Regional Hydrological Impacts of Climatic Change—Hydroclimatic Variability
(Proceedings of symposium S6 held during the Seventh IAHS Scientific Assembly at Foz do Iguaçu, Brazil, April 2005). IAHS Publ. 296, 2005.

Downscaling atmospheric circulation data for monsoon rainfall forecasting in India

ANUPAM K. SINGH[1], ERWIN ZEHE[2] & ANDRAS BARDOSSY[3]

1 *Institute of Water Resources Management, Hydraulics and Rural Engineering (IWK), University of Karlsruhe, D-76128 Karlsruhe, Germany*
anupam.singh@iwk.uka.de

2 *Institute of Geoecology, University of Potsdam, D-14476 Golm-Potsdam, Germany*

3 *Institute of Hydraulic Engineering, University of Stuttgart, D-70550 Stuttgart, Germany*

Abstract The potential of a surface-based approach for rainfall downscaling has been explored using a statistical method. The methodology has been applied in a highly seasonal semiarid monsoon-dominated region of India. An automatic circulation pattern classification method is used in which daily rainfall occurrence has been conditioned on CP type using a fuzzy-rule based process and the rainfall is forecast as a stochastic process coupled to the circulation pattern. The model was calibrated for a 10-year period, 1985–1994 and also validated. Model parameters obtained from 1985–1994 daily time-series were used to predict the long-term monsoon rainfall during 1961–1994 for the Jhabua station. The predicted mean monthly rainfall shows a good fit with observed rainfall within a mean variability range of 5 to 15%. The results thus obtained may be used for predicting the arrival of the monsoon, agricultural and crop planning, farming risk assessment, rainfall–runoff modelling, water balance studies and the development of climate change scenarios.

Key words fuzzy-rule model; monsoon; rainfall downscaling

INTRODUCTION

Rainfall modelling and its forecasting is one of the important factors for catchment-level water resources management decision making. The monsoon variability in Asia brings drought and famine during some seasons and devastating flood-like situations during the other seasons. The Indian Ocean atmospheric circulation influences more than 1.5 billion people in arid and tropical Asia. Thus prediction of rainfall is an essential input parameter for decision support modelling, farming risk reduction as well for hydrological impact assessment studies. Accurate prediction of monsoon rainfall at regional or local scale can improve planning to mitigate the adverse impacts and to take advantage of early warning systems not only for water resources operations but also for agriculture, where more than 70% of the total work force is still employed (Clark *et al*., 2000). Thus a better understanding of the monsoon rainfall cycle and its forecasting is clearly of a scientific and a social value.

Modelling the dynamics of the atmospheric circulation is sensitive to small changes in local rainfall. It is evident from several research studies that large scale weather indices can be downscaled for the forecasting of hydrometeorological variables at the catchment scale (Clark *et al*., 2001; Wilby, 2001). The growing demand for climate scenarios for future hydrological as well drought and flood forecasting impact studies has created a need for downscaling methods. Goodess (2000) was of the opinion that statistical downscaling methods are relatively simple to apply, do not require large amounts of observed data, and are transferable between regions. In their review of statistical downscaling techniques, Von-Storch *et al*. (2000) were of the view that statistical downscaling offers a straightforward method of testing GCM's abilities in simulating regional and local details.

The fuzzy model used for the prediction of seasonal monsoon rainfall in the Anas catchment, India, is based on the atmospheric circulation pattern of 500 hPa geopotential heights and station rainfall measurements. The algorithm employed here is an improved version of the stochastic downscaling proposed by Bardossy *et al.* (2002) for possible application in extreme monsoon climates. The model computes distributed rainfall using kriging's external-drift interpolation method for the monsoon season at any point within the catchment independent of point measurements. For a detailed description of the stochastic fuzzy based model used for the Anas catchment refer to Bardossy *et al.* (2002) and Singh (2004).

MODELLING METHODOLOGY

Bardossy & Plate (1992) and Von-Storch *et al*. (2000) are of the opinion that regional climate is conditioned by climate on a larger scale. Thus the conceptual relationship between local rainfall expressed as $Z(t,u)$ and large scale circulation pattern $W(t,u)$ may be expressed by a deterministic function f as shown in equation (1):

$$Z(t,u) = f\{W(t,u)\} \tag{1}$$

For rainfall, a two step method is applied here. In the first step the pressure patterns have been classified according to the circulation pattern types using fuzzy-rule based logic, then in the second step, conditional probability analysis has been conducted to derive deterministic functions for conversion into rainfall. The stepwise modelling methodology is presented below.

