SPATIAL DISAGGREGATION FOR STUDIES OF CLIMATIC HYDROLOGIC SENSITIVITY

By Daniel Epstein¹ and Jorge A. Ramírez²

ABSTRACT: The use of deterministic atmospheric general circulation models (GCMs) to understand potential global climate change under doubled CO₂ forcing has prompted a need for better understanding of local hydrologic impacts. Incongruities in model resolutions do not allow for GCM output to be directly used as forcing in the smaller-scale hydrologic models. In this work, daily spatial disaggregation techniques are applied to the upper Rio Grande basin in Colorado, simulating local temperature and precipitation regimes, and preserving spatial covariance structures at all spatial scales. Canadian Climate Centre GCM output is disaggregated to site-specific locations within the study basin. The Precipitation Runoff Modeling System is then used to examine hydrologic sensitivity under the disaggregated climate forcing. The results from this sensitivity indicate that under spatially disaggregated, site-specific, climatic forcing, significant snowpack-accumulation decreases occur. This results in total annual runoff decreases of, on average, 17.7%. A seasonal shift toward earlier in the year is observed in peak runoff, soil moisture storage, and evapotranspiration.

INTRODUCTION

The potential implications of global climate change have become the focus of numerous water resource studies over the past decade (Hay et al. 1992; Cooley 1990; Lettenmaier and Gan 1990; Avery and Leavesley 1988; Gleik 1987). There is no conclusive evidence that climate is currently changing beyond the scope of natural variation. However, changes in temperature, precipitation, cloud cover, vegetation, wind patterns, and seasonal variability are all potential consequences of greenhouse climate forcing (Wagonner 1990). It is the estimation of the magnitude and variability of these changes that is of concern. As a better understanding of the physical processes involved in large-scale phenomena is achieved and modeled, better understanding of more regional impacts is needed. Whether it is due to anthropogenic or natural causes, large-scale process changes need to be resolved into smaller scales. It is at this level, the regional, or mesoscale, and even at the extreme local level, where hydrologic impacts must be evaluated for purposes of decision support.

Current projections of global change have been developed from large-scale, physical atmospheric global climate models (GCMs) that attempt to describe atmospheric response to CO₂ forcing. Presently, due to computational limitations, most GCMs operate globally with a resolution ranging from 2° × 2° to 10° × 10° latitude/longitude. The resulting climate projections from these models cannot be directly used as input for models at the resolution of interest to hydrologists. The hydrologic processes of interest


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commonly occur at scales on the order of tens to thousands of square kilometers. At these scales, spatial variability, geomorphology, and other mesoscale and local-scale processes tend to dominate resulting climatic regimes. The difficulty, then, arises in developing localized hydrologic responses to global-process changes. It is the bridging of this spatial incongruity between the large-scale change, and regional and local climate that is the focus of this work.

Giorgi and Mearns (1991) provide a relatively complete overview of historical techniques applied to this spatial resolution problem as it pertains to catchment hydrology. The methodologies typically used for analysis of local hydrology, ranging from stochastic analysis of historical climates and paleoclimates to adjustment of historical climate by a mean change in state, frequently do not account for temporal variability in climate fields, and never account for spatial variability. More recent works (Hay et al. 1992; Barros and Lettenmaier 1993; Bardossy and Plate 1992) attempt to account for scale issues. Hay et al. propose a stochastic disaggregation model for weather-type analysis. Precipitation fields are regressed on weather type in the Delaware basin. Climate-change forcing is accounted by adjustment of transition matrices and sojourn times. Barros and Lettenmaier apply multigrid methods to describe interactions between land-surface influences and large-scale circulations. In their procedure, an orographic precipitation model is coupled to a surface energy model to predict latent and sensible heat fluxes. Bardossy and Plate developed a site-specific precipitation model that accounts for spatial and temporal intermittence conditioned on large-scale circulations. In addition, limited application of cascading GCM output to mesoscale precipitation models, and then to deterministic rainfall runoff models is presented by Avery and Leavesely (1988).

The work herein demonstrates the direct application of empirical disaggregation techniques to both temperature and precipitation data for application in resolving GCM output to regional and local climate regimes. The hydrologic response of the upper Rio Grande basin to climate-change forcing is explored by application of resulting localized climate to the Precipitation Runoff Modeling System (PRMS) of the U.S. Geological Survey (USGS). A two-level disaggregation scheme is used. Grid data from the Canadian Climate Centre's (CCC's) GCM overlaying the state of Colorado are first disaggregated into regions of distinctly similar seasonal climate regimes. These regions are next disaggregated into data sets corresponding to individual climate stations within Colorado.

