceeding spring and summer months (Barnett et al 2004; Stewart et al 2005; Bedford and Douglass 2008). Research across this region has highlighted that many basins are experiencing warmer and drier climatic conditions overall, which is beginning to affect water resource availability (Dettinger 2005; Hamlet et al 2005; Regonda et al 2005). A shift in the timing and size of peak snowmelt runoff, for example, would require changes in water storage operations and releases to meet demands and prevent possible flooding from storage facility failure. From an ecological point of view these potential changes in local hydroclimatology would impact both spawning times and habitat availability for various aquatic species through flow alterations and increases in water temperature. This has already been documented in many stream systems throughout the Rocky Mountains, western United States (Covich et al 2003; Leppi et al 2012).

A change in the timing of snowmelt in response to a warmer and drier climate also has the ability to pose a

serious threat to the agricultural and recreational economic sectors of the western United States. The agriculture industry brings in around US\$4 billion each year to the state of Colorado alone. However, this is being threatened by warming temperatures with increased evaporation and earlier snowmelt leading to an increase in demand and competition for water resources that are already stretched to breaking point (Wagner and Baldwin 2003). Recreation in mountain environments across the western United States and other similar regions reliant on snowpack and snowmelt would also be severely hit placing greater pressure on water resource managers to meet demands. At greatest risk from a decreasing snowpack are the skiing industry, which would suffer from shorter seasons, and the white-water rafting industry, which could expect reductions in peak streamflow events (Lettenmaier et al 1999; Battaglin et al 2011). This places a further strain on diminishing water resources by sourcing the water for the artificially generated snow from local creeks (Wagner 2003).

Thus, the potential impacts of climate change on water resources within snowmelt-fed mountain river basins are wide-reaching and demand significant attention from local water resource planners. However, the majority of this research has focused on larger basins,

which are not wholly applicable for water resource planners of smaller mountain basins requiring higher resolution data. The key for water resource planners of these smaller mountain basins will be to project and plan for future changes in climate on a more localized basin scale. This may enable them to better prepare for potential impacts to local water resource availability and develop sustainable management practices.

General circulation models (GCMs) have been the forbearer to predicting future climates at various scales resulting from increased greenhouse gas-emission scenarios. Various GCMs developed at several climate institutions are available through the Intergovernmental Panel on Climate Change (IPCC). Although GCM resolution and accuracy has increased over the last decade, they are still generally unsuitable for application toward local-scale research and analysis (Wilby and Wigley 1997; Diaz-Nieto and Wilby 2005). As an example, GCM resolution is often produced at a scale in the order of 2.5° (about 300 km gridcells), whereas local-scale climate change analysis requires a scale on the order of 0.125° (<15 km gridcells) in order to capture local-level effects and processes (Salathe 2005; Timbal and Jones 2008). In the case of mountain environments GCMs generally fail to simulate surface climate variables due to the more complex surface topography present (Martin et al 1997).

One particular technique that has been developed to address this issue is statistical downscaling (SDS) (Ray et al 2008). SDS translates large-scale information from a coarse GCM gridcell scale down to the point scale of local climate station observations, making it more suitable for local level analysis. This is particularly crucial when considering changes to local hydrology arising from climate change that focuses on the basin scale (Salathe et al 2007). This method derives local climate information by developing a linear statistical model relating large-scale lower-to-upper atmospheric variables produced by a GCM (known as predictors, eg mean sea level pressure, geopotential height) to local surface climate variables available at climate stations (known as predictands, eg air temperature, precipitation) (Easterling 1999; Timbal et al 2003). Historical predictor data used to build the linear statistical relationship between the predictor and historical predictands are commonly taken from National Center for Environmental Prediction/ National Center for Atmospheric Research (NCEP/NCAR) reanalysis data (Timbal and Jones 2008). For precipitation, the choice of predictor variables is a particularly crucial step in the development of an SDS model as they should be able to capture the main forcings of precipitation development both historically and under a changed climate scenario (Charles et al 1999; Frias et al 2006; Timbal et al 2008). In particular, predictors that measure atmospheric circulation as well as moisture should be incorporated into any SDS model (Pittock 1993;

Wilby and Wigley 1997; Charles et al 1999). Indeed, Charles et al (1999) further found that predictors that measure relative moisture over absolute values developed a downscaling model that reproduced more accurate surface precipitation results.

