Use of Regional Climate Model Output for Hydrologic Simulations

L. E. HAY,* M. P. CLARK,+ R. L. WILBY,# W. J. GUTOWSKI, JR.@ G. H. LEAVESLEY,* Z. PAN,@
R. W. ARRITT,@ AND E. S. TAKLE@

*Water Resources Division, U.S. Geological Survey, Denver, Colorado
+Cooperative Institute for Research in Environmental Sciences, University of Colorado, Boulder, Colorado
#Department of Geography, King's College London, Strand, London, United Kingdom
@Department of Agronomy, Geological and Atmospheric Sciences, Iowa State University, Ames, Iowa

(Manuscript received 5 October 2001, in final form 1 May 2002)

ABSTRACT

Daily precipitation and maximum and minimum temperature time series from a regional climate model (RegCM2) configured using the continental United States as a domain and run on a 52-km (approximately) spatial resolution were used as input to a distributed hydrologic model for one rainfall-dominated basin (Alapaha River at Statenville, Georgia) and three snowmelt-dominated basins (Animas River at Durango, Colorado; east fork of the Carson River near Gardnerville, Nevada; and Cle Elum River near Roslyn, Washington). For comparison purposes, spatially averaged daily datasets of precipitation and maximum and minimum temperature were developed from measured data for each basin. These datasets included precipitation and temperature data for all stations (hereafter, All-Sta) located within the area of the RegCM2 output used for each basin, but excluded station data used to calibrate the hydrologic model.

Both the RegCM2 output and All-Sta data capture the gross aspects of the seasonal cycles of precipitation and temperature. However, in all four basins, the RegCM2- and All-Sta-based simulations of runoff show little skill on a daily basis [Nash–Sutcliffe (NS) values range from 0.05 to 0.37 for RegCM2 and −0.08 to 0.65 for All-Sta]. When the precipitation and temperature biases are corrected in the RegCM2 output and All-Sta data (Bias-RegCM2 and Bias-All, respectively) the accuracy of the daily runoff simulations improve dramatically for the snowmelt-dominated basins (NS values range from 0.41 to 0.66 for RegCM2 and 0.60 to 0.76 for All-Sta). In the rainfall-dominated basin, runoff simulations based on the Bias-RegCM2 output show no skill (NS value of 0.09) whereas Bias-All simulated runoff improves (NS value improved from −0.08 to 0.72).

These results indicate that measured data at the coarse resolution of the RegCM2 output can be made appropriate for basin-scale modeling through bias correction (essentially a magnitude correction). However, RegCM2 output, even when bias corrected, does not contain the day-to-day variability present in the All-Sta dataset that is necessary for basin-scale modeling. Future work is warranted to identify the causes for systematic biases in RegCM2 simulations, develop methods to remove the biases, and improve RegCM2 simulations of daily variability in local climate.

1. Introduction

In recognition of the economic significance of water resources in the United States, many studies have sought to examine the effects of climate change on components of the hydrologic budget. The most common approach has been to combine basin-scale hydrologic models with climate change scenarios derived from general circulation model (GCM) output (see Watson et al. 1996). Due to their coarse resolution, GCMs overlook numerous climatological details necessary for accurate runoff estimation at the basin scale. The advent of higher-resolution GCMs may improve the situation; however, hydrologic modeling at the basin scale requires climatological information on scales that are generally far smaller than the typical grid size of even the highest-resolution GCMs commonly used for climate simulations (e.g., Phillips 1995).

In order to translate (''downscale'') information from the coarse-resolution GCMs to the basin scale for hydrologic modeling, methods are needed that resolve subgrid-scale information in the simulated fields. One way to achieve this is by statistical downscaling (Wilks 1995; Wilby et al. 1999). In this approach, empirical relations are developed between features reliably simulated by a GCM at grid-box scales (e.g., 500-hPa geopotential height) and surface predictands at subgrid scales (e.g., precipitation occurrence and amounts). An alternative approach is through dynamical downscaling, in which a regional climate model (RCM) uses GCM output as initial and lateral boundary conditions for much more spatially detailed climatological simulations over a region of interest. RCMs capture geographical details

---

Corresponding author address: Dr. L. E. Hay, U.S. Geological Survey, Denver Federal Center, Box 25046, MS 412, Denver, CO 80225.
E-mail: lhay@usgs.gov

TABLE 1. Study basins.

	Study basin:			
	Animas River at Durango	East fork of the Carson River near Gardnerville	Cle Elum River near Roslyn	Alapaha River at Statenville
State	Colorado	California/Nevada	Washington	Georgia
Gauging station ID	09361500	10309000	12479000	02317500
Drainage area (km^2)	1792	922	526	3626
Elevation range (m)	2000–3700	1600–3000	680–1800	40–125
Number of HRUs	121	96	124	180
Number of stations in All-Sta dataset				
Precipitation	38	37	27	20
Temperature	30	21	14	14
Number of RegCM2 grid points	8	7	5	12
Best three-stations sets (Best-Sta)				
Precipitation	Durango Cascade Lizard Head Pass	Twin Lakes Hagan's Meadow Lobdell	Fish Lakes Stampede Stevens Pass	Moultrie Fitzgerald Tifton
Temperature	Durango Vallecito Dam Rico	Tahoe Valley Twin Lakes Blue Lakes	Baring Cle Elum Stampede	Quitman Cordele Ashburn
Snowfall bias (%)	30	0	10	0
% days with precipitation (# stations)	71% (15 stations)	23% (1 station)	64% (4 stations)	57% (11 stations)

more precisely than the coarse-resolution GCM. Although the computational requirements of such an approach are demanding, rapid advances in computer power over the past decade have allowed RCMs to become a major tool in climatological studies allowing for longer runs as well as finer resolution.

Wilby et al. (2000) examined the hydrological response in the Animas River basin of Colorado to dynamically and statistically downscaled output from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis (Kalnay et al. 1996). They found that in terms of modeling hydrology, both statistical and dynamical downscaling provided greater skill than the coarse-resolution data used to drive the downscaling. The output from the RCM used in the dynamical downscaling was simulated by RegCM2 (Giorgi et al. 1996), using the continental United States domain and a grid spacing of 52 km. Despite the higher level of sophistication and physical realism associated with dynamical downscaling, hydrographs simulated using dynamically downscaled precipitation and temperature were not generally as realistic as those simulated using statistically downscaled precipitation and temperature.

Statistical downscaling (SDS), however, is ultimately limited by the assumption of stationarity in the empirical relations (i.e., skillful SDS results for the present climate do not necessarily translate to skillful forecasts of future climate). The nonstationarity in empirical climate relations is well documented (e.g., Ramage 1983). Dynamical downscaling does not suffer from such shortcomings. Though some parameterization in an RCM may have an empirical basis, RCM simulations of local climate are more physically based than SDS and thus are more acceptably transferable from current to future climates. However, RCM simulations of current climate have not been extensively tested (Takle et al. 1999). There is a strong need for a systematic assessment of current RCM output in order to evaluate the skill of (and confidence in) RCM simulations, especially as drivers for impacts assessment models, and to identify areas for model improvement. This paper will evaluate an RCM-surface climate, by using the RegCM2 (Giorgi et al. 1996) simulated precipitation and temperature as input to a hydrologic model.

Four basins were chosen for this analysis: 1) Animas River at Durango, Colorado (Animas); 2) east fork of the Carson River near Gardnerville, Nevada (Carson); 3) Cle Elum River near Roslyn, Washington (Cle Elum); and 4) Alapaha River at Statenville, Georgia (Alapaha). The surface hydrology of the first three basins (Animas, Carson, and Cle Elum) is dominated by snowmelt. The Carson and Cle Elum basins are also characterized by frequent rain-on-snow events in the winter months. The Alapaha basin is a low-elevation rainfall-dominated basin. Tables 1 and 2 list some of the defining features of each basin, and Fig. 1 shows the location of each. In this study, for each of the four basins, daily precipitation and temperature were derived from RegCM2 and used as inputs to a hydrologic model. Since the hydrological response of the basin is an integration of the regional climate (in time and space), the results presented here will provide insights into the overall realism of the RegCM2 precipitation and temperature time series for four basins in the United States. This study examines the limits of what one can do with RegCM2 output that has been configured using the continental United States as a domain and run on a 52-km (approximately) spatial resolution, and what the implications are for a RegCM2 to be able to handle details of climate at those limits.

TABLE 2. Elevation ranges.

	Elevations ranges (m) for each study basin											
	Animas River at Durango			East fork of the Carson River near Gardnerville			Cle Elum River near Roslyn			Alapaha River at Statenville		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
HRUs	2011	3060	3728	1645	2300	2959	680	1337	1799	44	85	122
Best three-stations												
Precipitation	2010	2609	3109	2438	2560	2804	1027	1162	1241	316	338	353
Temperature	2010	2341	2682	1906	2260	2438	235	678	1219	172	287	404
All stations												
Precipitation	1720	2686	3536	718	1909	2804	52	813	1829	112	227	455
Temperature	1720	2328	3536	718	1104	2804	52	328	1640	112	197	455
RegCM2 grid nodes	1895	2579	2987	1586	1926	2166	279	802	1401	23	64	139

2. Data

For each basin, two types of daily data were compiled for the purpose of hydrologic modeling: 1) measured-station data and 2) RegCM2 output.

a. Station data

Daily maximum and minimum temperatures and precipitation data from stations in and around each basin were compiled from the National Weather Service (NWS) and snow telemetry (SNOTEL) databases. The NWS data were retrieved from the Utah Climate Center's Weather Data Online (available online at http://climate.usu.edu/Free/). SNOTEL data were retrieved from the Natural Resources Conservation Service (available online at ftp://162.79.124.23/data/snow/snotel/snothist/). Figure 2 shows the location of the NWS and SNOTEL stations used for each basin study.

b. Regional climate model output

The RCM output was simulated by RegCM2 (Giorgi et al. 1996), using the continental U.S. domain of the Project to Intercompare Regional Climate Simulations (PIRCS) experiments (see Fig. 1 in Takle et al. 1999). Precipitation was simulated using the Grell (1993) convection scheme and the simple warm-cloud explicit moisture scheme of Hsie et al. (1984). The simulations also used the CCM2 radiation package (Briegleb 1992), the BATS version 1e surface package (Dickinson et al. 1992), and the nonlocal boundary layer turbulence scheme of Holtslag et al. (1990).

A 10-yr run (1979–88) was conducted using 6-h output from the NCEP–NCAR reanalysis to define initial and boundary conditions. These were supplemented by observations of water-surface temperature in the Gulf of California and the Great Lakes, which are poorly resolved in the reanalysis.

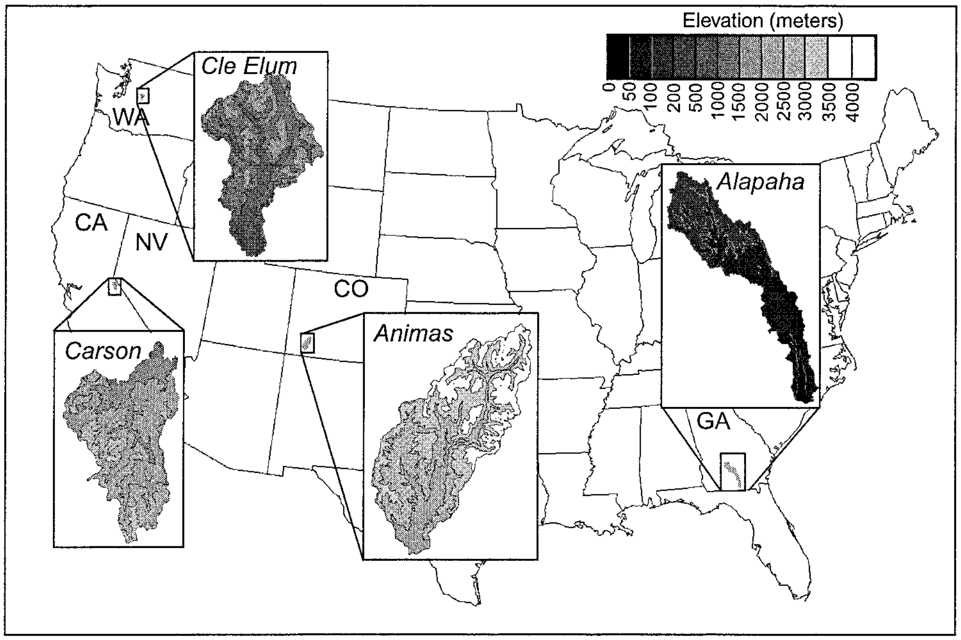

FIG. 1. Location of study basins.