**MODEL DEVELOPMENT**

**Disaggregation**

The use of disaggregation techniques in hydrology for generation of synthetic series has become a relatively common approach. The goal of any disaggregation process is to resolve either temporal or spatial series into more resolute series. For example, temporal disaggregation might simulate monthly or seasonal data from annual values. Spatial disaggregation might resolve streamflow into components for separate channel distribution. The power of disaggregation techniques rests in the fact that the parameter-estimation procedure ensures preservation of relevant statistics at successive levels of aggregation.

The first general model for disaggregation can be attributed to Valencia and Schaake (1972, 1973). The general model developed by Valencia and Schaake takes on the form

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where $Y = a$ matrix of higher order, or disaggregated series; $A = a$ parameter matrix; $X = a$ matrix of lower order, or aggregated series; $B = a$ parameter matrix; and $v = a$ matrix of independent standard normal deviates. More recent developments have extended and improved original modeling capabilities resulting in fewer parameters and more efficient estimation techniques (Mejía and Rouselle 1976; Lane 1979; and Santos 1983). The model described by (1) can adequately describe temporal as well as spatial variability. Thus, it is applicable in both temporal and spatial domains. The Valencia Schaake model preserves all linear relationships between variables at all levels of aggregation. In application of (1) to the spatial disaggregation of climatic data, preservation of the existing spatial mean and covariance structure within Colorado at all levels of aggregation is of utmost importance. Parameter-estimation procedures that ensure preservation of first- and second-order moments at all levels of aggregation have been developed as indicated in Appendix I (Valencia and Schaake 1972; Salas 1980).

Data Processing

Daily minimum and maximum temperature and precipitation data are taken from the Colorado Climate Center’s state database for inclusion into the spatial domain models. One hundred fourteen weather stations with data covering 1965 through 1989 are identified for potential use. Of these records, 52 temperature, and 56 precipitation stations are selected based on missing data and spatial representation considerations.

Seasonality, over the 25-year record, for each station and each climate variable was removed. At every station $i$ a daily 25-year mean was calculated, as

$$
\bar{X}_{25,i,t} = \frac{1}{25} \sum_{j=1}^{25} X_{i,t(j)}
$$

where $i =$ given station; $t =$ day of the year; $j =$ year; and $X =$ climate variable. A residual series for each station is created, removing the long-term daily average as follows:

$$
X^*_{i,t(j)} = X_{i,t(j)} - \bar{X}_{25,i,t}
$$

The spatial disaggregation models are developed relating, through parameter estimation, specific station series (i.e., local climate) to two levels of aggregations of historical records, corresponding to regional and synoptic climate regimes, respectively. First, climate stations are grouped and averaged according to regions of distinctly similar climate. Second, regional series are averaged into a single large-scale climate series. Regional groupings of Colorado climate regimes were first proposed by Doeskin et. al (1983). These regions are aggregations of Colorado stations based on long-term records. Divisions are primarily functions of magnitude and seasonal distributions of precipitation. Average temperature distributions are used when geographical and regional climate characteristics dictate. Fig. 1 demonstrates regional climate regimes for Colorado. Table 1 associates individual stations to climate regions With one exception, the classification shown is used for this work. The single outlier station, Hermit, geographically sits on the border of two regions, 17 and 23. Climatically, it compares poorly
FIG. 1. Colorado Climate Regional Groupings (Taken from Doeskin et al. 1983)

with both. As a result the Hermit station is placed in the region that minimizes the reproduced correlation error. Of the 25 regions originally proposed, 21 temperature, and 23 precipitation regions are used. Lack of temperature data within regions 5, 6, 7, and 9, and lack of precipitation data in regions 6 and 9 require their omission from these models.

Regional data series are calculated from weighted averages

\[ X_{R,t} = \sum_{j=1}^{N_R} \omega_j X_{j,t} \]

where \( N_R \) = number of stations within a given region \( R \); and \( \omega_j \) = weight assigned a given station \( j \). A weight of \( 1/N_R \) is assigned all temperature stations. Precipitation station weights are calculated using contributing areas. Regional climate series are further aggregated into a single large-scale series corresponding to a GCM grid point. Weighted averages of the 21 temperature and 23 precipitation regions are used, respectively. Weights are \( 1/N, N \) being the number of regions for temperature data; and a contributing area percentage for precipitation data. At both the regional and large-scale level, single daily disaggregation models are developed for both minimum and maximum temperature. Twelve separate models, one for each month, are developed for daily precipitation data. The seasonal model structure more accurately describes the precipitation statistics, better maintaining relevant moments.