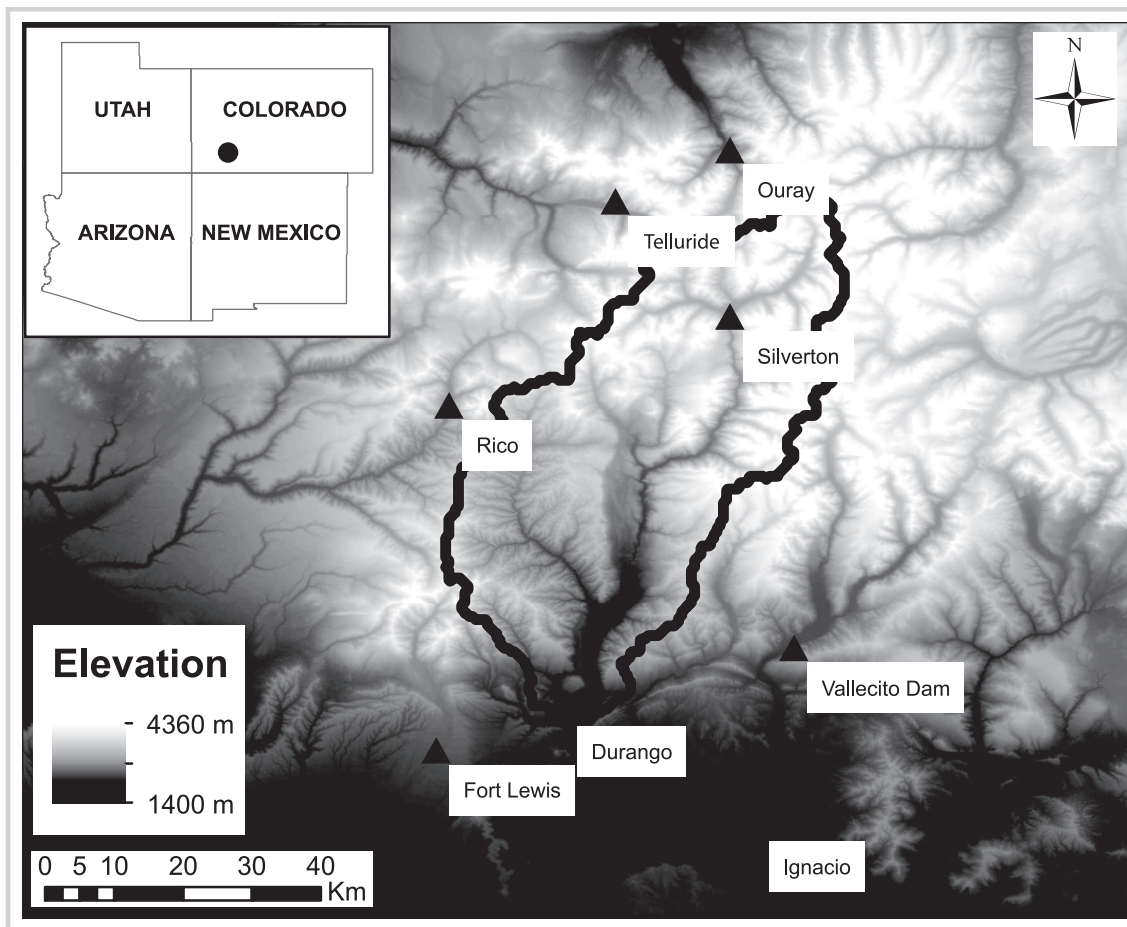
A major challenge to SDS in mountain environments is the spatial heterogeneity implicit in these locations, which will significantly affect surface precipitation over smaller river basins. Local topographic controls of precipitation include elevation and aspect. In order to account for this heterogeneity during the downscaling process it is essential to have long-term precipitation records for a series of surface-level stations at different elevations (Céleri et al 2007; Buytaert et al 2010). This approach has subsequently been used to successfully downscale climate variables across a wide range of locations, including mountain environments (Kidson and Thompson 1998; Landman et al 2001; Timbal et al 2003; Tryhorn and DeGaetano 2011).