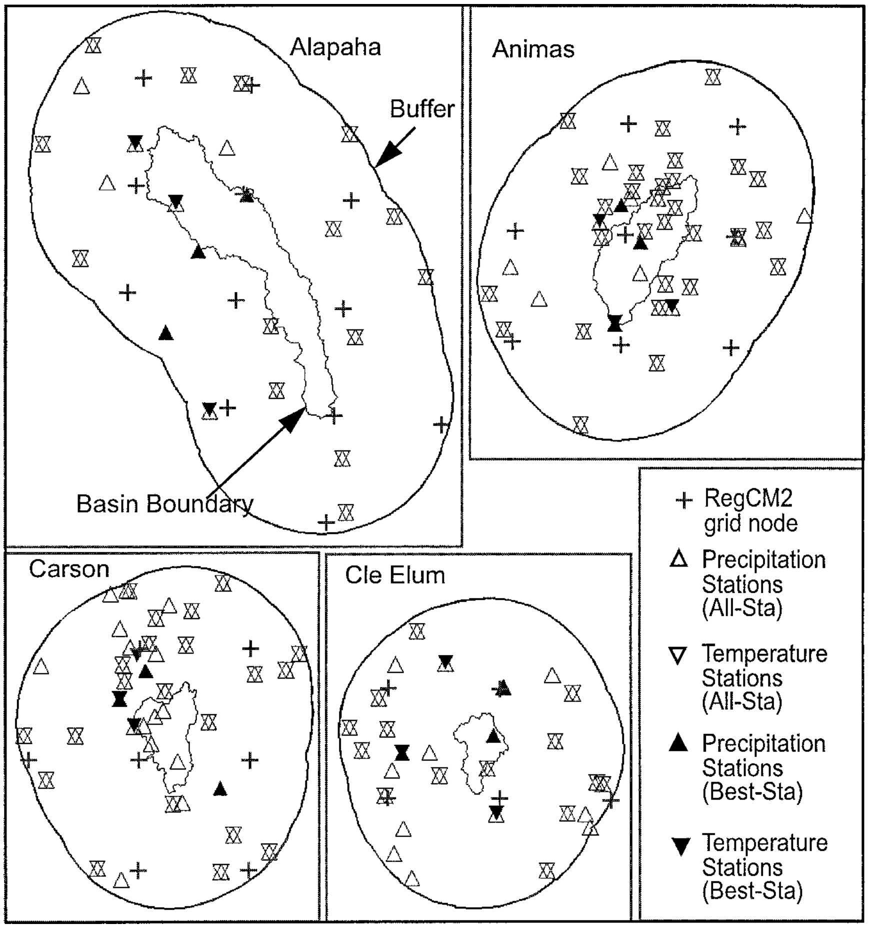

FIG. 2. Station locations and RegCM2 grid points used in each basin.

The RegCM2 grid spacing is 52 km on a Lambert conformal projection of the midlatitudes. Figure 2 shows the RegCM2 grid points chosen for analysis in each of the four study basins. A buffer equal to that of the RegCM2 grid spacing was generated around each basin boundary, and all RegCM2 grid points that fell within this buffered area were chosen for this analysis (see Fig. 2). This provided 8 grid points for the Animas, 5 grid points for the Cle Elum, 7 grid points for the Carson, and 12 grid points for the Alapaha (Table 1). The area of a RegCM2 grid box is approximately 2500 km^2, larger than the drainage area of three of the four basins (Table 1). The four basins are comparable in size to the smallest scales resolved by the RegCM2. Thus, they represent a fairly stringent test of the limits of the model's downscaling capability.

3. Hydrologic model

The hydrologic model chosen for this study is the U.S. Geological Survey's (USGS) Precipitation Runoff Modeling System (PRMS) (Leavesley et al. 1983; Leavesley and Stannard 1995). PRMS is a distributed-parameter, physically based watershed model. Distributed parameter capabilities are provided by partitioning a watershed into hydrologic response units (HRUs). Basin and HRU delineation, characterization, and parameterization were done for each basin using a geographic information system (GIS) interface. HRUs were delineated identically for each basin by 1) subdividing the basin into two flow planes for each channel, 2) subdividing the basin using three equal area elevation bands, and 3) intersecting the flow-plane map with the elevation-band map. The number of HRUs resulting from this process for each basin are listed in Table 1. The elevation ranges of the HRUs are listed in Table 2.

A conceptual diagram of PRMS is shown in Fig. 3 (Leavesley et al. 1983). PRMS uses daily inputs of the climate variables precipitation, maximum temperature, minimum temperature, and solar radiation. Precipitation, maximum temperature, and minimum temperature are available at most climate stations across the United States. Solar radiation is generally not measured at the climate stations used in this study, so shortwave and longwave radiation were computed empirically using algorithms in PRMS [see Leavesley et al. (1983) for

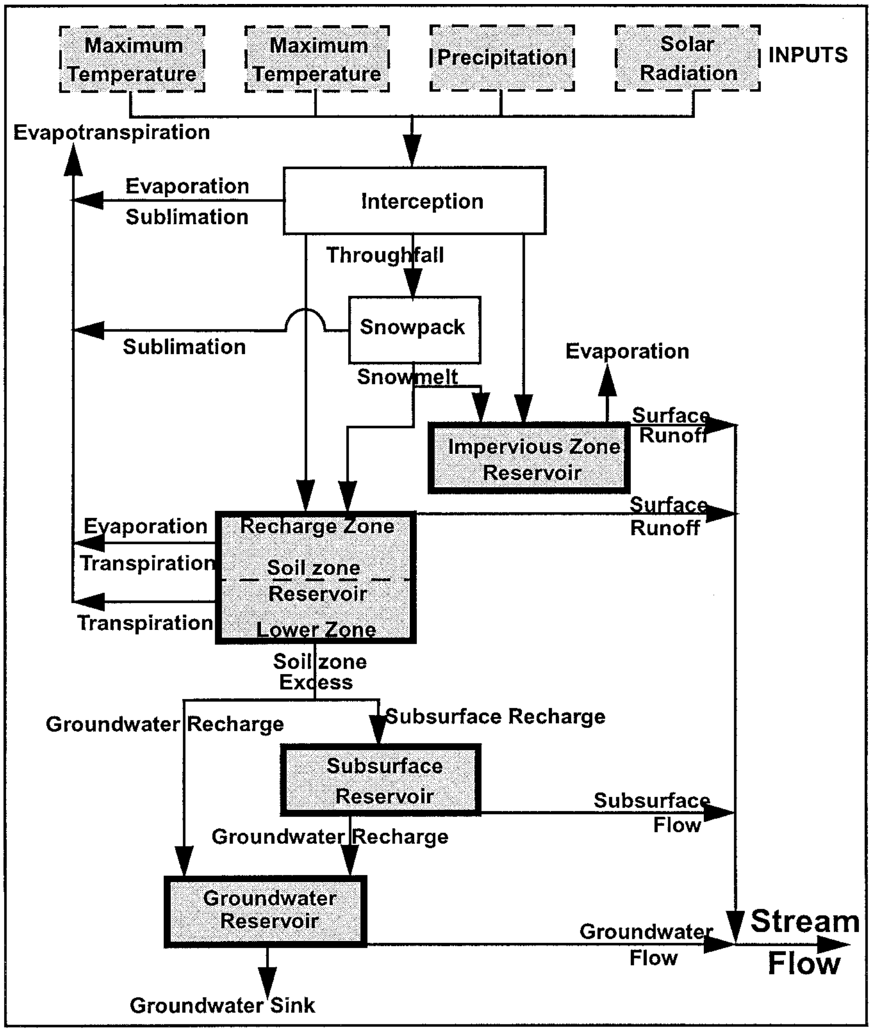

FIG. 3. Conceptual diagram of PRMS (Leavesley et al. 1983).

more information]. PRMS is conceptualized as a series of reservoirs (impervious zone, soil zone, subsurface, and groundwater) whose outputs combine to produce streamflow. For each HRU, a water balance is computed daily and an energy balance is computed twice each day. The sum of the water balances of each HRU, weighted by unit area, produces the daily watershed response.

Hydrologic model parameters describing topographic, vegetation, and soils characteristics were generated for each HRU from four digital databases using a GIS: 1) USGS three-arc second digital elevation models; 2) state soils geographic (STATSGO) 1-km gridded soils data (U.S. Department of Agriculture 2000); 3) U.S. Forest Service 1-km gridded vegetation type and density data (U.S. Department of Agriculture 1992); and 4) USGS 1-km gridded land use/land cover data (Anderson et al. 1976). For cases in which an HRU contained more than one soil or vegetation type, the dominant soil or vegetation type was used. An objective parameter estimation and calibration procedure was used to prevent biasing parameter estimates to any particular meteorological data set (Leavesley et al. 2002a). Using this procedure, no changes are made to GIS-generated spatial parameters. Calibration focused on the water balance parameters affecting potential evapotranspiration and precipitation distribution, and on subsurface and groundwater parameters affecting hydrograph shape and timing (Leavesley et al. 2002a). Other model parameters were based on parameter sets from model applications to comparable basins in the same region (Leavesley et al. 1992).

a. Spatial distribution of climate variables—The xyz methodology

The hydrologic model PRMS needs reliable estimates of daily precipitation, maximum temperature, and minimum temperature at each HRU. A method was developed whereby measured precipitation and maximum and minimum temperature data from a group of stations (or RegCM2 grid points) could be spatially distributed from one point (a single daily mean value) to each HRU in a basin (Hay et al. 2000; Hay and Clark 2000). The method allows for station data and RegCM2 grid points to be distributed similarly, both starting as a single daily mean value.

Significant geographic factors affecting the spatial distribution of precipitation, maximum temperature, and minimum temperature distributions within a river basin are latitude (x), longitude (y), and elevation (z). To account for seasonal climate variations, the multiple linear regression (MLR) equation (Eq. 1) was developed for each basin and month for each dependent variable [the climate variables (CVs): precipitation, maximum and minimum temperature) using the independent variables of x, y, and z from a set of climate stations that fell within the buffered areas designated in Fig. 2:

$$\mathrm{CV} = b_1x + b_2y + b_3z + b_0. \tag{1}$$

The monthly MLR equations were computed to determine the regression surface that described the spatial relations between the monthly dependent CV and the independent xyz variables. Equation (1) describes a plane in three-dimensional space with ''slopes'' b_1, b_2, and b_3 intersecting the CV axis at b_0. Note that for each month the best MLR equation did not always include all the independent variables.