At all levels of aggregation, interstation and interregion correlation comparisons are examined for validation purposes. Over an infinite number of simulations, the correlation structure of the disaggregated data should be indistinguishable from the actual correlation structure of the observations. Temperature and precipitation data from 1990 were used to validate the
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<th>Latitude (3)</th>
<th>Longitude (4)</th>
<th>Elevation (m)</th>
<th>Temperature (6)</th>
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models. For demonstration purposes only, disaggregated time series at Del Norte, Colorado within the study basin, are compared to observations. Fig. 2 represents this distribution for daily maximum and minimum temperature models. Fig. 3 presents this distribution for monthly total precipitation. Clearly observed is the excellent performance of the disaggregation technique. Although not shown, the covariance structures are preserved very well, in particular for temperature data. The covariance structure in the precipitation fields is not preserved as well as in temperature fields. This can be attributed to highly variable precipitation data, normality assumptions, and a single year of validation data. While other, more complex techniques are available, such as conditional AR modeling, or weather-type analysis, the overall successful verification of the chosen disaggregation models using only a single year of data given the inherent variability typically associated with climatic series, demonstrates their applicability to the spatial

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resolution difficulties associated with regional and local analysis of global climate change perturbations.

GCM Forcing

Data from the CCC’s GCM are used as forcing for disaggregation. The CCC model is a second generation, 10-layer, 3.75° × 3.75° model developed by Boer et al. (1984). Over a North American window, this corresponds to 570 grid points mapped on a polar projection. This window extends between the latitudes of 20°N and 90°N, and between the longitudes of 150°W and 40°W. Unlike its predecessor and many of the other first-generation GCMs, the CCC incorporates a diurnal and annual cycle, ocean heat transport, and more sophisticated hydrologic parameterizations. Included are prognostic equations for soil moisture, snow accumulation, and forest vegetation. Two scenarios are simulated by the CCC GCM, a 1 × CO₂ forcing and a 2 × CO₂ forcing. A summary of aggregated global results under the 2 × CO₂ forcing includes a 3.5°C increase in temperature, a 3.8% increase in precipitation, and a 2.2% decrease in cloud cover. Three years of equilibrium climate data are applied to the disaggregation approach.

To objectively evaluate hydrologic sensitivity under a doubled CO₂ forcing, baseline conditions must be established. In this sensitivity analysis, baseline hydrology will be modeled using the site data disaggregated from the 1 × CO₂ CCC grid data. The assumption is not that this disaggregation process can model and predict present climate. Instead, it allows for consistent modeling due to CO₂ forcing as described by GCM output. Regional minimum and maximum temperature, and precipitation series are calculated for the entire state in the first level of disaggregation. Station series in regions 17 and 23 are then calculated at the next level. Two stations, Hermit (region 23) and Del Norte (region 17) are located within the Upper Rio Grande basin. The disaggregated series from these two stations are used as input for the hydrologic model.

The minimum and maximum temperature series disaggregated under the 2 × CO₂ scenario at Del Norte is compared to the 1 × CO₂ forcing in Fig. 4. The comparison for Hermit is provided in Fig. 5. Readily apparent in both is a slight increase in temperature from baseline condition (1 × CO₂).
FIG. 4. Comparison of Disaggregated Doubled CO₂ Average Minimum and Maximum Temperature to Baseline at Del Norte, Colorado

Also of interest is the noticeable seasonable change in the magnitude of increase. This confirms the IPCC summaries (Houghton et al. 1990), which reported larger temperature increase under doubled CO₂ during winter months at this latitude.

Double CO₂ precipitation is compared with baseline at Del Norte and Hermit in Figs. 6 and 7, respectively. At both stations a slight decrease in annual precipitation is observed from baseline. However, this decrease is due to decreases in precipitation during only a few months. In all other months the baseline average is comparable or slightly smaller than doubled CO₂ conditions.