While forecasts of this nature have been undertaken for larger mountain river basins, including the Colorado River Basin as a whole (CWCW 2010), they are somewhat lacking on a more localized scale more suited to smaller river basins. The main problem in bridging this change in basin scale lies with the availability of the necessary surface-level climate data for SDS. Smaller basins will often not have this data and as a result any SDS analysis will struggle to recreate historical surface-level conditions across the basin, even before any future projections are attempted. The purpose of this research was to analyze the potential of SDS to project future climate scenarios for a typical small snowmelt-fed mountain basin within the main Colorado Basin itself, the Animas River. In doing so, water resource planners of these kinds of basins may have greater access to more useful data, from a scale perspective at least, to plan for possible necessary sustainable practices concerning their water resources.

Study area

The Animas River basin covers an area approximately 1860 km² located within the larger Colorado River basin amongst the San Juan Mountains between 37.12 and 38.52 degrees latitude and 106.87 and 108.27 degrees longitude (Figure 1). The climate is typical of western U.S. mountain environments with mean annual temperatures ranging from 1.7 to 7.8°C between Silverton and Durango, located at the mouth of the basin. Mean annual precipitation ranges from 482 to 610 mm with the majority falling as snow in the month of January. The basin is typically free of snow during the months of July and August. The river, therefore, exemplifies a classic mountain snowmelt-controlled hydrological system, with the largest seasonal flows beginning in April–June in response to the spring snowmelt season (Figure 2). During this period, up to

FIGURE 1 The Animas River Basin and major towns. (Map by C. Andrew Day)

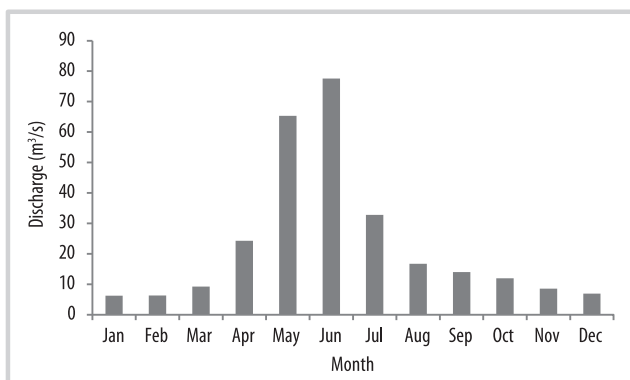


25 mm of snow water equivalent melt occurs each day within the basin (Blair 1996).

The region around the basin is still relatively sparsely populated, with the town of Durango being the only major population center (13,900 people) within the basin, although several smaller towns may be found in and around the proximity of the basin. However, the alpine environment attracts an increased tourist population in

the winter/spring snow season (CWCB 2005). The river is generally unregulated above Durango, but a major new water resource project, the Animas-La Plata project, came into operation in the spring of 2009. This included the construction of a pumping plant in Durango that will withdraw water from the Animas River into the Ridges Basin Reservoir just south of Durango, in order to meet the water requirements of the Southern Ute Indian Tribe.

FIGURE 2 Mean monthly streamflow at Durango, 1950–2007.



Methodology

Three main atmospheric datasets were utilized in this research. The Western Regional Climate Center (WRCC 2012) provided the first dataset, monthly data for mean snowpack season (December–March) and snowmelt season (April–July) surface air temperature and total snowpack season precipitation from 8 climate stations located in and around the Animas basin for the period 1950–2007 (Table 1; Figure 3). These 2 seasonal periods reflect the 2 most crucial stages for the water resources of the basin—the late winter/early spring build-up of snowpack, and the late spring/early summer melting of the snowpack.

TABLE 1 Climate station coordinates (decimal degrees) and elevation.

Station	ID	Latitude	Longitude	Elevation (m)
Durango	052432	37.28	107.88	1984
Fort Lewis	053016	37.23	108.05	2316
Ignacio	054250	37.13	107.63	1963
Ouray	056203	38.02	107.68	2390
Rico	057017	37.68	108.03	2676
Silverton	057656	37.80	107.67	2825
Telluride	058204	37.95	107.82	2643
Vallecito Dam	058582	37.38	107.58	2332

SDS, chosen due to its proven success in previous climatological studies, enabled the translation of large-scale forecasted GCM output for the Animas Basin to local surface observations of climate. This technique used the historical monthly climate data from the 8 climate stations to build a statistical relationship with the second dataset, lower-to-upper atmospheric variables covering the same period as the historical NCEP/NCAR climate reanalysis data, available at the National Oceanic and Atmospheric Administration (Kalnay et al 1996). By downscaling to a series of individual surface stations scattered in and around the basin and located at a range of different elevations, the spatial heterogeneity present in the Animas River Basin could be accounted for. As a result topographic controls of precipitation, including elevation and aspect, were taken into account by the model.