To estimate the daily CVs for each HRU, the following procedure was followed: 1) mean daily CVs and corresponding mean x, y, and z values from a set of stations or grid points were used with the slopes of the monthly MLRs in Eq. (1) to estimate a unique y intercept (b_0^{est}) for that day, and 2) equation 2 was then solved using b_1, b_2, and b_3 from Eq. (1) and the x, y, and z values of the HRUs:

$$\mathrm{CV}_{(\mathrm{HRU})} = b_0^{\mathrm{est}} + b_1x_{(\mathrm{HRU})} + b_2y_{(\mathrm{HRU})} + b_3z_{(\mathrm{HRU})}. \tag{2}$$

The distribution technique is identical for station and RegCM2 grid-node output: the same MLR equations are used but the time series of mean daily CVs and their corresponding mean x, y, and z values are obtained from either station data or from the RegCM2 grid points to estimate a unique b_0^{est} for that day. Thus, for a given day the slope of the MLRs for the CVs remained constant, but the y intercept changes based on the mean CV and xyz values.

b. *Exhaustive search analysis*

The MLR-distribution methodology provides spatial ''maps'' of precipitation and temperature based on *regional* relations between latitude, longitude and elevation, and local climate. However, these MLR equations do not provide a perfect fit with observations; the regional MLR equations often under estimate or overestimate the mean precipitation (or temperature) in the smaller basins used for hydrologic simulations. Also, difficulties in precipitation measurement (particularly precipitation gage undercatch associated with snowfall events) may lead to significant errors in hydrologic simulations.

To address these issues, an exhaustive search (ES) analysis was used to 1) determine the ''optimal'' precipitation- and temperature-station sets to anchor the xyz distribution methodology (Hay et al. 2000; Wilby et al. 1999); 2) provide an estimate of snowfall-measurement bias associated with the above precipitation-station set (Hay et al. 2000); and 3) define a separate precipitation-station set to determine daily precipitation frequency. The ES analysis was executed using water years 1989–96. Climate stations were tested in the ES analysis if they had less than 5% missing record for water years 1989–96 and the period of the RegCM2 data (1979–88). This excluded many of the SNOTEL stations whose records did not begin until the mid 1980s.

To start the ES search, each climate station was tested individually for its ability to anchor the xyz methodology. Precipitation and temperature stations were tested separately since the best precipitation station choice generally differed from the best choice for temperature distribution in a basin. For every combination of these precipitation and temperature xyz-station sets, a snowfall bias error (described below) and a station set to indicate precipitation frequency (described below) were tested. Time series of precipitation, maximum temperature, and minimum temperature for each of these combinations were calculated and used as input into PRMS. Measured and simulated runoff were compared by examining the sum of the daily absolute errors between the two.

Previous work using this method of station selection in the Animas River basin (Wilby et al. 2000) highlighted the problem of gauge undercatch, estimated to be as much as 20–50% for snowfall in mountainous terrain (Sevruk 1989). Milly and Dunne (2002) found that a 10%–20% bias in precipitation was typical for basins examined around the world. An attempt to correct for these biases in snowfall was made by testing undercatch amounts from 0%–50% during snowfall events for each station combination tested in the ES analysis. This bias correction in the ES analysis actually compensates for the net effect of a number of biases related to precipitation measurement, such as gauge undercatch, gauge location, and/or lack of gauges at high elevation. It may also correct for other problems in PRMS, such as overestimation of ET.

Precipitation frequency was incorporated into PRMS based on a set of precipitation stations separate from the set selected for use in the xyz methodology. Preliminary work with the precipitation-station set chosen to anchor the xyz methodology indicated that the optimal xyz-station set used to produce the volume of precipitation for a day was not always the best set to determine whether there actually was precipitation on that day. Therefore, for each ES search, a separate precipitation-station set was used to indicate a rain or no-rain day (i.e., if any of the stations in the chosen set had precipitation, then the *xyz* methodology was enacted to distribute precipitation on that day).

Further ES searches using the above procedure were run to test all possible combinations of two, three, and four station groups comprising the *xyz*-station sets. For each ES search, the best *xyz*-station set for temperature and precipitation with an associated snowfall bias and precipitation frequency was determined by comparing the absolute error in runoff. The ES analysis ended when the absolute error associated with the above combination showed no significant improvement from one group to the next. Table 1 lists the ''best'' temperature and precipitation station sets and Fig. 2 shows their locations. In addition, Table 1 lists the snowfall bias associated with the precipitation-station set and percentage of days with precipitation and associated number of stations used to designate the precipitation frequency for each basin.

This ES procedure avoids the need for an exhaustive calibration of hydrologic model parameters. Model calibration is used quite often in hydrologic modeling to avoid the reality of serious biases in precipitation (Milly and Dunne 2002). The ES procedure is similar to many of the model calibration procedures that are in widespread use and will indirectly compensate for problems in other routines in the hydrologic model. However, the problems with precipitation bias are corrected at their source, thus reducing the need to directly calibrate any of the GIS-generated spatial parameters. In this study these estimates of spatial parameters were not calibrated to avoid biasing them to any specific meteorological time series.

c. *Input datasets*

The input datasets for the hydrologic model are derived from two sources: 1) RegCM2 output and 2) measured-station data. In order to assess the performance of the RegCM2-based simulations of runoff it became necessary to develop an appropriate baseline. Our hydrologic modeling strategy consists of selecting the station set that provides the best simulation of runoff (Best-Sta from the ES analysis), and then tune a small select group of model parameters to provide the best possible simulation of runoff given the chosen station set time series (Leavesley et al. 2002b). No such calibration is performed on the RegCM2 model inputs. Thus, use of the calibrated Best-Sta mean time series to assess RegCM2 performance will lead to conclusions that are favorable to the station-based simulations and unfavorable to RegCM2-based runoff simulations.

To provide a fair means of comparing the relative performance of RegCM2- and station-based runoff simulations, new input datasets consisting of regionally averaged station measurements were developed. These datasets (hereafter referred to as ''All-Sta'') include data on precipitation and temperature for all stations that fell within the RegCM2 buffers (Fig. 2), but excludes the station set (Best-Sta) determined using the ES procedure and used for model calibration. The Best-Sta set is only used in this study to provide the best possible set of model parameters, and this parameter set is used for both the RegCM2- and All-Sta simulations. The ES analysis is used to determine the Best-Sta datasets but is not used in the RegCM2 or All-Sta datasets. RegCM2 and All-Sta simulations are corrected for systematic bias (Bias-RegCM2 and Bias-All, respectively) to distinguish errors in hydrologic simulations associated with model biases from errors in hydrologic simulations associated with model problems in capturing daily climate variations. All input datasets are summarized in Table 3.

Table 3. Meteorological inputs to the hydrology model.

No.	Abbreviation	Description
1	Best-Sta	Best three-station set determined through ES analysis
2	RegCM2	RegCM2 grid nodes within buffered area
3	All-Sta	All stations within buffered area excluding ''Best-Sta'' stations
4	Bias-RegCM2	''RegCM2'' with a Bias correction applied
5	Bias-All	''All-Sta'' stations with a Bias correction applied
6	Test1	''Best-Sta'' precipitation, ''Bias-RegCM2'' max and min temperature
7	Test2	''Best-Sta'' max temperature, ''Bias-RegCM2'' min temperature and precipitation
8	Test3	''Best-Sta'' min temperature, ''Bias-RegCM2'' max temperature and precipitation

4. Hydrologic model input data

The hydrologic model PRMS was forced with meteorological variables derived from two sources: 1) RegCM2 output and 2) measured-station data. RegCM2 output for the United States was available from 1979 to 1988. In each basin, PRMS was initialized with station data from 1 October 1977 to 31 December 1978 to remove the bias from the state variables. Then, 10 years (1979–88) of daily mean precipitation, maximum temperature, and minimum temperature from climate stations and RegCM2 output (outlined in Table 3) were distributed using the *xyz* methodology to the HRUs in each basin to produce daily runoff.

a. *Precipitation*

The RegCM2 output has a significantly higher number of precipitation days than measured at individual stations. Such differences occur partly because the RegCM2 precipitation represents an area (grid cells approximately 52 km × 52 km) not a point. To evaluate these differences directly, Fig. 4 compares the percentage of precipitation days between the All-Sta data and the RegCM2 output (see Table 3 for dataset description) over successively larger areas, starting from the center of each basin. In Fig. 4, each square (circle) represents

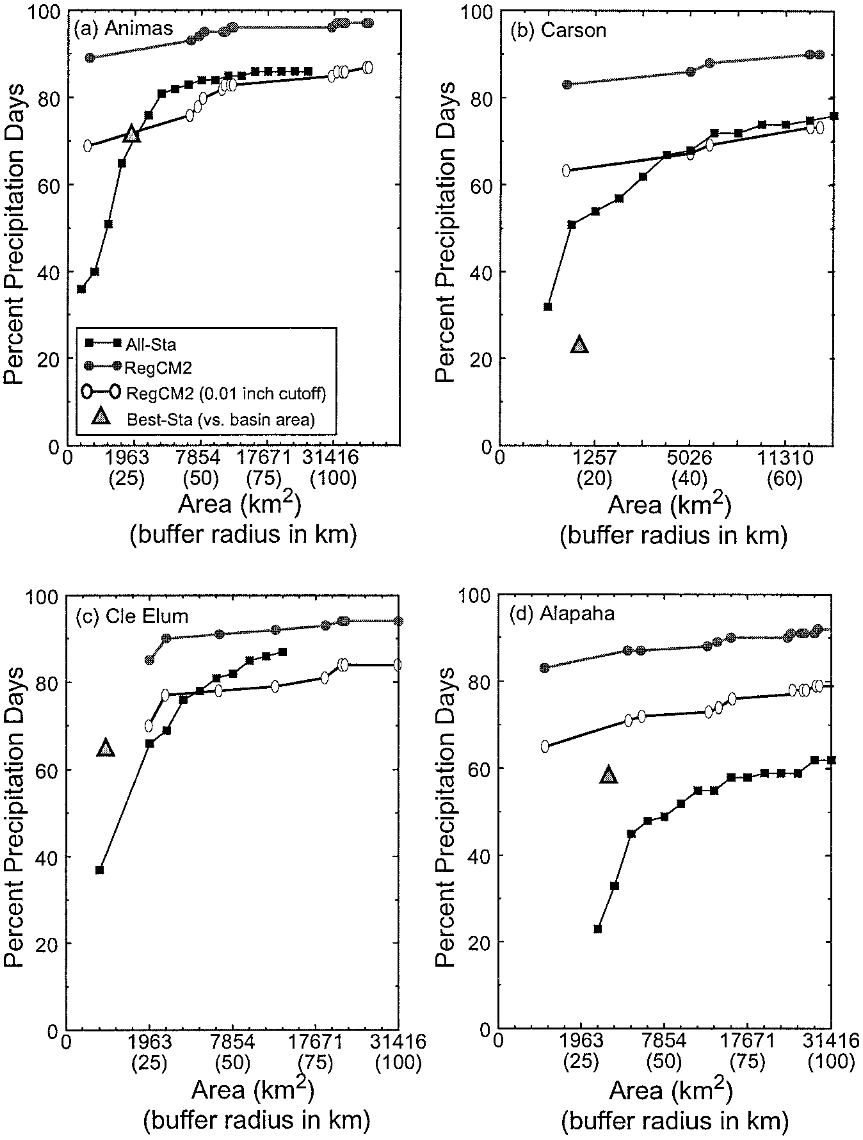

FIG. 4. Percent precipitation days with increasing buffer size for station data and RegCM2 output.

the inclusion of an additional station (RegCM2 grid point). The triangle in each plot indicates the percent precipitation days associated with the Best-Sta dataset (plotted vs basin area). As expected, increases in area (and the number of stations) are accompanied by increases in the percentage of precipitation days. However, notice that in each basin the RegCM2 starts with a significantly higher number of precipitation days at the smallest area (Fig. 4). Part of these differences occur because even a trace of RegCM2-generated precipitation will show up as a precipitation day (vs the 0.01-inch detection limit from the stations). When the station detection limit of 0.01 inches is applied as a cutoff to the RegCM2 output (open ovals in Fig. 4), there is close concurrence with the station data (with the exception of the Alapaha River basin); but due to the large area represented by a single RegCM2 grid box, there is still a higher percentage of precipitation days than what was determined from the exhaustive search analysis (Table 1 and triangle in Fig. 4).