Classification of circulation types

The model uses a fuzzy-rule based logic concept for circulation pattern definition. The days with a similar range of geopotential heights are assigned the same CP type. The classification is carried out using normalized pressure anomalies $g(i,t)$ of daily geopotential height data (i stands for grid point and t for day). The normalized pressure anomalies $g(i,t)$ can be defined as:

$$g(i,t) = \frac{P(i,t) - \overline{P}}{\sigma_P} \tag{2}$$

where $\overline{P}$ is average pressure during time t at N number of observations, and σ_p is the standard deviation of daily pressure data.

The rainfall probability on a given day is calculated by considering the threshold ϑ for the daily rainfall amount. Thus the objective function $O_1(\vartheta)$ can be defined as:

$$O_1(\vartheta) = \sum_{i=1}^{s} \sqrt{\frac{1}{T} \sum_{t=1}^{T} \left\{ p(CP(t))_i - \overline{p_i} \right\}^2} \tag{3}$$

where s is the number of stations, T number of days, $p(CP(t))_i$ is the probability of rainfall exceeding the threshold ϑ on a day with given CP at station i, and $\overline{p_i}$ is the probability of a day with rainfall exceeding ϑ for all days within the time period T.

For the amount of rainfall on a given day for a given station, the following objective function is defined:

$$O_2 = \sum_{i=1}^{S} \frac{1}{T} \sum_{t=1}^{T} \left| \left(\frac{z(CP(t))_i}{\overline{z_i}} \right)^{1.5} \right| \tag{4}$$

where $z(CP(t))_i$ is the mean rainfall amount on a day with a given CP at station i and $\overline{z_i}$ is the mean daily rainfall without classification at the same station. Higher values of $O_1(\vartheta)$ and O_2 indicate a better classification. A detailed discussion on classification can be found in Bardossy *et al.* (2002).

Rainfall downscaling

The seasonal cycle of the parameters is modelled by applying Fourier series as described in Bardossy & Plate (1992). The probability of rainfall at time t and location u depends on circulation pattern $\widetilde{A}_t$ and can be expressed as:

$$P\left[W(t,u) > 0 \mid \widetilde{A}_t = a_i\right] = P\left[Z(t,u) > 0 \mid \widetilde{A}_t = a_i\right] = p_{\alpha_i}(u,t) \tag{5}$$

The distribution of daily rainfall amount at location u, $F_{\alpha i}(z \mid u)$ also depends on circulation pattern $\widetilde{A}_t$ and time t which can be expressed as:

$$P\left[Z(t,u) < z \mid \widetilde{A}_t = \alpha_i, Z(t,u) > 0\right] = F_{\alpha_i}(z,u) \tag{6}$$

where $z(CP(t))_i$ is the mean rainfall amount on a day with a given CP at station i and $\overline{z_i}$ is the mean daily rainfall without classification at the same station. Bardossy *et al.* (2002) stated that higher the values of $O_1(\vartheta)$ and O_2 indicate a better classification.

DATA SOURCES AND DATABASE

As explained the circulation pattern type approach described above requires daily time series of mean geopotential heights at 5° × 5° grid spatial resolution for the optimized window (05°N,40°E and 35°N,95°E) over the Indian sub-continent. The NCEP re-analysis data sets of 500 hPa geopotential heights were obtained from the National Meteorological Centre for Atmospheric Research (NCAR) on CD-ROM for the period 1962–1994.

The daily rainfall data for the Anas catchment were obtained from the State Water Data Centre, Bhopal for 10 rainfall stations. The Jhabua and Sardarpur stations have the longest records of 42 years while the Thandla and Petlabad stations have records for 35 years. The rest of the stations have daily rainfall records for between 1984 and 1999, and are limited to just ten-year periods. Thus a common data set period, both for daily geopotential heights and rainfall time series for the ten stations, from 1 January 1985 to 31 December 1994 has been chosen. Since 80–85% of the rain falls during the monsoon season (June–September) and influences hydrological processes, agriculture and economic activities within the catchment, the rainfall downscaling analysis was limited to the monsoon season only.