Various upper atmospheric predictor variables, chosen on the strength of their relationship with the surface climate data provided the input data for the downscaling model. For precipitation this included both atmospheric moisture and circulation predictors. Stepwise multiple linear regression selected the best predictors for the statistical model. This method included only predictor variables that explained a significant proportion of the historical variance of monthly surface air temperature and precipitation for each climate station at $P \leq 0.05$. Variables not meeting these criteria were rejected from the model. This linear relationship could then be applied to the same upper atmospheric predictor variables generated by 3 GCM scenario outputs to generate future monthly surface air temperature ($^{\circ}\text{C}$) and precipitation (mm) values to the year 2099. Thirty-year means of surface air temperature and precipitation, centered on 2050 (2035–2064) and 2080 (2065–2094), could then be compared to the historical means.

Two GCM outputs using 3 different future global scenarios provided the third dataset, future predictor variables for the downscaling model available from the World Data Center for Climate through the IPCC (2012).

These included the National Center for Atmospheric Research (NCAR) CCSM3 and the Max-Planck-Institut for Meteorology ECHAM5 models, chosen due to their widespread use and skill in forecasting both air temperature and precipitation compared to other models (Salathe et al 2007). Despite the past success of these GCMs in recreating and forecasting temperature and precipitation, historical GCM predictor variables were also obtained for both GCMs in order to account and adjust for any potential discrepancies between the reanalysis data and the GCM data, which could then be projected onto the future air temperature and precipitation basinwide. The historical GCM scenario included the 20th-century atmospheric reconstruction (20C3M) scenario. Three future scenarios were incorporated within the GCMs. These scenarios are defined by the IPCC's Special Report on Emissions Scenarios (SRES), which includes a steady increase in CO_2 emissions (the A2 scenario), the B1 scenario that gives a more balanced usage of renewable and nonrenewable energy sources and hence lower CO_2 emissions, and the A1B or "business as usual" scenario, which reflects a continuation of current CO_2 emission trends (IPCC 2001). Figure 3 displays the location of the closest reanalysis and GCM gridpoints in relation to the Animas River Basin and climate stations. The higher resolution of the GCM gridpoints in relation to the reanalysis grid points necessitated that the 4 closest GCM gridpoint values for each model be extracted and averaged to give 1 overall gridpoint value as per Cavazos and Hewitson (2005).

Results

Linear regression determined the best statistical relationship between the reanalysis predictor and surface-level predictand variables to build a model for downscaling the climatic predictand variables. For monthly air temperature, near-surface-level air

FIGURE 3 Reanalysis and GCM gridpoint locations in relation to Animas River Basin and climate stations (inset box shows reanalysis gridpoint expanse in relation to Animas River Basin).