Figures 5a–8a show the daily basin precipitation mean by month for the Best-Sta, RegCM2, Bias-RegCM2 (described later), All-Sta, and Bias-All (described later) datasets for the four river basins. Comparison of the RegCM2 and All-Sta with the Best-Sta precipitation dataset shows that both the RegCM2 and All-Sta capture the gross aspects of the seasonal cycle of precipitation in all four basins, although there are some large discrepancies. In the Alapaha River basin (Fig. 5a), RegCM2 values are significantly lower than

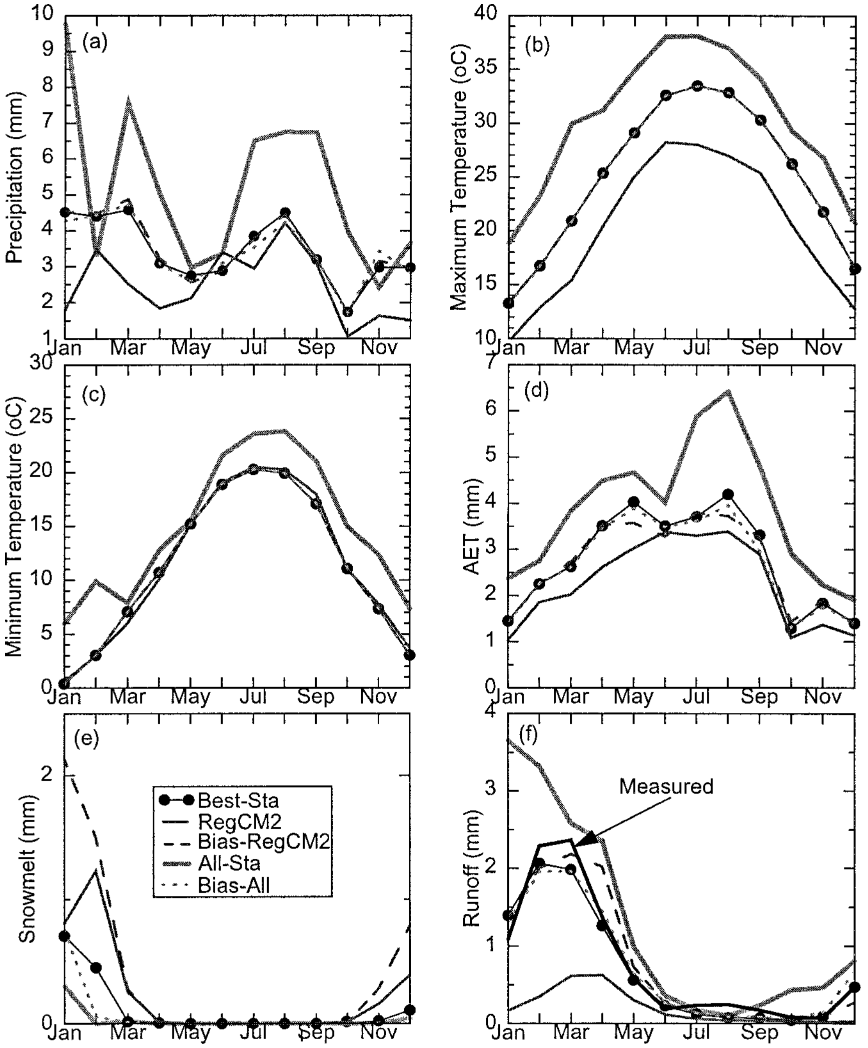

FIG. 5. Alapaha River basin daily basin mean by month for (a) precipitation, (b) max temperature, (c) min temperature, (d) actual evapotranspiration, (e) snowmelt, and (f) runoff.

Best-Sta in the winter months (Nov–Apr) but are much closer to the Best-Sta values than the All-Sta. In the Animas River basin (Fig. 6a), RegCM2 precipitation values are lower than Best-Sta in the winter months (Oct–Mar) and higher than Best-Sta precipitation in the summer months (May–Sep). All-Sta precipitation values are lower than the RegCM2 values in the winter months and similar to Best-Sta in the summer. In the Carson River basin (Fig. 7a), RegCM2 precipitation values are higher than Best-Sta in the summer months (May–Sep). All-Sta values are closer in value to Best-Sta in the summer months than RegCM2 and higher than the Best-Sta and RegCM2 values in the winter months. In the Cle Elum River basin (Fig. 8a), RegCM2 and All-Sta precipitation values are similar and significantly lower than Best-Sta values in the winter months (Nov–Feb).

Based on these results, the raw RegCM2 and All-Sta precipitation datasets were "corrected" for biases. The bias corrections were made on a monthly basis using a gamma transform that preserved the precipitation distribution. This procedure is similar to the transform method suggested by Panofsky and Brier (1968). The RegCM2 (and All-Sta) precipitation biases were corrected using the following steps: 1) the RegCM2 precipitation values were forced to have the same number of precipitation days as the Best-Sta dataset (Table 1). Since the RegCM2 precipitation always had more precipitation days than the Best-Sta (Fig. 4), this was accomplished by (a) ranking the RegCM2 precipitation output and (b) setting all values to zero with ranks equal to or lower than the number of dry days in the Best-Sta dataset. 2) Fit a gamma distribution was fitted to the resultant Best-Sta and RegCM2 time series (restricted to precipitation days). 3) For each RegCM2 precipitation day (i.e., all RegCM2 values above the thresholds identified in step 1b), compute the cumulative probability in the gamma distribution fitted to the RegCM2 output, and then replace the raw RegCM2 value with

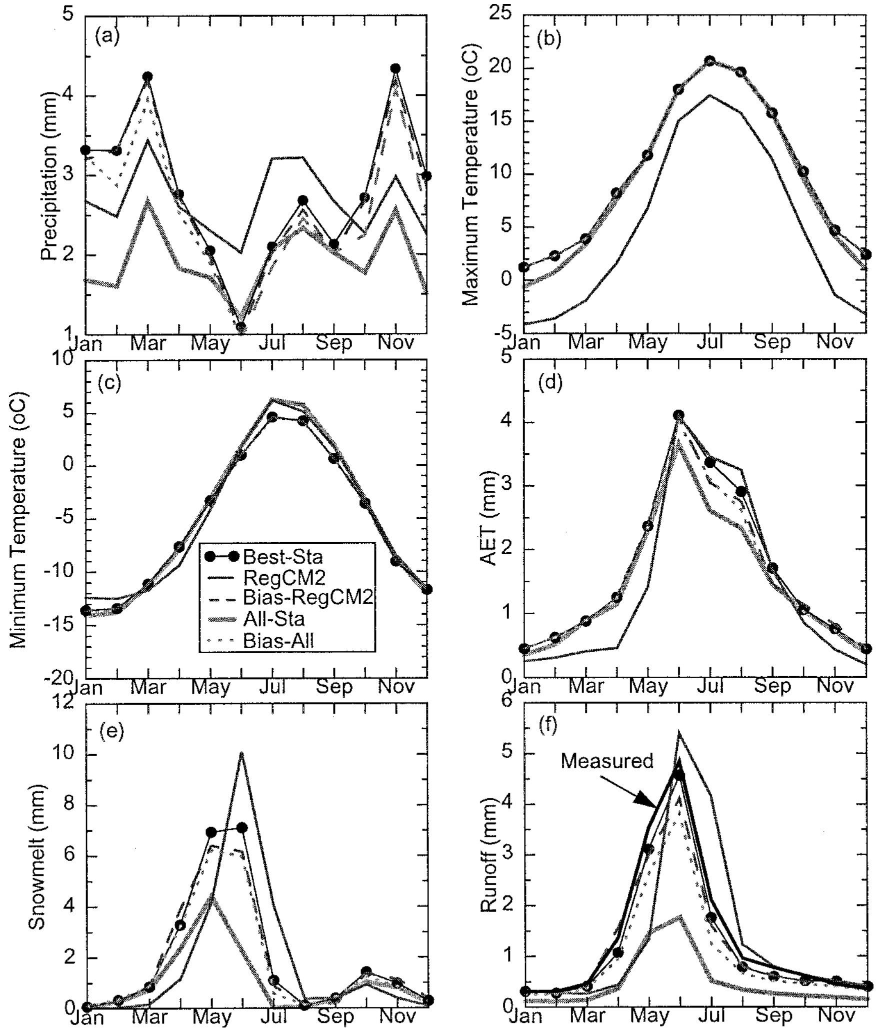

FIG. 6. Animas River basin daily basin mean by month for (a) precipitation, (b) max temperature, (c) min temperature, (d) actual evapotranspiration, (e) snowmelt, and (f) runoff.

the precipitation amount associated with the matched cumulative probability in the gamma distribution fitted to the Best-Sta data. An example of this approach is given in Fig. 9, which shows the cumulative probability of precipitation for RegCM2 output (Fig. 9a) and Best-Sta data (Fig. 9b) for the Animas River basin in January. Note from Fig. 6 that the RegCM2 model underpredicts cold-season precipitation in the Animas. For a RegCM2 precipitation value of 10 mm, the cumulative probability in the fitted gamma distribution is 0.83. In the gamma fit to the measured data, a cumulative probability of 0.83 is associated with a precipitation value of 15 mm. For this particular case, the bias correction increases the RegCM2 prediction from 10 to 15 mm.

Precipitation-day frequency is corrected using a method identical to step 1, except the station set used is the Best-Sta set determined from the exhaustive search analysis for precipitation frequency. Because there were only 10 years of RegCM2 output available for this study, an independent dataset was not used to produce the RegCM2 precipitation bias corrections. From Figs. 5a–8a, it is evident that monthly values of Bias-RegCM2 and Bias-All are similar to Best-Sta data.

The bias adjustments to the RegCM2 precipitation may correct the monthly mean values (Figs. 5f–8f), but daily values of Bias-RegCM2 precipitation do not contain the day-to-day variability present in the Best-Sta or All-Sta values for any of the basins. Figure 10a shows for each basin the R-square values by month for precipitation calculated using 1) Bias-RegCM2 and Best-Sta values and 2) Bias-All and Best-Sta values. The R-square values using Bias-RegCM2 precipitation output (Fig. 10a) are generally low for most months, especially in the Alapaha River basin (remaining near 0.0 for a large portion of the year). Relatively higher values occur in the winter months and the lowest values occur in the summer months. The R-square values using Bias-All precipitation output are much higher than those from Bias-