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APPLICATION

Study Basin

The Rio Grande extends south from the San Juan Mountains of south-central Colorado, through New Mexico, and into Texas and Mexico before reaching the Gulf of Mexico. In the United States alone, roughly 101,000 km² drain into the total 2,900 km reach. Of this U.S. drainage, approximately 19,000 km² are in Colorado. Within Colorado, the Rio Grande flows from its headwaters in the San Juan Mountains, extending out through the Rio Grande fan, into the San Luis Valley of the Alamosa Basin and down into the Taos plateau region of New Mexico. The study area for this project is upstream of Del Norte, Colorado. This corresponds to roughly 35% of the total contributing drainage within the state, or 3,471 km². In this sub-basin, the Rio Grande flows primarily in mountain, and intermontane regions. The continental divide partially encircles the basin, forming the western boundary, and parts of the northern and southern boundaries.
There has been extensive geohydrologic development within the Alamosa Basin, downstream of Del Norte, but very little upstream. The ground water downstream can be considered a heterogeneous mix of unconfined, and confined leaky aquifers separated by clay or unfractured volcanic rock (Hearne and Dewey 1988). In addition, the region is heavily faulted. In conjunction with heavy water mining, this makes for very complex, and not well understood ground-water recharge relationships. Upstream of Del Norte, much of the area is thick quaternary and tertiary volcanic rock. Although extensively layered with discontinuous zones of permeable alluvium, the general pattern of flow from rainfall or snowmelt is directly through permeable areas, into the aquifer system, discharging either directly to surface flow or, in the farther downstream reaches, into the Alamosa Basin aquifers (Hearne and Dewey). Much of the lower study basin is considered semiarid. Del Norte receives, on the average, less than 280 mm of precipitation per year. Hermit receives less than 410 mm. Precipitation falls consistently throughout the year. However, much of the volume occurs during late summer and early fall due to orographic convective systems. Snowpack contributes greatly to surface and subsurface runoff. Permanent pack begins formation in late October. Accumulation at high elevations can continue into May. Historically, very few large events contribute to pack accumulation. Numerous small snow events provide for the significant proportion of snow depth.

Precipitation Runoff Modeling

Hydrologic modeling is performed using PRMS, a deterministic, distributed-parameter rainfall-runoff model developed by the USGS. The model has been used extensively in rural basins dominated by snowmelt processes (Brendecke et al. 1985; Kuhn 1988; Fontaine 1987). For modeling purposes, the study basin is divided into Hydrologic Response Units (HRUs) ranging in size from 15 km² to 350 km². Spatial processing is done using the Geographic Resource Analysis Support System (GRASS), a Geographical Information System (GIS) software package. Units are classified based on elevation, slope, aspect, soils, and vegetation groupings. Thirty-eight principal response units are identified. Each unit is parameterized, and modeled separately. HRU average characteristics are used. Basin response is the aggregation of all unit responses.

Water balance is performed on a series of surface, soil, and subsurface reservoirs. Output from these reservoirs combine to form basin response. Inputs to the model include temperature, precipitation, and solar radiation (optional). Outputs can be any number of reservoir responses aggregated at the HRU or basin level. Complete discussion of the conceptual model design and process parameterization is available in the PRMS users manual (Leavesley et al. 1983).

The precipitation runoff model is calibrated on 15 years of data (1965–1979). Calibration is performed by manual adjustment of nondistributed, temporally distributed, and spatially distributed parameters according to the following steps:

1. Adjust radiation and temperature parameters until simulated temperature and evapotranspiration approximate actual.
2. Adjust precipitation and snow parameters until snowpack water equivalent reflects spatial distribution of historical snow course data.
3. Adjust individual HRU soil moisture capacities until annual simulated runoff volume reflects historical gauge record.

4. Adjust surface runoff, subsurface flow, and ground-water parameters to reflect hydrograph recession curve.

5. Adjust soil infiltration capacities and soil recharge capacities to account for individual HRU contributions to surface runoff.

A plot of historical daily streamflow near Del Norte is compared to the final model calibration simulation (Fig. 8). The largest difference in modeled response occurs during 1977. This corresponds to a very low precipitation year with an extremely low snowpack. In general, the model does not reproduce low flow and double recession hydrographs as well as average and above average flows. The root mean square error (RMSE) over calibration is calculated to be 13.85 cms. The modeling efficiency, a modeling error measurement relative to actual variability (Nash and Sutcliffe 1970; Gan and Burges 1990) is 0.82.