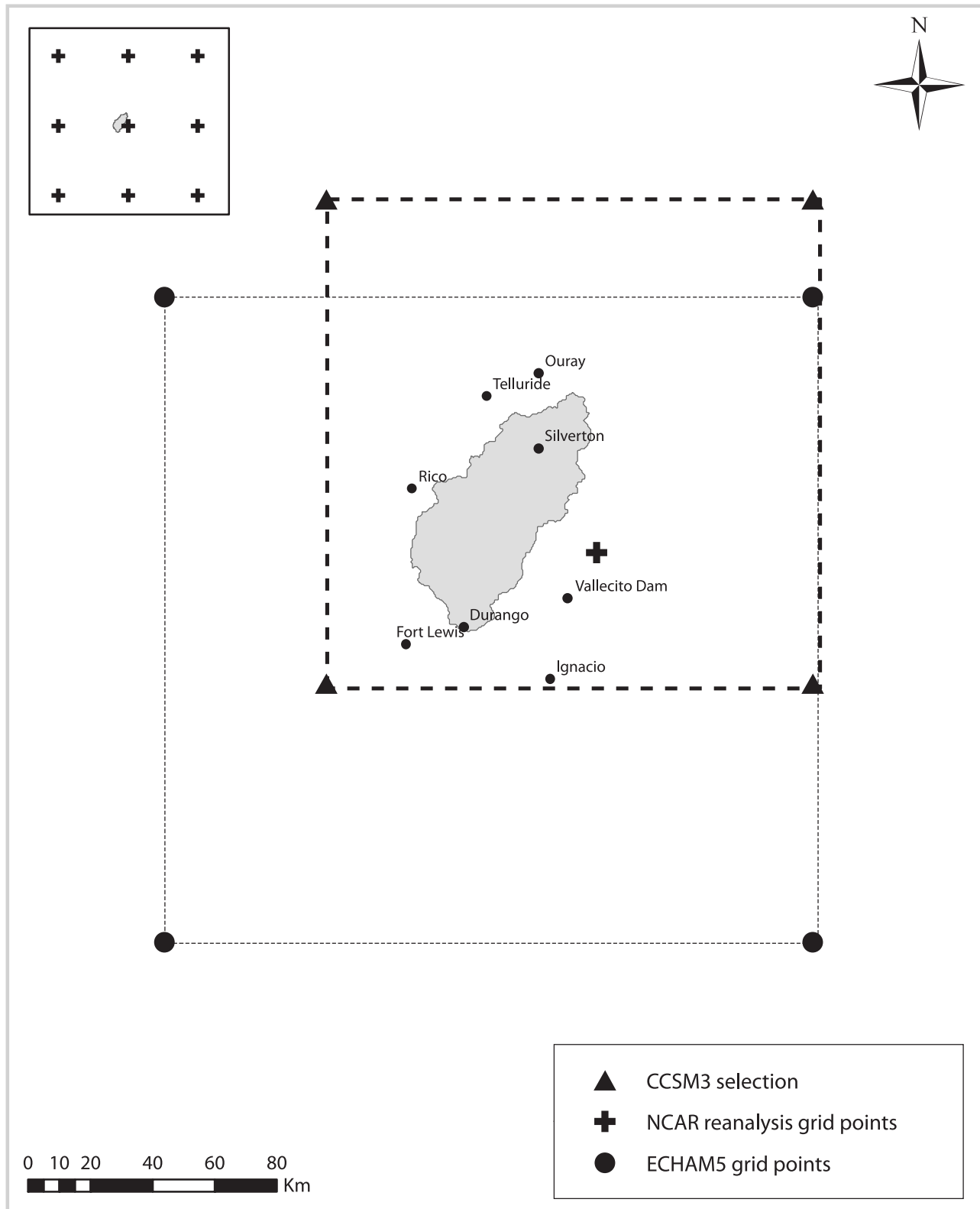


TABLE 2 Surface-level air temperature (°C) and reanalysis data regression by climate station.

Station	r^2	P	Coeff.	SE
Durango	0.98	<0.01	0.882	0.005
Fort Lewis	0.98	<0.01	0.885	0.004
Ignacio	0.97	<0.01	0.909	0.007
Ouray	0.99	<0.01	0.853	0.003
Rico	0.98	<0.01	0.785	0.004
Silverton	0.98	<0.01	0.865	0.004
Telluride	0.97	<0.01	0.828	0.005
Vallecito Dam	0.98	<0.01	0.887	0.005

temperature proved to be the single best predictor variable using the reanalysis dataset, giving r^2 values ranging from 0.97 to 0.99 among the 8 climate stations in the basin (Table 2). Figure 4 displays observed versus modeled historical mean basinwide snowpack and snowmelt season air temperature. For precipitation, multiple linear regression determined that relative humidity (%), v-wind velocity (north-south wind component, m/s), and u-wind velocity (east-west wind component, m/s) at the 500 mb pressure level provided the strongest statistical relationship with the surface-level monthly precipitation. However, r^2 values were lower than for surface-level air temperature, ranging from 0.27 to 0.37 (Table 3). This often occurs for precipitation owing to the more complex surface-atmospheric mechanisms responsible for generating and controlling

precipitation compared to air temperature (Busuioc et al 2001). All statistical relationships not significant at the $P \leq 0.05$ level were rejected from the analysis. Following the substitution of historical GCM predictors into the downscaling model, it became apparent that both GCMs overpredicted historical monthly precipitation relative to the reanalysis reconstruction. In order to correct this bias the mean extra precipitation at each station was calculated for each month of the historical GCM reconstruction and then subtracted from the future downscaled GCM scenario projections. Figure 5 displays observed versus modeled historical mean basinwide snowpack season precipitation. While the downscaled precipitation model generally captures the mean aspects of the historical precipitation distribution, it performs poorly with regards to the more extreme events.