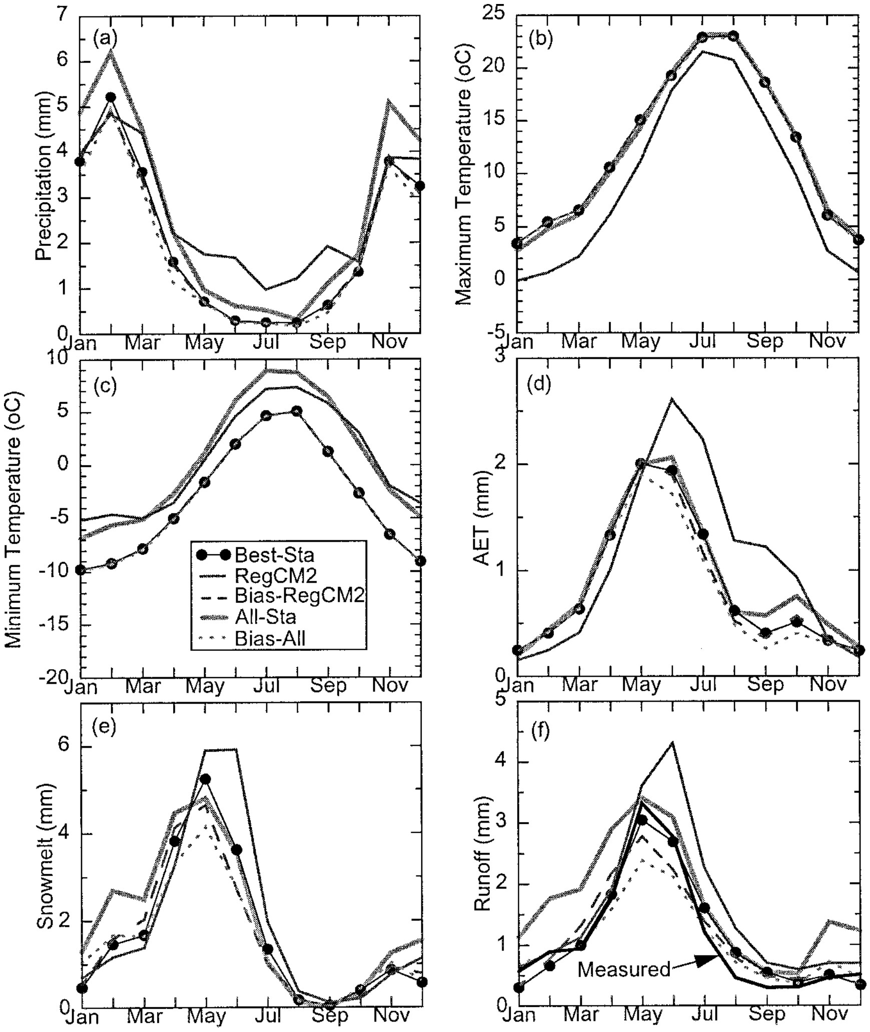

FIG. 7. East fork of the Carson River basin daily basin mean by month for (a) precipitation, (b) max temperature, (c) min temperature, (d) actual evapotranspiration, (e) snowmelt, and (f) runoff.

RegCM2, most notably in the Alapaha River basin. These results indicate that the RegCM2 output does not contain the day-to-day variability present on the All-Sta precipitation data compiled at the same spatial resolution.

b. Temperature

Figures 5b–8b and 5c–8c show the daily basin maximum and minimum temperature mean by month for the Best-Sta, RegCM2, Bias-RegCM2 (described later), All-Sta, and Bias-All (described later) datasets for the four river basins. RegCM2 maximum temperature values are significantly lower than Best-Sta data (with exception of Cle Elum), sometimes by as much as 6°C. All-Sta maximum temperature values are similar to Best-Sta values, with the exception of the Alapaha River basin (Fig. 5b), where All-Sta values are significantly higher than Best-Sta values. RegCM2 minimum temperature values are similar to Best-Sta values in the Alapaha (Fig. 5c) and Cle Elum (Fig. 8c) River basins, and higher than Best-Sta values in the Carson River basin (Fig. 7c). All-Sta minimum temperature values are higher in the Alapaha (Fig. 5c) and the Carson River basin (Fig. 7c).

A simple bias correction was performed on the raw RegCM2 and All-Sta maximum and minimum temperature datasets to produce the Bias-RegCM2 and Bias-All temperature datasets, respectively. Biases were removed in the RegCM2 (and All-Sta) datasets by 1) computing a monthly climatology of the RegCM2 maximum and minimum temperature for each day; 2) subtracting the daily RegCM2 value of maximum and minimum temperature from that climatology (to produce a daily anomaly value); and 3) adding the daily maximum and minimum temperature anomaly from the RegCM2 model to the corresponding Best-Sta monthly station climatology of maximum and minimum temperature. Because there were only 10 years of RegCM2 output avail-

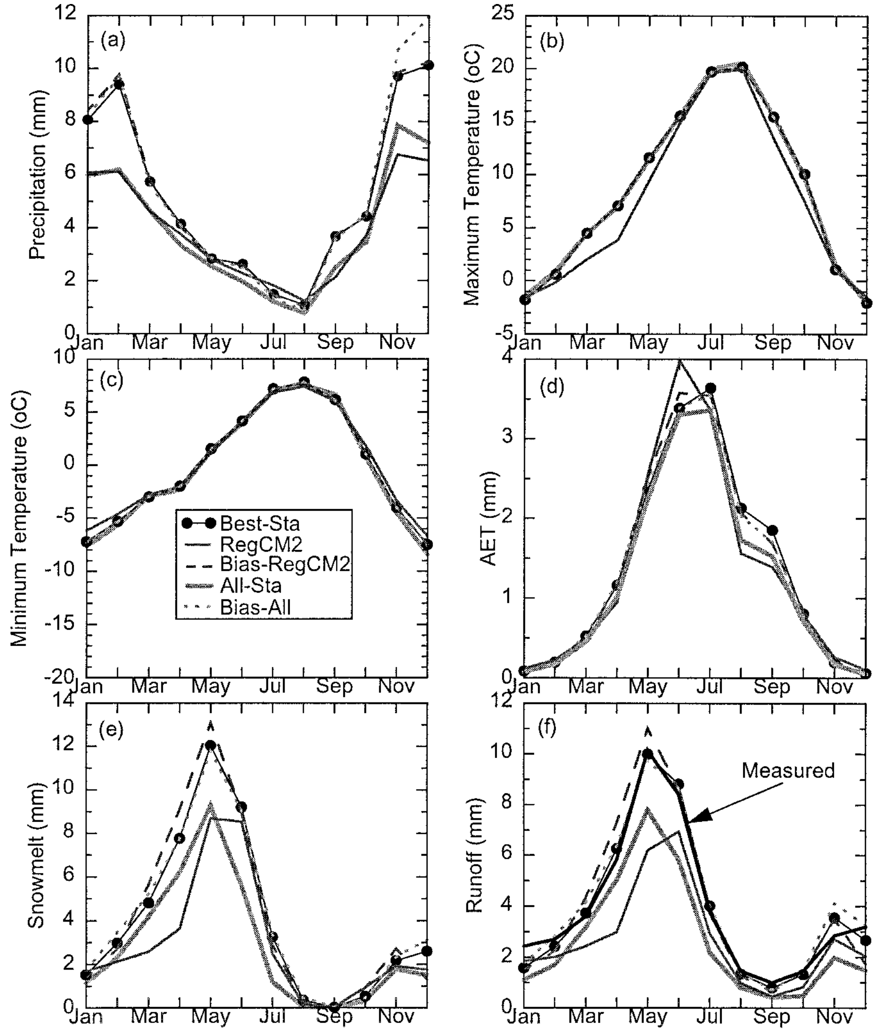

FIG. 8. Cle Elum River basin daily basin mean by month for (a) precipitation, (b) max temperature, (c) min temperature, (d) actual evapotranspiration, (e) snowmelt, and (f) runoff.

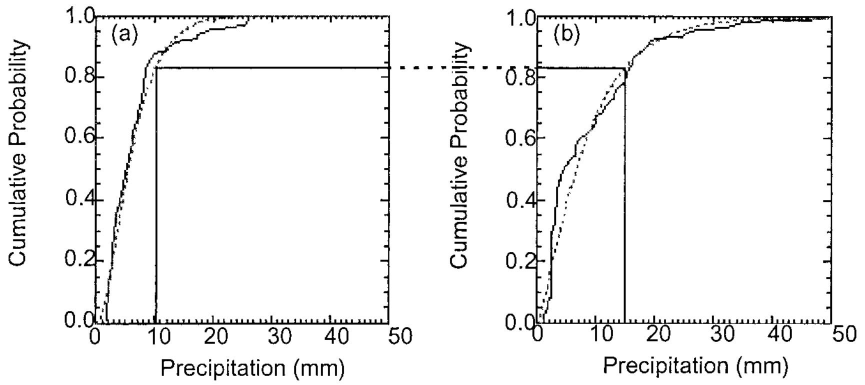

FIG. 9. Cumulative probability of precipitation for (a) RegCM2 output and (b) Best-Sta station data for the Animas River basin in Jan.

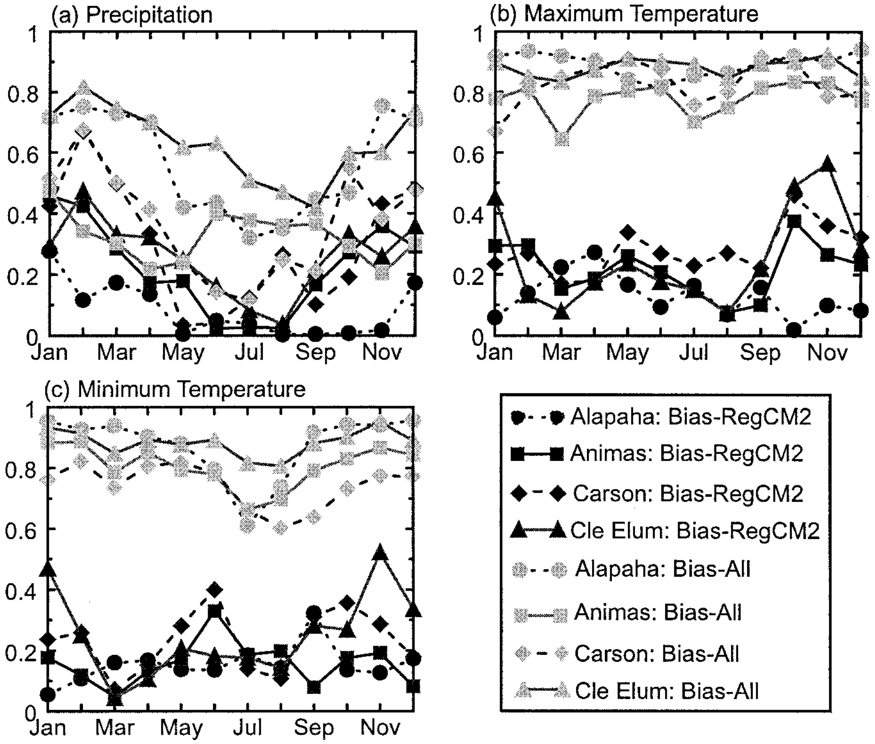

FIG. 10. The R-square values by month for each basin calculated using 1) bias-corrected RegCM2 and best three-station values and 2) bias-corrected all stations and best three-station values for (a) precipitation, (b) max temperature, and (c) min temperature.

able for this study, an independent dataset was not used to produce the maximum and minimum temperature bias corrections. Due to the nature of the temperature bias correction, the monthly climatologies of Bias-RegCM2, Bias-All, and Best-Sta are the same (see Figs. 5b–8b and 5c–8c).

Bias adjustments to the RegCM2 temperature may correct the monthly mean values (Figs. 5b, 5c–8b, and 8c), but similar to precipitation, daily values of Bias-RegCM2 temperature do not contain the day-to-day variability present in the Best-Sta or All-Sta values for any of the basins. Figures 10b,c shows for each basin the R-square values by month for maximum and minimum temperature calculated using 1) Bias-RegCM2 and Best-Sta values and 2) Bias-All and Best-Sta values. R-square values by month using Bias-RegCM2 output for maximum and minimum temperature are generally low for all months and are significantly less than the R-Square values calculated using Bias-All data. Temperature station data compiled at the scale of the RegCM2 output still contains day-to-day variability present in the ''Best-Sta'' dataset. The RegCM2 output may have identical monthly means values, but does not contain the day-to-day variability in temperature present in the measured station data.