Of significance in calibration of PRMS to the spatial characteristics of the upper Rio Grande are two distinctly different segments of hydrograph recession. A second peak, smaller (though on occasion larger) than the peak summer flow, is associated with fall recession. Storm events during this time of year typically occur in very localized regions as high-intensity, short-
duration events. Soil moisture is also typically well below capacity. The second peak can be attributed to either melt off of early-fall snow events or high-intensity short-duration convective thunderstorms. The difficulty in modeling both types of events is that both are of localized nature, and thus cannot be adequately described within the limited, distributed-parameter framework of PRMS.

To handle the two-phase recession, contributions from subsurface flow and base flow are separated. Base flow is calibrated to reflect the second, or later season recession. Subsurface flow, the immediate response from the saturated soil zone, is then calibrated to match the recession due to the late season snowmelt and convective thunderstorms. It was not possible to catch the second peak in all years. In particular, very short duration high-intensity runoffs are underestimated. For example, during September 1970 two very large single-day runoff events were recorded at the Del Norte gauge. Simulated flow hints at two very small increases in flow. The recorded flow spikes could be indicative of high-intensity, short-duration events in a limited area in which the modeled average soil-moisture conditions are not reflective of the actual conditions, or, perhaps a high-intensity, short-duration event, confined to a limited area that was not captured in the precipitation gauge record.

In general, simulated flows do reflect the overall trend of the actual gauge record. One portion of the hydrograph that the model consistently underestimates is very early snowmelt from lower elevations in March and April. During calibration of soil moisture and snow infiltration capacity parameters, numerous large spikes of surface runoff were observed in the modeled runoff, primarily early in the year. Adjustment of parameters to regulate these unrealistic spikes necessitated damping early snowmelt in general. The volume discrepancies during these months are not significant. In addition, the model tends to underestimate peak flow and volume in both double recession years, and low years of low precipitation and snowmelt.

PRMS is validated on 10 years of data (1980–1989). Parameterizations, as determined in calibration, are held constant. The RMSE over the 10 years is 21.49 cms. The modeling efficiency is 0.67. As expected, the validation error is larger than the calibration error. Validation hydrographs

![FIG. 9. Validated versus Actual Runoff at Del Norte, Colorado](image-url)
are presented in Fig. 9. In general, model validation simulations underestimate peak discharge and annual volumes. As with calibration simulations, double recession hydrographs and daily variability are not readily modeled, although the overall hydrograph trend is maintained.

The relative errors associated with modeling double recession flows should not be considered a problem in the context of the sensitivity analysis of this work, which is based on simulated GCM equilibrium climate. This modeling application is not intended for predictive purposes. Calibration of a very large basin to runoff at a single location, with limited spatial knowledge of precipitation, results in a linearization of basin response. Much of the daily variability is lost. Instead, it should be understood that the daily-runoff model adequately describes the physical mechanisms for runoff within the basin. In addition, it must be understood that the physical processes modeled are dynamic. This work does not attempt to describe process changes that could occur under altered climate. Those feedbacks that would describe physical-process changes are beyond the scope of this work.

ANALYSIS

Disaggregation Results

The doubled atmospheric CO₂ scenario modeled by the CCC’s GCM is applied to the two-stage disaggregation models. The resulting temperature and precipitation regimes are representations of local climate at specific stations with Colorado. Aggregate results within the study basin above Del Norte result in an approximate average 3.5°C temperature increase and less than 1.5% decrease in annual precipitation. The precipitation decrease in this high alpine basin is significantly different than the increase observed in average global precipitation encoded in the CCC data used.

Surface Runoff

These changes in local climate applied to a physical, deterministic daily runoff model result in an average decrease in total annual runoff of 17.7%. Fig. 10 depicts simulated runoff compared to baseline conditions. A marked

FIG. 10. Comparison of Doubled CO₂-Induced Surface Runoff versus Baseline at Del Norte, Colorado.
seasonal phase shift is observed in the doubled CO$_2$ runoff hydrograph. Peak flow occurs 1 to 2 months earlier. Moderate decreases in runoff are seen during summer and early fall months. Significant increases occur during March and April.

**Snow Water Equivalent**

The most significant impact on basin response to climate change forcing is a tremendous decrease in snowpack water content. Fig. 11 compares baseline pack water equivalent to simulated doubled CO$_2$ conditions. There is a sharp decrease in all months over all years. Peak water content decreases by as much as 35%. In addition, a similar seasonal shift in accumulation and depletion is observed as in runoff. Peak volume occurs approximately
FIG. 13. Comparison of Doubled CO₂-induced Evapotranspiration versus Baseline, Upper Rio Grande Basin, Colorado

1 month earlier than under baseline conditions. Not only significant is the decrease in pack volume, but the shortening of the snow season, and the resulting implied distribution of melt timing as well.