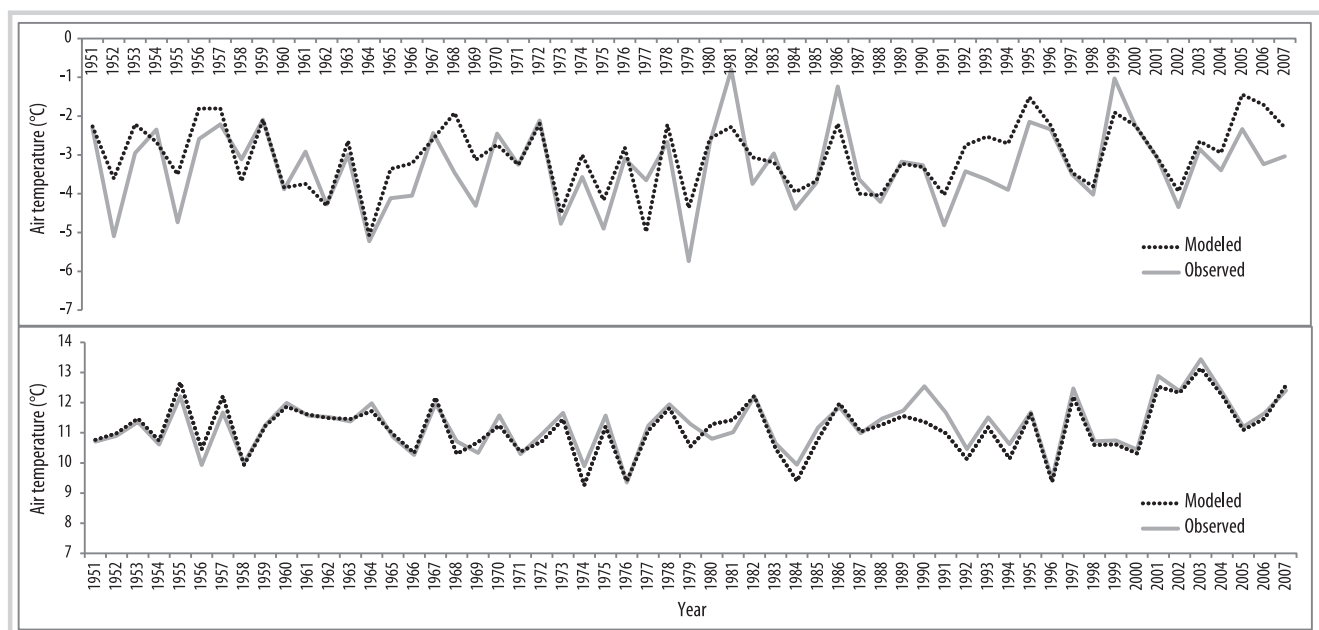
FIGURE 4 Modeled versus observed downscaled historical mean basinwide air temperature for snowpack (top) and snowmelt (bottom) seasons.

TABLE 3 Surface-level precipitation (mm) and reanalysis data regression by climate station.

Station	r^2	500 mb relative humidity (%)			500 mb v-wind (m/s)			500 mb u-wind (m/s)		
		<i>P</i>	Coeff.	SE	<i>P</i>	Coeff.	SE	<i>P</i>	Coeff.	SE
Durango	0.35	<0.01	2.242	0.327	<0.01	2.895	0.563	–	–	–
F. Lewis	0.37	<0.01	2.207	0.279	<0.01	2.319	0.482	–	–	–
Ignacio	0.28	<0.01	1.287	0.294	<0.01	2.052	0.525	<0.01	0.942	0.442
Ouray	0.27	<0.01	2.021	0.218	–	–	–	–	–	–
Rico	0.36	<0.01	2.870	0.403	<0.01	2.214	0.721	<0.01	2.425	0.607
Silverton	0.29	<0.01	1.684	0.304	<0.01	2.057	0.528	<0.01	1.559	0.457
Telluride	0.34	<0.01	2.077	0.337	–	–	–	<0.01	1.143	0.337
V. Dam	0.37	<0.01	2.829	0.406	<0.01	3.970	0.701	0.05	1.036	0.607