5. Hydrologic model output

Figure 11 shows the simulated mean annual water balance components [evapotranspiration (ET) using Jensen–Haise, precipitation, and simulated runoff] and the measured runoff for each basin. Figures 5d–8d, 5e–8e, and 5f–8f show the basin daily mean by month of actual evapotranspiration, snowmelt, and runoff simulated by PRMS using the Best-Sta, RegCM2, Bias-RegCM2, All-Sta, and Bias-All datasets as input.

a. Actual evapotranspiration

By definition, the bias corrections to the precipitation and temperature (Bias-RegCM2 and Bias-All) result in similar actual evapotranspiration (AET) as that simulated using Best-Sta. In the Alapaha River basin, the underestimate of RegCM2 AET reflects both the below-normal precipitation (less available soil moisture) and the below-normal temperatures (lower potential ET rates; Fig. 5d). Similarly, the positive biases in precipitation and maximum temperature in the All-Sta simulation can explain the higher rates of AET in the Alapaha. In the Animas, although RegCM2 consistently underpredicts maximum temperature throughout the year (lower potential ET rates), the RegCM2 AET values are similar to the Best-Sta values in the summer months (Fig. 6d). This most likely occurs because RegCM2 overpredicts summertime precipitation, possibly leading to higher available soil moisture. Similar patterns are evident in the east fork of the Carson (Fig. 7d).

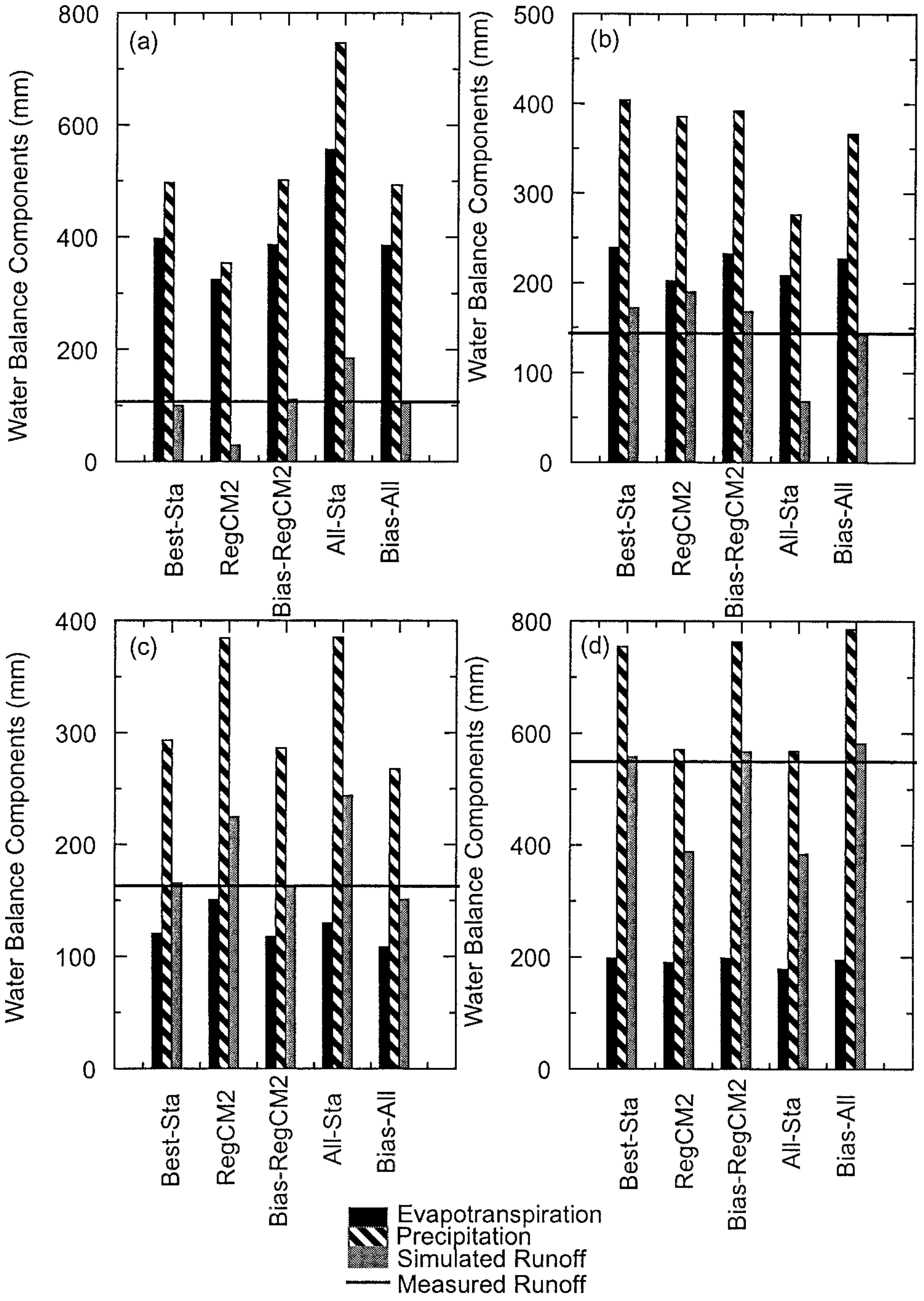

FIG. 11. Mean annual water balance components for the (a) Alapaha, (b) Animas, (c) east fork of the Carson, and (d) Cle Elum.

b. Snowmelt

The snowmelt simulated by PRMS is summarized in Figs. 5e–8e. Minimal snowmelt is simulated in the Alapaha River basin (Fig. 5e). Colder RegCM2 maximum temperatures in the Animas and Carson River basin (Figs. 6b, 7b) delay the snowmelt (Figs. 6e, 7e). The lower All-Sta precipitation in the Animas and Cle Elum River basins (Figs. 6a, 8a) lowers the amount of snowmelt (Figs. 6e, 8e).

c. Runoff

Figures 5–8f show the daily basin mean runoff values by month expressed as a depth (mm day^{-1}) and Fig. 11

shows the mean annual water balance components for each basin. In the Alapaha, the more frequent but smaller-magnitude storms generated by the RegCM2 have a mean monthly depth that is about 80% of the measured mean monthly (Fig. 5a). The significant smaller average monthly runoff simulated using the RegCM2 storms (Fig. 5f) can be attributed to the smaller magnitude of the individual storms present in the RegCM2 output. Figure 4d indicates a 90% rainday occurrence in the RegCM2 output, compared with 58 and 62 percent rainday occurrence in the Best-Sta and All-Sta datasets, respectively. For direct-runoff computation at a 24-h time step, the PRMS model uses a contributing area concept similar to that used by many watershed models. The area contributing runoff during rainfall, and the magnitude of the runoff from this area are functions of antecedent soil moisture content and the 24-h rainfall amount. This relation is nonlinear with larger storms and wetter soil conditions generating proportionally larger amounts of runoff than that from drier soil conditions and smaller storms. Thus, precipitation from larger storms will reach river networks fairly quickly, whereas precipitation from smaller storms will replenish soil reservoirs and remain available for ET. Note that almost all of the precipitation in the raw RegCM2 simulation is lost through ET (Fig. 11a), resulting in very low runoff (Fig. 5f). The less frequent but larger-magnitude storms in the Best-Sta data produce a simulated runoff response that is much closer to the measured basin runoff (Fig. 5f). The larger precipitation volumes for the All-Sta produced excessively high runoff values.

In the Animas (Fig. 6), significantly lower RegCM2 maximum temperature values translates into delays in spring runoff. Similar delays in spring runoff from lower RegCM2 maximum temperature are seen in each of the snowmelt basins (Figs. 6–8f). Lower All-Sta precipitation in the Animas results in underestimation of runoff. Similar but less extreme runoff responses are seen in the Cle Elum (Fig. 8). In the east fork of the Carson (Fig. 7), higher All-Sta and RegCM2 precipitation values translate into an overestimation of runoff.

6. Diagnosis of hydrologic modeling error

PRMS-simulated runoff using RegCM2 and All-Sta input datasets did not reproduce realistic hydrographs in any of the basins. Runoff simulated using the Bias-corrected RegCM2 and All-Sta datasets are much closer to measured mean monthly runoff than those simulated using the raw data. But, comparisons of runoff values on a mean monthly basis can be misleading. As shown in Fig. 10, the bias correction, essentially a magnitude correction to the raw climate datasets, does not correct for errors in daily temporal variability. A comparison of daily runoff is a more stringent test of the capabilities of RegCM2 to simulate observed climate.

Figure 12 shows plots of measured versus simulated daily runoff and the corresponding Nash–Sutcliffe (NS) coefficient of efficiency statistic (Nash and Sutcliffe 1970). Figures 12a–d show the measured versus simulated daily runoff using the Best-Sta data; Figs. 12e–h show the measured versus simulated runoff using the RegCM2 output; Figs. 12i–l show the measured versus simulated runoff using the Bias-RegCM2 output; Figs. 12m–p show the measured versus simulated runoff using the All-Sta data; and Figs. 12q–t show the measured versus simulated runoff using the Bias-All data as input to PRMS for the four basins. For PRMS outputs simulated using the Best-Sta data (Fig. 12a–d), the NS values are all above 0.7, indicating a good fit even with minimal calibration of the PRMS model parameters. In contrast, for PRMS outputs simulated using RegCM2 and All-Sta data (Figs. 12e–h, 12m–p), the resulting NS values are much lower (less than 0.4 to near 0.0 for the RegCM2 and less than 0.6 to near 0.0 for the All-Sta). For PRMS outputs simulated using Bias-RegCM2 output, model skill improves, but in all basins the NS values are significantly lower than those simulated using the Best-Sta. This is most apparent in the Alapaha River basin, in which the NS value is only 0.09 (compared to 0.76 for PRMS outputs simulated using Best-Sta data). For PRMS outputs simulated using Bias-All data, model skill improves significantly in every basin. Most notably, the Alapaha River basin NS score increases to 0.72 (compared to 0.76 when using Best-Sta and 0.09 when using Bias-RegCM2).

Figures 5–8 show that the Bias-RegCM2 and Bias-All input datasets can be used to produce realistic simulations of mean monthly runoff, but, with the exception of the Carson River basin, Bias-RegCM2 simulations of daily runoff are rather poor and of less skill than Bias-All (Fig. 12). The questions to be answered for each basin are 1) the timescale at which the Bias-RegCM2- and Bias-All-based simulations produce realistic runoff and 2) which climate variables have the greatest effect on runoff.

In an attempt to address question 1, the Bias-RegCM2-, Bias-All-, and Best-Sta-runoff simulations were summed over successively longer time intervals (up to 120 days), and the NS goodness-of-fit score was recomputed (Fig. 13). In order for runoff simulated using Bias-RegCM2 output to have NS values similar to that simulated using Best-Sta data, Bias-RegCM2 output would have to be summed on 108-, 44-, and 114-day intervals for the Animas, Carson, and Cle Elum River basins, respectively (see Fig. 13). For the Alapaha River basin, even temporally averaged runoff simulations on seasonal timescales (120 days) have NS values much lower than daily simulations with Best-Sta data. In comparison, in order for runoff simulated using Bias-All data to have NS values similar to that simulated using Best-Sta data, Bias-All output would have to be summed on 5-, 26-, 4-day intervals for the Alapaha, Carson, and Cle Elum River basins, respectively (see Fig. 13). For the Animas River basin, temporally averaged runoff simulations produced using Bias-All output on seasonal