Soil Moisture
Baseline climate conditions result in a pattern of soil moisture approaching saturation in May or June due to spring snowmelt infiltration. Summer evapotranspiration and minimal additional snowmelt or precipitation input result in a minimum soil moisture content in September. As late summer convective storms and early winter snowmelt contribute water to the soil column, moisture content increase until a winter frozen upper zone and cold temperatures produce little additional contribution from infiltration to soil moisture. PRMS handles water-balance accounting in such a manner that a minimum soil-to-ground water demand must be satisfied prior to addition to soil reservoirs. As a result, for 3–4 months a year, during midwinter, soil moisture content remains constant. Then, as spring snowmelt provides additional water to an unfrozen soil zone, moisture content increases, again approaching saturation in May or June. Fig. 12 compares daily baseline soil moisture storage with the doubled CO₂ scenario. In both scenarios, soil reservoir storage approaches capacity for 1–2 weeks during the peak snowmelt season. The seasonal distribution of soil moisture storage, again, indicates a marked phase shift. Capacity is approached during April or May as opposed to May or June. Constant winter storage is still observed, though for a much shorter duration, and at a higher level. This shift contributes to producing higher runoff rates in early spring and lower runoff rates in summer.

Evapotranspiration
High variability in daily evapotranspiration (ET) requires examination of monthly total data. Fig. 13 presents these data comparing baseline conditions to the doubled scenario. The maximum actual evapotranspiration decreased and was shifted earlier under the climate-change forcing, although potential ET increases. Maximum monthly actual evapotranspiration decreased by as
much as 18.7% from baseline conditions. Seasonal differences are patterned very closely with soil moisture. Late fall and winter ET typically increase, whereas late spring and summer ET decreases.

**COMMENTARY AND CONCLUSIONS**

The most significant effect of doubling CO₂ on basin response is the very large reduction in winter snowpack accumulation. The large decrease in pack water equivalent can be attributed to temperature change. In particular, large seasonal increases in temperature during snow accumulation months produce a greater number of rain and rain-on-snow events than under baseline conditions. In conjunction with minimal decrease in precipitation, as modeled under the disaggregation scenarios, the temperature change results in an energy balance at the snowpack surface that allows for less accumulation, decreasing the pack capacity to hold water. Consequently, more water is available for ET and soil moisture. Runoff, snowmelt, soil-moisture, and evapotranspiration timing all change. The snowpack melt timing significantly changes runoff characteristics. Spring rain-on-snow event that, under baseline conditions, would typically be snow events, contribute greatly to the earlier runoff timing.

Results of this work corroborate conclusions by other investigators. Decrease in annual runoff volumes under doubled CO₂ forcing were obtained in numerous studies, including Lettenmaier and Gan (1990), Nash and Gleik (1991), and Cooley (1990). The Lettenmaier and Gan work on the Sacramento–San Joaquin basin, also a snowmelt runoff dominated basin, indicates a direct sensitivity of runoff to temperature increase. This conclusion is also reached in the Cooley work on small basins in Montana. The Nash and Gleik study on the Colorado River concludes that runoff is more sensitive to precipitation change. Model runs from the Nash study result in less than a 10% decrease in annual runoff volume under no change in precipitation. Decreases as high as 30% were observed when precipitation was decreased by 10%. However, as opposed to the studies mentioned, the results presented here are derived using climatologically and hydrologically consistent climatic data, at least within the mathematical formulation of physically based atmospheric and hydrologic models. Consequently, individual temperature and precipitation effects cannot be isolated.

The changes in soil moisture that occur can also be attributed to snowpack influences. Higher potential ET and less spring snowmelt produce conditions that decrease summer-fall soil moisture storage. Typical soil columns are well below moisture capacity during winter months. Greater water availability and a smaller window for frozen upper soil zones during this time significantly increase storage. Comparison of phase shift and timing indicates consistency with other processes.

Seasonal evapotranspiration changes reflect seasonal soil moisture storage changes. The observed differences in ET compared with changes in soil moisture imply that although ET is still sensitive to potential ET (and thus temperature change) soil moisture conditions play a significant role. This is consistent with semiarid climates in which evapotranspiration is under soil control.