When compared to the historical means, projections in the mean basinwide climate variables differed significantly based on the model and scenario used. Tables 4 and 5 show changes in SDS air temperature and precipitation to 2050 and 2080 compared to the historical mean. Also shown are the future projections of surface air temperature and precipitation from the host GCMs compared to their historical means, again taken as an average from the 4 gridpoints of each GCM encompassing the Animas River Basin. Snowmelt season air temperature displays the greatest above historical mean values to 2050 and 2080 for both SDS models, with increases ranging from 2.4–3.8°C by 2050 to 2.8–5.6°C by 2080. GCM projection increases were smaller and narrower in range (1.1–2.3°C by 2050 and 1.5–4.3°C by 2080). Snowpack season air temperature showed lower mean increases of 0.8–1.7°C by 2050 and 1.0–3.2°C by 2080 for both SDS models compared to historical means. Conversely GCM projections again displayed narrower ranges but greater increases in air temperature overall (1.2–2.6°C by 2050 and 1.4–3.1°C by 2080). Basinwide precipitation displayed negligible to modest changes to the historical mean. For example SDS 2050 mean projections ranged from a decrease by 12% to a decrease by 1% across all scenarios. By 2080, these SDS projections decreased slightly further

ranging from a 6% to 20% decrease across all scenarios. The GCM projections were fairly similar across all scenarios ranging from a 14% to 1% decrease by 2050 and decreases by 15% to 4% by 2080.

For all variables, the SDS CCSM3 model generally projected the more severe changes in climatic variables across the 3 scenarios. Consequently, differences in snowpack season air temperature between the SDS and GCM output were generally greater for the CCSM3 model compared to the ECHAM5 model although the maximum difference was only 1°C. Snowmelt season air temperature differences were similar for the ECHAM5 SDS and GCM outputs with no values greater than 1°C, but the CCSM3 output differences were all greater than 1°C. Differences in precipitation between the SDS and GCM output were also greater for the CCSM3 model, with a maximum difference of 13% versus 6% for the ECHAM5 outputs. The greater agreement between the SDS and GCM output for the ECHAM5 model implies that the SDS method verifies the GCM projections to a greater degree than the CCSM3 model.

The differences in output between the SDS and GCM output for future precipitation suggest that the SDS models may be effective in capturing local surface changes in precipitation across the basin. By

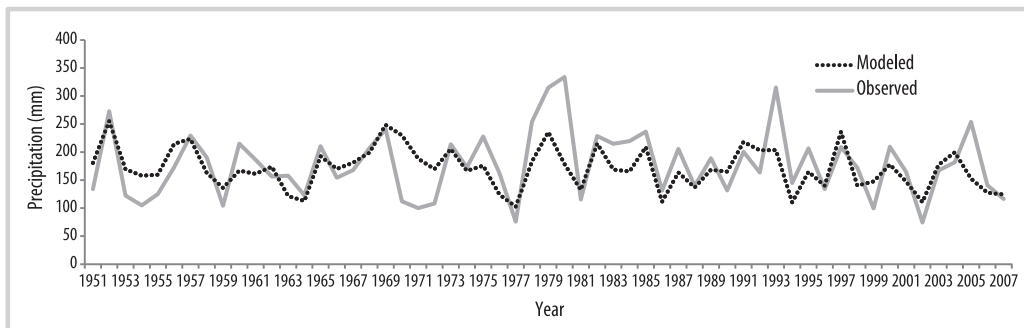
FIGURE 5 Modeled versus observed downscaled historical mean basinwide snowpack season precipitation.

TABLE 4 CCSM3 SDS and GCM scenario projected mean basinwide climatological changes to 2050 and 2080 based on historical mean values.

