4.2 STATISTICAL AND DYNAMICAL DOWNSCALING OF GLOBAL MODEL OUTPUT FOR U.S. NATIONAL ASSESSMENT HYDROLOGICAL ANALYSES

W.J. Gutowski, Jr. (1)*, R. Wilby (2,3), L. E. Hay (4), C.J. Anderson (1), R.W. Arritt (1), M. P. Clark (4), G. H. Leavesley (4), Z. Pan (1), R. Silva (1), E. S. Takle (1)

(1) Iowa State University, Ames, Iowa
(2) National Center for Atmospheric Research, Boulder, Colorado
(3) University of Derby, Derby, UK
(4) U.S. Geological Survey, Denver, Colorado
(5) University of Colorado, Boulder Colorado, USA

1. NTRODUCTION

Analyses performed for the US National Assessment require accurate projections of climate at scales below those resolved by global General Circulation Models (GCMs). Two techniques have been developed that counter this deficiency: semi-empirical (statistical) downscaling (SDS) of GCM outputs, and regional climate models (RCMs) nested within a GCM. To date, few studies have compared SDS and RCM output, or the significance of any differences between the two when their output is fed to climate impact models (e.g., Mearns et al., 1999). We compare these two approaches for producing hydroclimate input to a number of river basins targeted for the National Assessment. The primary global, driving "model" for both approaches is the NCEP/NCAR reanalysis. This project builds on previous intercomparisons, namely the Project to Intercompare Regional Climate Simulations (PIRCS) and two recent statistical downscaling intercomparison projects.

Several features distinguish SDS and RCM approaches to regional climate simulation. Statistical approaches are relatively fast, allowing the user to develop ensembles of climate realizations and thus obtain confidence interval estimates. Robust SDS typically strives for succinct representation of physical features that control the region's climate. Because any simplified representation of regional physics is likely incomplete, stochastic variability is generally added to account for missing physics. RCMs are based on fundamental conservation laws for mass, energy and momentum and thus contain more complete physics than SDS. However, the more complete physics significantly increases computational cost, which limits RCM simulation. Thus, typical RCM studies use only a single realization of a climate.

2. METHODS AND DATA

This comparison focuses on the river basins in Table 1. Observations of daily precipitation (P) and minimum and maximum temperature (TMIN, TMAX) produced by snow telemetry (SNOTEL) and U.S. National Weather Service (NWS) stations provide the basis for calibrating the SDS and for evaluating SDS and RCM simulations. River discharge from the basins, measured by the U.S. Geological Survey (USGS) provides additional observations for model evaluation. Both the SDS and the RCM use NCEP/NCAR reanalyses (Kalnay et al., 1996) for driving data sets. RCM boundary conditions also use observations of water-surface temperature in the Gulf of California and the North American Great Lakes, which are under-resolved in the reanalysis.

The SDS method in this study uses step-wise multiple linear regression to identify parsimonious sets of atmospheric variables in gridded, large-scale analyses that are used to predict local daily TMIN, TMAX and P (Wilby et al., 1999). The SDS uses separate regression equations for each climatological season and output variable. RCM output comes from RegCM2 (Giorgi et al., 1996), which simulated a continental U.S. domain at approximately 50-km resolution. At this resolution, some basins are contained within a single gridbox, whereas other are resolved by several gridpoints.

TMIN, TMAX and P output from both models was fed into the USGS Precipitation-Runoff Modeling System (PRMS; Leavesley et al., 1983), a distributed hydrologic model. The PRMS computes snowpack (when appropriate) and river discharge for the basins.

The SDS was calibrated using observations for the water years 1987-1995. The RCM simulated the calendar years 1979-1988. Comparison of SDS and RCM output uses the water years 1980-1986. For this period, the SDS produced an ensemble of 20 realizations.

3. INITIAL RESULTS

For the Animas basin, both SDS and RCM methods reproduce general features of observed statistics of precipitation and temperature. Both also display some bias with respect to observations: too much light precipitation (both), slightly warm TMIN bias during the cold half of the year (both), and a substantial cool TMAX bias (exceeding 4 ˚C) during the cold half of the year (RCM). For the Animas basin hydrology, the most important bias is the RCM's cool TMAX which delays spring snowmelt. The hydrology simulation is relatively insensitive to SDS and RCM warm TMIN biases. Also, because the accumulated snowpack governs the annual discharge cycle, the

* ***Corresponding author address***: William J. Gutowski, Jr., 3021 Agronomy, Iowa State University, Ames, IA 50011; gutowski@iastate.edu.

hydrology simulation is insensitive to simulation biases in precipitation intensity distribution.

These results are dependent on the climatology of the basin simulated. One could easily imagine alternative situations where cool TMIN bias (e.g., initiating snowpack accumulation too early) or P bias would govern error in discharge simulation. The wide spatial distribution of basins in Table 1 allows further evaluation of dependence on specific regional climatology. In addition, the present study's SDS and the RCM have both used output from the Hadley Centre GCM to drive additional, climate-change simulations. These cases can show the range of hydrological response that arises from analyzing climate change impacts with different, but physically plausible, downscaling approaches

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TABLE 1: Study Basins

#	Basin Name	State	ID	Lat. [° N]	Long. [° W]	Area [km^2]
1	Animas R. at Durango	CO	09361500	37.2	107.5	1792
2	East Fork Carson R.	NV	10309000	38.5	119.4	922
3	Cle Elum R. near Roslyn	WA	12479000	47.1	121.0	526
4	Suwanee					
	at Fargo	GA	02314500	30.4	82.3	3263
	Alapaha R. near Alapaha	GA	02316000	31.2	83.1	1717
	Alapaha R. at Statenville	GA	02317500	30.4	83.0	3626
	at Branford	FL	02320500	29.6	82.6	20409
5	Cedar					
	at Charles City	IA	05457700	43.0	92.4	2730
	near Austin	MN	05457000	43.4	92.6	1101
	Little Cedar R. near Ionia	IA	05458000	43.0	92.3	792
	at Janesville	IA	05458500	42.4	92.3	4302
6	Dry Fork R. at Hendricks	WV	03065000	39.0	79.4	1453
7	Neversink R. near Claryville	NY	01435000	41.5	74.3	445
8	San Pedro R. at Charleston	AZ	09471000	31.4	110.1	3196
9	Starweather Coulee nr Webster	ND	05056239	48.2	98.6	700