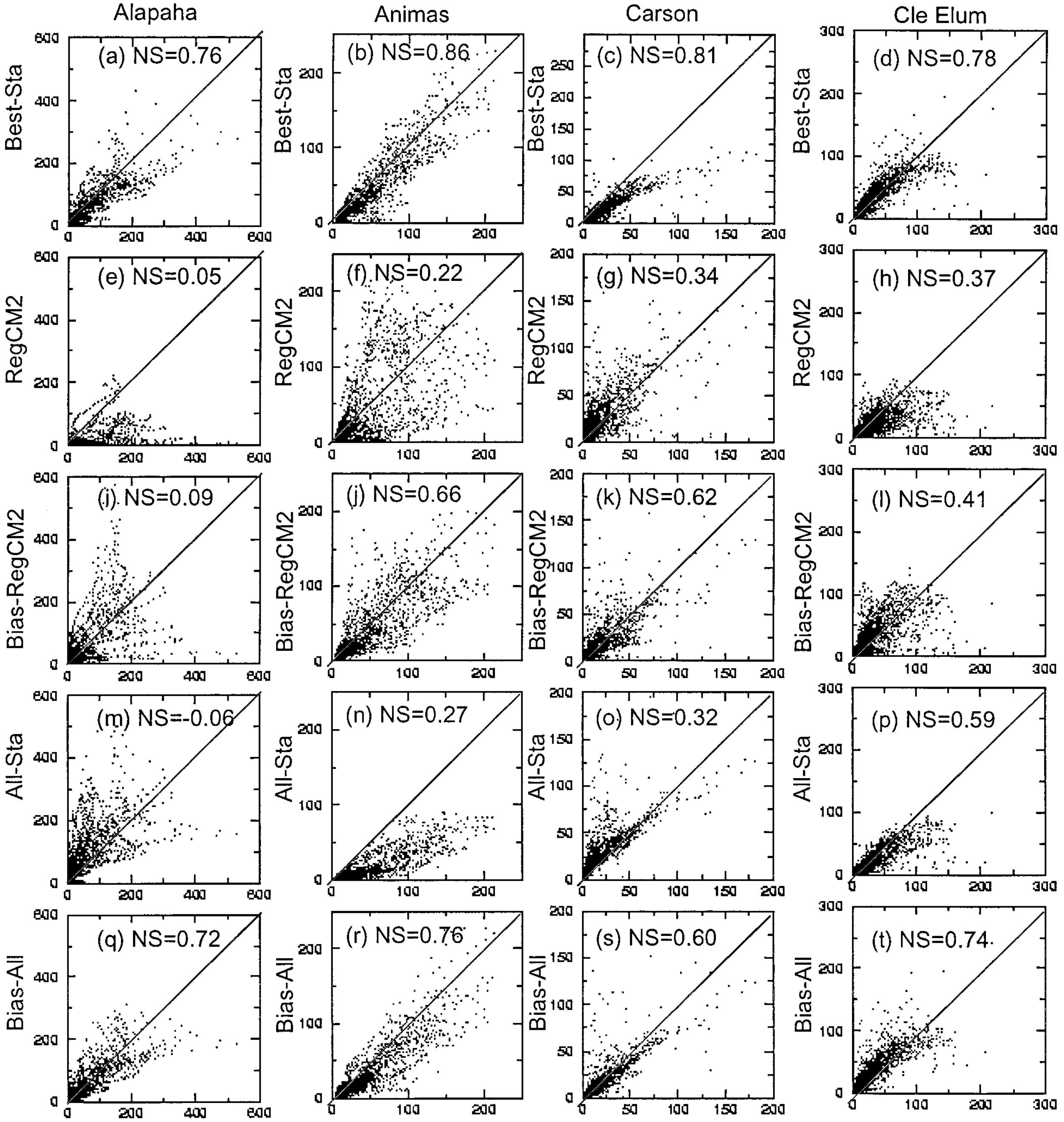

FIG. 12. Measured vs simulated daily runoff and corresponding Nash–Sutcliffe goodness-of-fit statistic (NS) for the Alapaha, Animas, Carson, and Cle Elum River basins. Simulated runoff produced using daily time series from best three-station data; raw RegCM2 output; bias-corrected RegCM2 output, all stations; and bias-corrected all stations.

timescales (120 days) have NS values lower than daily simulations with Best-Sta data.

To evaluate which of these climate variables has the most effect on runoff, three tests were run. In each of the four basins, the Bias-RegCM2 time series of precipitation, maximum temperature, and minimum temperature were successively replaced with a time series of Best-Sta data. These tests included 1) Test1, Best-Sta precipitation with Bias-RegCM2 maximum and minimum temperature; 2) Test2, Best-Sta maximum temperature with Bias-RegCM2 precipitation and minimum temperature; 3) Test3, Best-Sta minimum temperature with Bias-RegCM2 precipitation and maximum temperature (see Table 3). Figure 14 shows the results of these test runs in PRMS: scatterplots of measured versus simulated daily runoff and corresponding NS val-

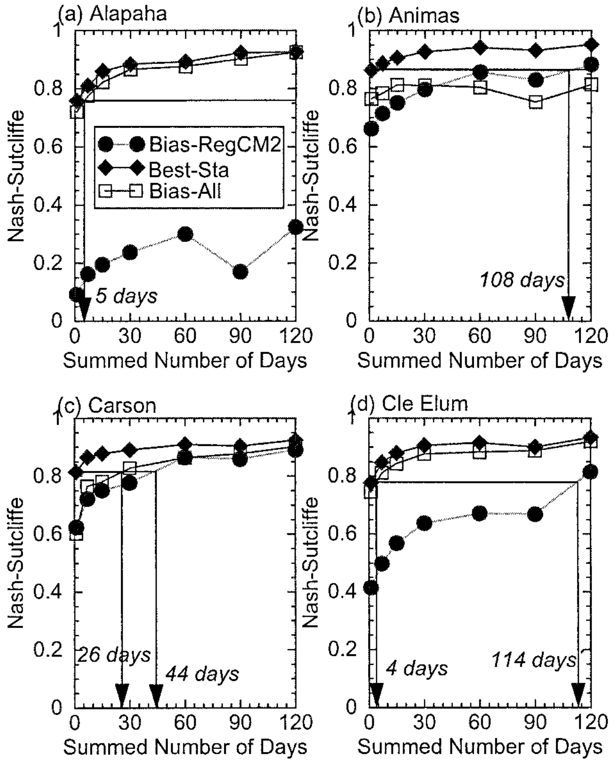

FIG. 13. Nash–Sutcliffe goodness-of-fit (NS) values calculated for the (a) Alapaha, (b) Animas, (c) Carson, and (d) Cle Elum River basins. NS values were calculated between measured and simulated runoff values summed on 1-, 5-, 15-, 30-, 60-, 90-, and 120-day intervals.

ues. The highest NS values are highlighted on the plots. What becomes evident from Fig. 14 is the importance of temperature in the snowmelt basins (Test2 gives the highest NS values) and precipitation in the rainfall-dominated basin (Test1 gives the highest NS values).

7. Discussion

This study was initiated to examine possibilities for using regional climate model output in hydrologic applications. Three initial daily datasets were composed from 1) best precipitation and temperature station sets for each basin determined through hydrologic model calibration (Best-Sta); 2) RegCM2 output; and 3) all stations (excluding Best-Sta sets) that fell within the buffered area used to extract the RegCM2 output (All-Sta). The Best-Sta datasets simulated realistic daily hydrographs in all four study basins. All-Sta datasets were tested to determine if an area as large as that covered by the RegCM2 grid points could produce realistic precipitation and temperature for basin-scale modeling. Both the All-Sta data and RegCM2 output of precipitation, maximum temperature, and minimum temperature produced unrealistic simulations of runoff in all four study basins when used as input to the hydrologic model. Bias corrections to the RegCM2 output and All-Sta data produced the next two input datasets: 4) Bias-RegCM2 and 5) Bias-All. Use of Bias-RegCM2 and Bias-All in PRMS resulted in more realistic monthly mean hydrographs, but comparison of daily values showed that with the exception of one basin (Carson), Bias-RegCM2 output was still not nearly as reliable in simulating daily runoff as Bias-All. The final three input datasets (Test1, Test2, and Test3) were produced to test which climate variables had the most effect on runoff. These tests clearly showed the significance of realistic temperature data in the snowmelt basins and realistic precipitation in the rainfall-dominated basins.

A summary of NS results produced using the eight input datasets in PRMS is shown in Fig. 15. Not surprisingly, Best-Sta data outperformed any of the other PRMS input datasets. In the Alapaha River basin, the only other PRMS input datasets that simulated realistic hydrographs were Test1 and Bias-All, highlighting the significance of realistic precipitation in this southeastern United States basin and the relative reduced significance of maximum and minimum temperature. The fact that Bias-All dramatically outperforms Bias-RegCM2 in this rainfall-dominated basin also indicates that precipitation averaged over a large area can have the daily variations necessary for basin-scale modeling. On the other hand, snowmelt-dominated basins are much more strongly controlled by maximum temperature. In these basins, daily variations in precipitation are less important, and only the volume of precipitation over the accumulation season (e.g., as represented in the 1 April snowpack) needs to be correct.

These results are consistent with Wilby and Dettinger's (2000) study of snowmelt-dominated basins in the Sierra Nevada. In their study they concluded that much of the hydrological ''skill'' arises from the fact that the snowpack acts as an integrator of the hydrologic processes. In a sense, the Leung et al. (1996) study also supports these results. Leung et al. (1996) drove a spatially distributed hydrologic model of a snowmelt-dominated basin in northwestern Montana using measured and regional climate model (RCM) output and concluded that runoff simulated using RCM output resulted in comparable, if not better, agreement with measured runoff than driving the model with measured data. In their study, measured data from two stations was distributed by assuming a constant lapse rate with altitude. The lapse rate for temperature was set at a constant 6°C km^{-1}. The RCM output was distributed using a subgrid parametrization scheme. In our study we have shown the importance of temperature in snowmelt dominated basins. The constant lapse rate used by Leung et al. (1996) to distribute the measured temperature data probably affected the runoff simulations. It is likely that their subgrid parametrization scheme corrected the biases in the RegCM2 temperature output, thus producing more realistic hydrographs than that using measured-temperature data.

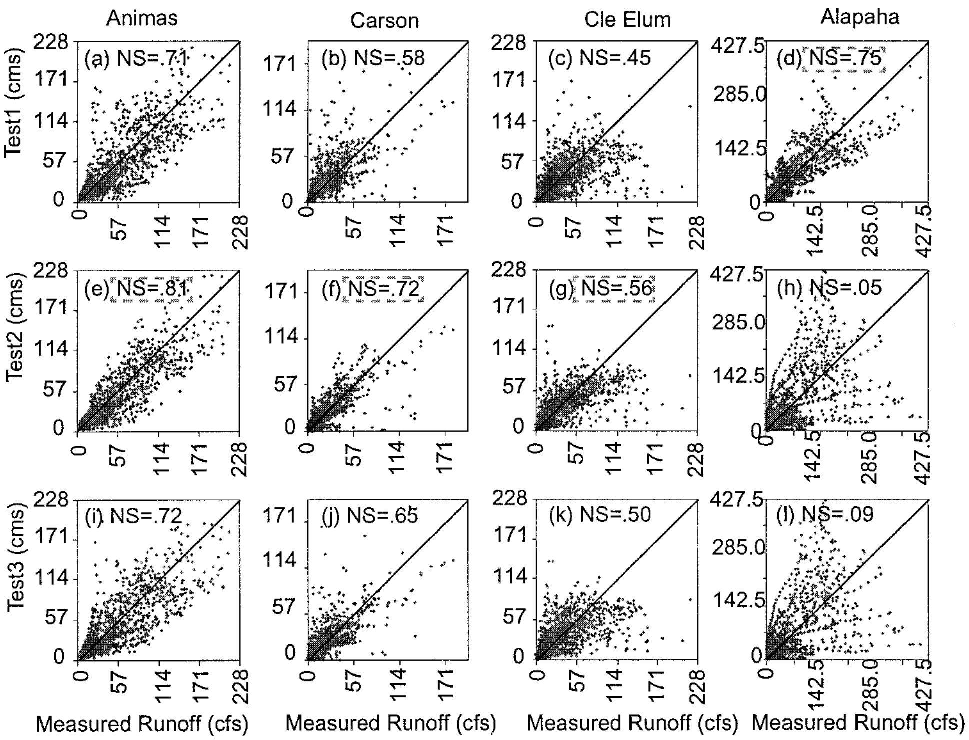

FIG. 14. Measured vs simulated runoff for the four basins (Animas, Carson, Cle Elum, and Alapaha) and corresponding Nash–Sutcliffe goodness-of-fit statistic (NS). Simulated runoff produced using three test input times series: (a)–(d) Test1, station precipitation with bias corrected RegCM2 max and min temperature; (e)–(h) Test2, station max temperature with bias corrected RegCM2 precipitation and min temperature; (i)–(l) Test3, station min temperature with bias corrected RegCM2 precipitation and max temperature.