Projected scenario	IPCC 2011 scenarios					
	A2		A1B		B1	
	2050	2080	2050	2080	2050	2080
SDS snowpack season precipitation (%)	−4	−20	−12	−20	−9	−6
GCM snowpack season precipitation (%)	−7	−15	−14	−7	−9	−4
SDS snowpack season temperature (°C)	1.1	2.9	1.0	2.0	0.8	1.0
GCM snowpack season temperature (°C)	1.8	2.8	1.8	2.2	1.2	1.4
SDS snowmelt season temperature (°C)	3.8	5.6	3.8	4.4	3.2	2.8
GCM snowmelt season temperature (°C)	2.3	4.3	2.3	3.0	1.1	1.5

incorporating a spatial spread of surface-level stations, even across a small basin, the spatial heterogeneity of the basin with regard to topographic controls of precipitation may be accounted for. However, the differences in the SDS versus the GCM projections suggest that the predictor variables chosen to downscale precipitation may not fully capture the changes in climate relevant to surface-level precipitation. In particular, as the historical analysis shows, the predictor variables are not capable of capturing extreme precipitation events. As a result, the reduced predictive power of the downscaled precipitation model to capture extreme precipitation events implies that these projections of precipitation are more likely to be conservative in nature. Nevertheless, the model ultimately provides the potential mean conditions that could be expected across the basin.

Conclusions

Following statistical downscaling of air temperature and precipitation across the Animas River Basin it may be

concluded that the basinwide climate could potentially change to varying degrees depending on the greenhouse gas emissions scenario used. In each case, for all scenarios, the basinwide climate is projected to become warmer and drier, with temperatures especially increasing during the snowmelt season months of April to July, which could begin to severely impact the availability of future water resources for projects including the Animas–La Plata unless more sustainable management of this water resource is drafted in. Although this study focuses on the Animas River, the wider availability of the necessary atmospheric datasets used in this research also allow these techniques to be applied to other mountain regions across North America and elsewhere. It should be noted, however, that while this technique successfully models surface air temperature on this larger scale, it does not capture the full range of precipitation, again owing to the more complex surface-to-atmospheric interactions involved in the development of this variable. Despite incorporating 8 different surface stations in the downscaling model it is unlikely that they fully represent

TABLE 5 ECHAM5 SDS and GCM scenario projected mean basinwide climatological changes to 2050 and 2080 based on historical mean values.

Projected scenario	IPCC 2011 scenarios					
	A2		A1B		B1	
	2050	2080	2050	2080	2050	2080
SDS snowpack season precipitation (%)	−6	−13	−7	−10	−1	−11
GCM snowpack season precipitation (%)	−8	−11	−1	−6	−1	−14
SDS snowpack season temperature (°C)	1.6	3.2	1.6	3.0	1.7	2.2
GCM snowpack season temperature (°C)	1.9	3.0	2.6	3.1	1.8	2.4
SDS snowmelt season temperature (°C)	2.5	4.2	2.8	4.2	2.4	3.4
GCM snowmelt season temperature (°C)	1.8	3.3	2.2	3.3	1.6	2.5

the major controls of precipitation development for the entire basin, especially orographic uplift and the local development of low-pressure systems with regard to synoptic-scale upper atmospheric circulation. This highlights the potential problems of utilizing SDS for smaller basins. It is vital that basins have the necessary spatial spread of surface climate stations in order to develop an SDS model that is capable of capturing the full range of surface air temperature and precipitation. The choice of predictor variables in downscaling precipitation is also a factor. They must be able to fully capture changes in surface-level precipitation both in the past and future climate scenarios, including both mean conditions and extreme events. This factor becomes especially important in basins where surface-level data are lacking. In this study projections of precipitation may be considered conservative and thus further research is required to more fully explore SDS methods with regards to precipitation variability and atmospheric controlling mechanisms, particularly in mountain environments.

Although these findings indicate the potential of SDS techniques in translating large-scale GCM projections to local observations in small mountain basins, they also highlight the dilemma facing many local-scale water resource planners who attempt to incorporate climate change data into their planning methods. In this case only 2 GCMs and 3 greenhouse gas emissions scenarios have been investigated, giving a total of 6 overall scenarios. The inclusion of other models may well project significantly different future scenarios, especially when considering the uncertainty surrounding precipitation in the southwest Colorado area (Ray et al 2008). Even this relatively small coverage has highlighted the scale or extent of future possible climate change for the Animas River Basin. The dilemma lies in how to adapt plans to deal with such a wide range of possibilities and potential error. Should the worst case scenario always be planned for, or should plans be drafted that may adapt and develop sustainable water resource management practices to any of the scenarios presented?

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