RESULTS AND DISCUSSION

The rainfall downscaling model results were simulated for two objective functions: conditional rainfall probability and conditional rainfall amount, which were obtained from wet and dry circulation types. The mean wet-day fraction for each station has also been calculated.

Conditional rainfall probability and amount

The computed conditional mean rainfall probabilities and conditional mean rainfall amounts for all ten stations in the Anas catchment during the 1985–1994 monsoon seasons are displayed in Fig. 1. For circulation type CP04, a high conditional rainfall probability of 0.54 with a conditional rainfall amount of 22.7 mm day^{-1} was observed. Although the conditional rainfall probability (0.40) for CP02 was found to be low compared to CP04, the conditional rainfall amount of 43.9 mm day^{-1} estimated is high. Also CP04, showed a relatively very high conditional wet-day fraction (0.57) but low frequency of occurrence just 5.8%. This shows that CP04 was responsible for a few large rainfall events, as compared to CP02 when a number of events of good rainfall amount do often occur. CP03 and CP08 have higher conditional probabilities of 0.45 and 0.41, with a conditional daily rainfall amount of 28.6 and 15.4 mm day^{-1}, respectively. The wet-day fraction for CP03 (0.39) was found to be lower than the wet-day fraction of CP08 (0.46). Thus it may be concluded that CP04 can be termed a cyclonic weather type which may occur seldom during the monsoon season each year.

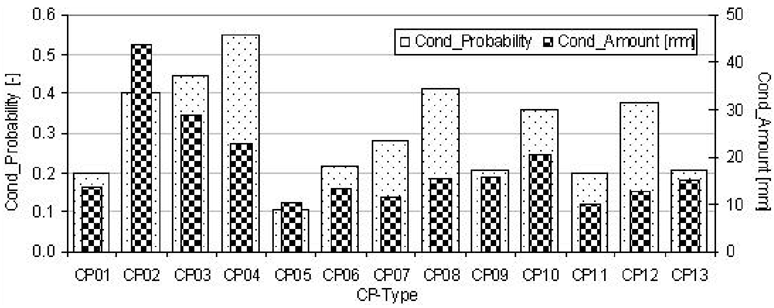

Fig. 1 The combined conditional rainfall probability and conditional rainfall amount for all the stations in Anas catchment for 12 CP types.

The dry CP types, such as CP09 and CP05, have low conditional rainfall amounts and high frequency of occurrence, 13.4 to 16.1%. For the CP types CP05 and CP09, a conditional rainfall probability of 0.22 and 0.11 and a conditional rainfall amount of 13.5 and 10.2 mm day^{-1} respectively were simulated. A low value for wet-day fraction indicates that CP09 contributed little to the rainfall on the given day as compared to high value (0.57) for CP04 with higher rainfall probability and rainfall amount. A low percentage of rainfall contribution from CP06, CP05, CP09 and CP11 may be due to the fact that there are many dry days with a small amount of rainfall.

Objective circulation pattern

The spatial distribution of mean pressure pattern anomalies for the 5° × 5° window at 500 hPa geopotential heights over the Indian Ocean further explains the phenomena of wet and dry CP types responsible for rainfall and drought in the Anas catchment. The wet circulation pattern types, such as CP04, are the cause of major rainfall in the study area. These CP types are influenced by high pressure over the Bay of Bengal and low pressure over the Arabian Sea. This forms a vortex kind of effect over the Indian sub-continent and is thus responsible for the heavy monsoon rainfall. On the contrary, for dry CP types such as CP09, the low pressure over the Bay of Bengal and high pressure over the Arabian Sea and south Plateau of China gave very little rainfall in the study area. Both the circulation patterns CP04 and CP09 present contrasting situations as shown in Fig. 2.

Observed and simulated rainfall

The statistics of monsoon season mean observed and simulated yearly rainfall totals for all the stations in the Anas catchment are given in Table 1. It is clear that the mean value shows the best compromise with an average error of 2.5% for the 10-year average. The highest error of 10.6% was predicted for the Udaigarh and 9.1% for the Jhabua, while the best fits of 1.2% for Rama and 2.3% for Bhabhra were obtained. This shows an excellent performance for the mean seasonal rainfall. However, the results from statistical downscaling for predicting the number of wet days at each station have not been so promising as an average error of 24.6% was calculated. For all the stations the model always simulated a greater number of rainy days than was observed. This difference was as high as 19 days for the station Rama and as low as 1 day for the Udaigarh station.

