6.8 DOWNSCALING NOAA'S SEASONAL PRECIPITATION FORECASTS TO PREDICT HYDROLOGIC RESPONSE

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1. INTRODUCTION

The translation of a seasonal climate forecast into a corresponding hydrologic response is a critical step to promote a wider acceptance and utilization of NOAA's forecasts in the water resources user community. The first step in modeling a future hydrologic responses is the stochastic generation of weather data that reflect forecasted conditions.

Stochastic weather generation by computer programs such as CLIGEN (Nicks and Gander, 1994), WGEN (Richardson and Wright, 1984), US CLIMATE (Hanson et al., 1994), and GEM (Johnson et al., 2000) are based on the following monthly precipitation statistics: mean, standard deviation and skew of daily precipitation, and the probability of occurrence of a wet day after a dry day (PWD), and the probability of occurrence of a wet day after a wet day (PWW). These two probability values are called transition probabilities. A method to adjust these precipitation statistics to reflect NOAA's forecasted seasonal precipitation conditions is the objective of this paper.

2. ADJUSTMENTS OF PRECIPITATION STATISTICS

First, NOAA's seasonal precipitation forecasts must be downscaled and disaggregated to the spatial and temporal scale at which weather generators operate. The spatial scale is a field, and disaggregate farm or small catchment, and the temporal scale is a month. Two steps are required to downscale the forecasts. First, the spatial downscaling to a location of interest is achieved by superposing the regionally forecasted departures for the probability of precipitation onto the precipitation distribution at the location of interest, as described in Schneider and Garbrecht (2002). Second, the temporal disaggreagtion is accomplished by a heuristic procedure that reformulates the suite of thirteen 3-month overlapping forecasts into 15 non-overlapping monthly forecasts, as described in Schneider and Garbrecht (2003). The forecasted monthly mean departures are added to the mean monthly precipitation amount to produce the monthly precipitation for forecasted conditions. With the seasonal precipitation forecasts reformulated for a location and at the monthly time scale, one can proceed to adjust the precipitation statistics of the weather generator to reflect a forecast.

A forecasted change in monthly precipitation must be partitioned between a change in number of wet days and a change in precipitation amount on wet days. A regression of number of wet days (N_{wd}) versus monthly precipitation (P), based on historical data, is used to capture the climatic particularities of the location and to determine the appropriate partitioning for the forecasted change of monthly precipitation (Fig. 1). The estimated change in the number of wet days due to a forecast can be read from the regression line. The change is added to the mean number of wet days to produce the mean number of wet days for the forecasted conditions.

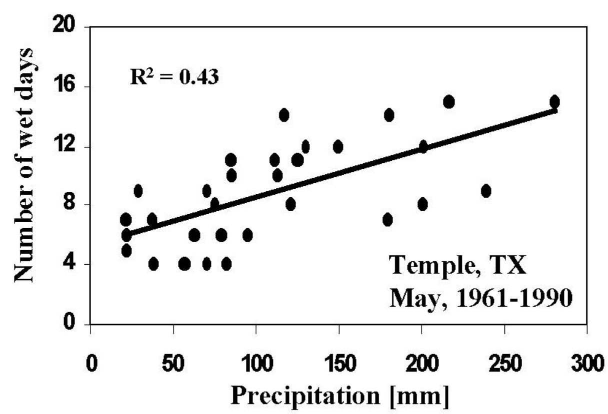

Figure 1. Regression between number of wet days and monthly precipitation for Temple, Texas, for the month of May based on 1961-1990 data.

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Finally, the forecasted monthly precipitation is divided by the forecasted number of wet days to produce the mean daily precipitation for forecasted conditions. Mean daily precipitation is one of the critical input parameters for the weather generator. Adjustment to the transition probability values are made by use of a regression of change in transition probability of wet after dry day (PWD) versus number of wet days (N_{wd}) (Fig. 2). The regression is based on historical data and accounts for climate particularities at the location of interest. The so identified change in transition probability value is added to the mean probability PWD to produce the value for forecasted conditions. Thereafter, the transition probability of wet after wet day (PWW) can be calculated by solving Equation 1 for PWW, where N_d is the number of days in the month (Hanson et al., 1994). These adjusted transition probabilities for forecasted conditions are the final two precipitation statistics needed by the weather generator.

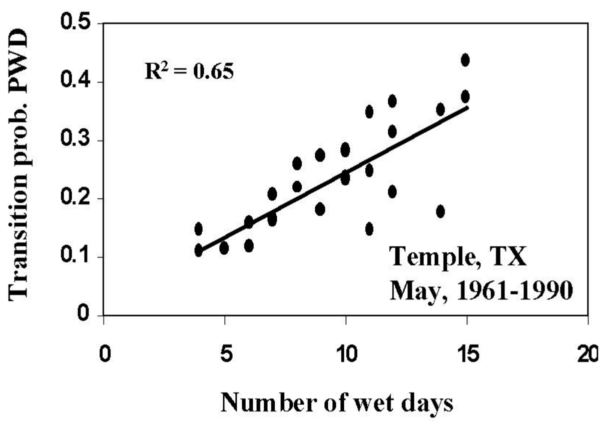

Figure 2. Regression between transition probability of wet day after dry day and number of wet days for Temple, Texas, for the month of May based on 1961-1990 data. (Note: some of the plotted points represent more than one overlapping data point.)