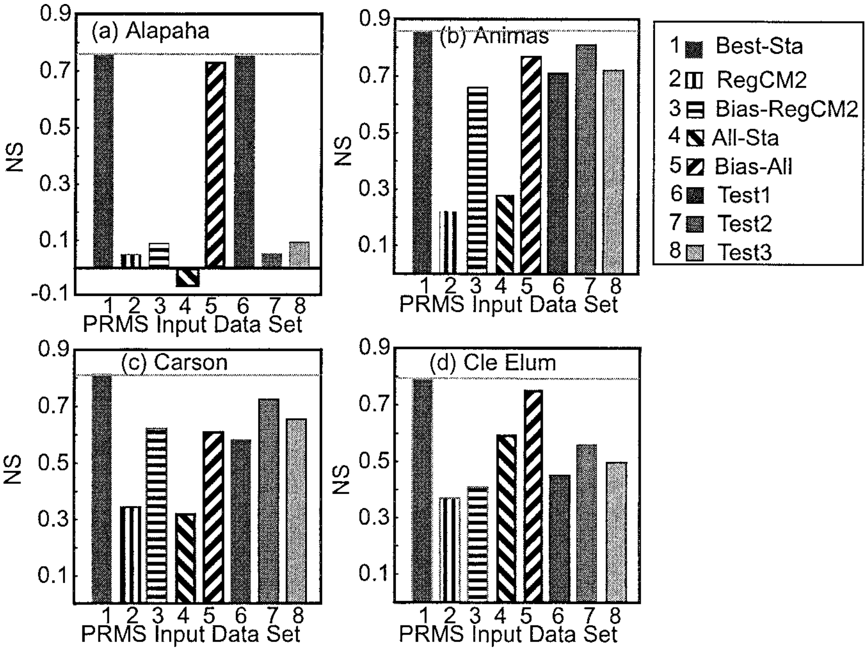

FIG. 15. Nash–Sutcliffe goodness-of-fit statistic (NS) for the (a) Alapaha, (b) Animas, (c) Carson, and (d) Cle Elum River basins. Simulated runoff produced using the following PRMS input datasets: 1, Best-Sta; 2, RegCM2 t; 3, Bias-RegCM2; 4, All-Sta; 5, Bias-All; 6, Test1; 7, Test2; and 8, Test3.

8. Conclusions

Daily precipitation and maximum and minimum temperature time series from a regional climate model (RegCM2) were used as input to a distributed hydrologic model for three snowmelt-dominated basins (Animas River at Durango, Colorado; east fork of the Carson River near Gardnerville, Nevada; and Cle Elum River near Roslyn, Washington) and a rainfall-dominated basin (Alapaha River at Statenville, Georgia). For comparison purposes, daily datasets of precipitation and maximum and minimum temperature were developed using measured station data that fell within the area used to extract the RegCM2 output (All-Sta). The All-Sta datasets are comparable in scale to the RegCM2 model resolution and provide an appropriate test to determine if output at this scale can be used for simulation of basin-scale hydrology.

Both the RegCM2 and All-Sta simulations capture the gross aspects of the seasonal cycles of precipitation and temperature. However, in all four basins large systematic biases in RegCM2 and All-Sta simulations of temperature and precipitation are evident, which translate into unrealistic simulations of mean-monthly hydrographs. In order to reproduce realistic mean-monthly hydrographs in each of the four basins studied, the RegCM2 and All-Sta output are corrected for biases (Bias-RegCM2 and Bias-All, respectively).

Simulated runoff based on Bias-RegCM2 output and Bias-All data were evaluated on a monthly and daily basis. On a mean monthly basis, runoff simulated using the Bias-RegCM2 and Bias-All sets are much closer to measured runoff than those simulated using the raw data. On a daily basis, with the exception of the Carson River basin, Bias-RegCM2-based simulations are rather poor and of less skill than Bias-All. Most notable are the results in the rainfall-dominated basin: Bias-RegCM2-based simulations show essentially no skill whereas Bias-All-based simulations reproduce realistic runoff. These results indicate that precipitation averaged over a large area can have the daily variations necessary for basin-scale modeling. In the snowmelt-dominated basins, which are strongly controlled by maximum temperature, capturing daily variations in precipitation was found to be less important, and only the volume of precipitation over the accumulation season needs to be correct.

In conclusion, climate data of similar resolution to that of the RegCM2 model can be made appropriate for basin-scale modeling when a bias correction is applied. This need for statistical correction (essentially a magnitude correction) may be somewhat troubling, but in the case of the large station dataset (All-Sta), the magnitude correction did indeed correct for the change in scale. This was not shown to be true for the bias-corrected RegCM2 output. The RegCM2 output could be corrected for magnitude but did not contain the day-to-day variability needed for basin-scale modeling present in the All-Sta dataset. The major advantage of using regional climate model output to simulate runoff is their physical realism. It is unknown if statistical corrections to model output will be valid in a future climate. Future work is warranted to identify the causes for (and removal of) systematic biases in RegCM2 simulations, and to improve RegCM2 simulations of daily variability in local climate.

REFERENCES

Anderson, J. R., E. E. Hardy, J. T. Roach, and R. E. Witmer, 1976: A land use land cover classification system for use with remote sensor data. U.S. Geological Survey Prof. Paper 964, 28 pp.

Briegleb, B. P., 1992: Delta-Eddington approximation for solar radiation in the NCAR Community Climate Model. *J. Geophys. Res.,* **97,** 7603–7612.

Dickinson, R. E., A. Henderson-Sellers, and P. J. Kennedy, 1992: Biosphere–Atmosphere Transfer Scheme (BATS) version 1e as coupled to NCAR Community Climate Model. NCAR Tech. Note 387+STR, 72 pp.

Giorgi, F., L. O. Mearns, C. Shields, and L. Mayer, 1996: A regional model study of the importance of local versus remote controls of the 1988 drought and the 1993 flood over the central United States. *J. Climate,* **9,** 1150–1161.

Grell, G. A., 1993: Prognostic evaluation of assumptions used by cumulus parameterizations. *Mon. Wea. Rev.,* **121,** 764–787.

Hay, L. E., and M. P. Clark, 2000: Use of atmospheric forecasts in hydrologic models in mountainous terrain. Part 2: Application to hydrologic models. *Proc. AWRA Spring Specialty Conf. on Water Resources in Extreme Environments,* Anchorage, AK, American Water Resources Association, 221–226.

——, R. L. Wilby, and G. H. Leavesley, 2000: A comparison of delta change and downscaled GCM scenarios for three mountainous basins in the United States. *J. Amer. Water Resour. Assoc.,* **36,** 387–397.

Holtslag, A. A. M., E. I. F. de Bruijn, and H. L. Pan, 1990: A high resolution air mass transformation model for short-range weather forecasting. *Mon. Wea. Rev.,* **118,** 1561–1575.

Hsie, E.-Y., R. A. Anthes, and D. Keyser, 1984: Simulations of frontogenesis in a moist atmosphere using alternative parameterizations of condensation and precipitation. *J. Atmos. Sci.,* **41,** 2701–2716.

Kalnay, E., and Coauthors, 1996: The NCEP/NCAR 40-Year Reanalysis Project. *Bull. Amer. Meteor. Soc.,* **77,** 437–471.

Leavesley, G. H., and L. G. Stannard, 1995: The precipitation–runoff modeling system—PRMS. *Computer Models of Watershed Hydrology,* V. P. Singh, Ed., Water Resources Publications, 281–310.

——, R. W. Lichty, B. M. Troutman, and L. G. Saindon, 1983: Precipitation–runoff modeling system: User's manual. Rep. 83-4238, U.S. Geological Survey Water Investigation, 207 pp.

——, M. D. Branson, and L. E. Hay, 1992: Using coupled atmospheric and hydrologic models to investigate the effects of climate change in mountainous regions. *Managing Water Resources During Global Change. AWRA 28th Annual Conference and Symposium,* R. Herrmann, Ed., American Water Resources Association, 691–700.

——, L. E. Hay, R. J. Viger, and S. L. Markstrom, 2002a: Use of objective distributed-parameter estimation methods to constrain model calibration. *Advances in Calibration of Watershed Models, Geophys. Monogr.,* Amer. Geophys. Union, in press.

——, S. L. Markstrom, P. J. Restrepo, and R. J. Viger, 2002b: A modular approach to addressing model design, scale, and parameter estimation issues in distributed hydrological modeling. *Hydrol. Processes,* **16,** 173–187.

Leung, L. R., M. S. Wigmosta, S. J. Ghan, D. J. Epstein, and L. W. Vail, 1996: Application of a subgrid orographic precipitation/

surface hydrology scheme to a mountain watershed. *J. Geophys. Res.,* **101** (D8), 12 803–12 817.

Milly, P. C. D., and K. A. Dunne, 2002: Macro-scale water fluxes. 1. Quantifying errors in the estimation of river-basin precipitation. *Water Resour. Res.,* in press.

Nash, J. E., and J. V. Sutcliffe, 1970: River flow forecasting through conceptual models. Part I: A discussion of principles. *J. Hydrol.,* **10,** 282–290.

Panofsky, H. A., and G. W. Brier, 1968: *Some Applications of Statistics to Meteorology.* The Pennsylvania State University Press, 224 pp.

Phillips, T. J., 1995: Documentation of the AMIP models on the World Wide Web. UCRL-MI-116384, Lawrence Livermore Laboratory, 14 pp.

Ramage, C. S., 1983: Teleconnections and the siege of time. *J. Climatol.,* **3,** 223–231.

Sevruk, B., 1989: Reliability of precipitation measurements. *WMO/IAHS/ETH Workshop on Precipitation Measurements,* Zurich, Switzerland, Dept. of Oceanography, Swiss Federal Institute of Technology, 13–19.

Takle, E. S., and Coauthors, 1999: Project to Intercompare Regional Climate Simulations (PIRCS): Description and initial results. *J. Geophys. Res.,* **104,** 19 443–19 461.

U.S. Department of Agriculture, cited 2002: Forest land distribution data for the United States: Forest Service. [Available online at http://www.srsfia.usfs.msstate.edu/rpa/rpa93.htm.]

——, 1994: State Soil Geographic (STATSGO) database—Data use information. Misc. Publ. 1492, Natural Resources Conservation Service, 107 pp.

Watson, R. T., M. C. Zinyowera, and R. H. Moss, 1996: *Climate Change 1995: Impacts, Adaptations, and Mitigations of Climate Change.* Cambridge University Press, 889 pp.

Wilby, R. L., and M. D. Dettinger, 2000: Streamflow changes in the Sierra Nevada, CA, simulated using statistically downscaled general circulation model output. *Linking Climate Change to Land Surface Change,* S. McLaren, and D. Kniveton, Eds., Kluwer Academic, 99–121.

——, L. E. Hay, and G. H. Leavesley, 1999: A comparison of downscaled and raw GCM output: Implications for climate change scenarios in the San Juan River Basin, Colorado. *J. Hydrol.,* **225,** 67–91.

——, ——, W. J. Gutowski, R. W. Arritt, E. S. Takle, Z. Pan, G. H. Leavesley, and M. P. Clark, 2000: Hydrological responses to dynamically and statistically downscaled climate model output. *Geophys. Res. Lett.,* **27,** 1199–1202.

Wilks, D. S., 1995: *Statistical Methods in the Atmospheric Sciences: An Introduction.* Academic Press, 467 pp.