The resulting CO₂-induced changes in the hydrologic response of the upper Rio Grande, as described, could have tremendous economic and social implications for Colorado, as well as for lower basin states. A 17.7% decrease in available water from runoff can have tremendous impacts on agricultural irrigation, power generation, recreational interests, and, po-
tentially, riparian habitat. A decrease in snowpack accumulation for this region will also be a detriment to the Colorado ski industry and state tourism—two prominent state industries that contribute to local economy. Changes in volume and runoff timing will result in altered reservoir operation and management. Interstate and international agreements will also be impacted. Because the changes in hydrologic response can have far-reaching effects, future policy and water resource development must, at minimum, include cognizance of potential greenhouse-induced change. Reasonable and rational approaches must be taken to understand climate change phenomena and the resulting implications on water resources.

Recognizing the limitations imposed by the different model structures and assumptions, the following conclusions can be drawn:

1. Under site-specific temperature increases, and decreases in precipitation, as obtained through spatial disaggregation of CCC global climate data, significant decreases in snow accumulation occur.
2. Increased temperatures result in more frequent rain and rain-on-snow events resulting in earlier runoff characteristics during spring months, and less runoff during summer and fall months.
3. Increases in precipitation as rain and decreases in snowpack holding capacity result in significant increases in soil moisture storage during winter and early spring months. Decreases in snowmelt during spring and summer result in a decrease in soil moisture during those months.
4. Evapotranspiration appears to be very sensitive to soil moisture conditions, increasing during winter and decreasing during summer.

The sensitivity of ET to vegetation conditions is not examined at this time. Expected changes include increases in biomass and large seasonal changes in carbon uptake resulting in potential changes in vegetative transpiration. Mechanisms for introduction of these processes in GCMs as well as basin hydrologic models are needed before complete understanding of evapotranspiration under climate-change forcing will be possible. These changes will impact every aspect of basin response.

The implications of this work are twofold. First, spatial disaggregation techniques can be successfully applied to GCM output. These techniques provide a mechanism to handle resolution incongruities associated with GCMs and basin hydrologic models. Temperature disaggregation to site-specific localities was performed maintaining high accuracy in preservation of the first two moments. Straight application of precipitation disaggregation is less accurate due to difficulties in meeting normal distribution requirements of disaggregation modeling. Second, examination of even gross sensitivity of the water resources of the upper Rio Grande must give rise to concern for long-term socioeconomic impacts. Impact assessment studies that take into account not only the spatial and temporal distribution of water demand, but also potential human responses to an altered regional climate as well as institutional and policy changes, must be performed.

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APPENDIX I. DISAGGREGATION MODEL PARAMETER ESTIMATION

The general form of the disaggregation equation is

\[ Y = AX + Bv \]  

For zero mean matrices \( X \) and \( v \), this implies that the expected value of \( Y \) is also zero. Parameter matrix \( A \) can be derived by taking expectations of both sides of (5). Postmultiplying (5) by the transpose of \( X \), \( X^T \), and taking expectations yields the following:

\[ E[YY^T] = AE[XX^T] + BE[vX^T] \]

Assuming that in (6) \( X \) and \( v \) are independent random vectors leads to

\[ E[YY^T] = AE[XX^T] \]

\[ A = S_{XX}S_{XX}^{-1} \]

where \( S_{XX} \) is the autocovariance matrix of \( X \), and \( S_{XY} \) is the cross-covariance matrix of \( Y \) and \( X \).

Estimators of parameter matrix \( B \) are derived by postmultiplying (6) by the transpose of \( Y \), \( Y^T \), and taking expectations. This leads to


and

\[ E[YY^T] = AE[XX^T] + BB^T \]

where it has been assumed that \( v \) is a random vector of spatially uncorrelated random variables. Using the above notation, (9) leads to

\[ BB^T = S_{YY} - S_{XY}S_{XX}^{-1}S_{YX} \]

Parameter matrices \( A \) and \( B \) are then estimated as a function of the spatial autocovariance and spatial cross-covariance matrices of the different levels of spatial aggregation in the process under consideration. However, the solution of (10) for parameter matrix \( B \) is not unique. Several decomposition techniques have been extensively described in the literature (Valencia and Schaake 1972; Young and Pissano 1968; Salas et al. 1980), and the reader is referred to those sources for additional details.

APPENDIX II. REFERENCES