$$N_{wd} = \frac{PWD}{1.0 - PWW + PWD} * N_d \qquad (1)$$

3. APPLICATION TO TEMPLE, TX

To illustrate the generation of daily precipitation for forecasted conditions the experimental stochastic weather generator SYNTOR was used. Program SYNTOR is similar to WGEN, but includes modifications for use with forecasted precipitation. SYNTOR is currently in the testing stage and is expected to be available by the end of 2004. Table 1 provides the baseline historical mean, standard deviation, skew and transitional probabilities of daily precipitation for the 1961-1990 data at Temple, TX. To test the model's ability to reproduce the statistical characteristics of a forecast, a hypothetical forecast departure for precipitation from this baseline was assumed: March, April, May and June precipitation were increased by 10, 15, 20 and 8 mm, respectively, (or 17, 19, 18 and 9% of mean monthly precipitation). SYNTOR calculated the regressions in Figs. 1 and 2 for all months, and automatically determined the forecast adjusted values for mean daily precipitation and transitional probabilities. Two 100-year long time-series of daily precipitation were generated for forecasted conditions. Each time series was generated with a different set of random numbers. The summary results of the two cases are shown in Table 1 and Fig. 3.

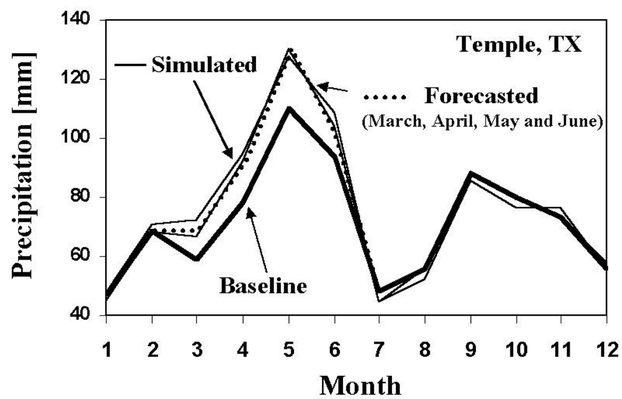

Figure 3. Mean monthly precipitation of baseline and for forecasted conditions.

On a monthly basis, the generated precipitation reflects the forecast departures well. The root-mean-square (RMS) difference between generated and target monthly precipitation was 2.9% for the first time series and 4.4% for the second time series. Maximum differences were 7.7% for both time series. The monthly differences between the generated and target values are inherent to the stochastic nature of weather generation and other model approximations. These observed differences are small compared to the magnitude of the forecasted change in precipitation.

4. CONCLUSIONS

A methodology to extend the use of stochastic generation of daily precipitation to reflect seasonal precipitation forecasts was presented. A hypothetical forecast for the months of March, April, May and June demonstrated the capability of the method to reproduce the statistical characteristics of the forecasts. It is recommended that the monthly forecast departures be about 10% of the mean or higher to elevate the forecast signal above the noise of the stochastic component of the weather generation process.

5. REFERENCES

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Table 1. Daily precipitation statistics and results of the application of weather generator SYNTOR to a hypothetical precipitation forecast for Temple, Texas.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	RMS
Input Data													
Mean mm	6.6	9.7	8.1	11.2	12.5	13.9	12.1	11.1	12.2	12.5	10.7	7.6	
St. Dev. Mm	10.9	16.8	12.9	15.9	19.2	20.1	16.7	14.6	17.7	15.9	14.8	11.0	
Skew coef.	4.4	4.9	3.0	2.4	3.2	2.5	1.9	1.8	2.6	1.7	2.3	2.2	
PWD	.163	.203	.198	.196	.207	.158	.109	.131	.181	.139	.155	.162	
PWW	.448	.392	.353	.357	.477	.455	.261	.325	.426	.461	.473	.480	
Monthly P. mm	46.9	68.5	58.9	78.5	110.2	93.7	48.1	55.7	88.0	79.8	73.2	55.9	
Forecast Departures mm	0.0	0.0	10.0	15.0	20.0	8.0	0.0	0.0	0.0	0.0	0.0	0.0	
Forecast Monthly P. mm	46.9	68.5	68.9	93.5	130.2	101.7	48.1	55.7	88.0	79.8	73.2	55.9	
Difference % **	0.0	0.0	17.0	19.2	18.1	8.5	0.0	0.0	0.0	0.0	0.0	0.0	
Generated Data													
Monthly P. mm Case 1	45.3	68.0	66.7	92.1	130.2	104.1	44.4	55.9	88.7	80.3	73.0	57.9	
Difference % **	-3.5	-0.79	-3.1	-1.5	-0.0	2.4	-7.7	0.4	0.8	0.6	0.3	3.6	2.9
Monthly P. mm Case 2	47.6	70.8	72.3	95.0	127.6	108.9	44.4	52.4	85.7	76.5	76.2	55.2	
Difference % **	1.4	3.3	4.9	1.6	-2.0	7.2	-7.7	-6.0	-2.6	-4.1	4.1	-1.2	4.4

** Difference between calculated and generated values.