The long-term time series of mean monthly rainfall totals for observed and simulated rainfall for stations Ranapur, Rama, Meghnagar and Sardarpur shows a good fit. For most of the rainfall stations the difference between the observed and simulated rainfall totals is under the 15% limit, except for the month of October where the simulation range was exceeded. The monthly cycle of rainfall totals for observed and simulated rainfall data have been found to be highly correlated. The order of Pearson-type correlation varies between 0.85 for station Petlabad to 0.99 for station Amba and Meghnagar (Table 2).

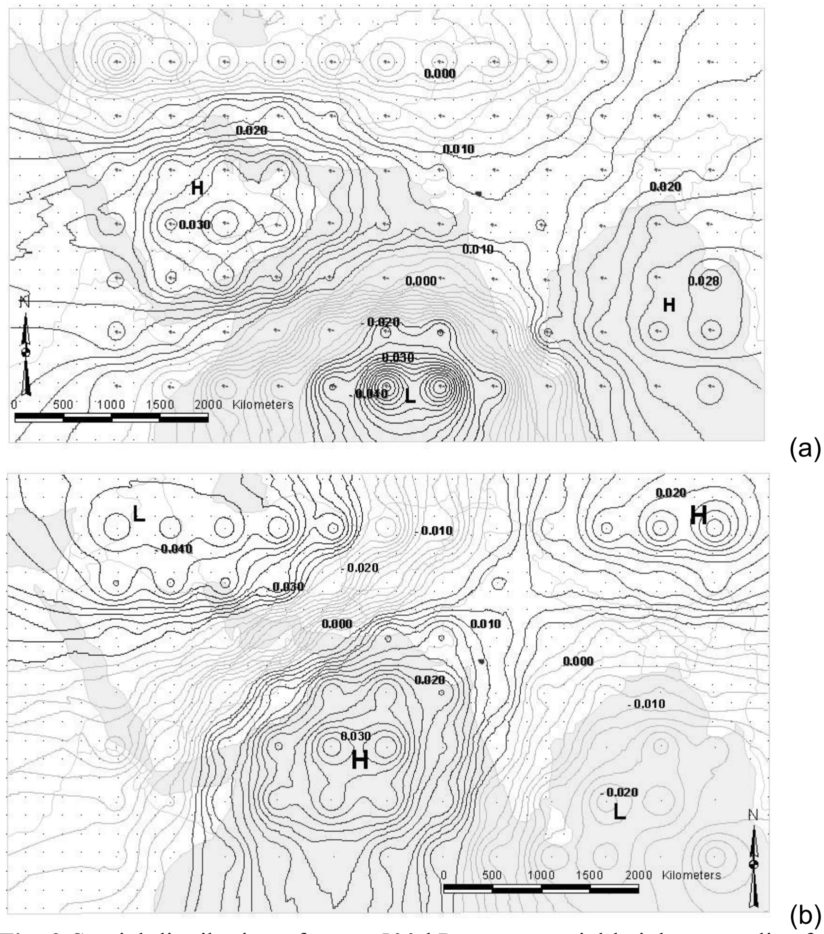

Fig. 2 Spatial distribution of mean 500 hPa geopotential height anomalies for: (a) wet CP04, and (b) dry CP09, for 12 CP types over the Indian sub-continent.

Table 1 Statistics of observed and simulated seasonal (June–October) rainfall totals for various stations (1985–1994) in the Anas catchment, India.

Station	Mean rainfall amount (mm)		Standard deviation (mm)		Number of wet days	
	Observed	Simulated	Observed	Simulated	Observed	Simulated
Jhabua	787.0	715.8	109.9	97.7	47.0	54.6
Ranapur	780.1	760.7	113.7	115.3	35.6	48.7
Udaigarh	817.3	729.8	98.2	99.9	52.0	53.7
Amba	852.3	873.9	129.9	120.1	39.2	55.3
Rama	934.3	922.8	127.5	110.0	39.4	58.3
Meghnagar	728.3	705.6	107.3	99.6	40.1	51.2
Thandla	881.1	844.1	116.5	115.6	48.3	55.7
Bhabhra	795.9	777.9	99.5	97.0	47.9	52.4
Sardarpur	769.2	775.4	93.2	79.5	38.7	51.9
Petlabad	1016.2	983.0	127.5	125.3	54.1	62.0

Table 2 Correlation between observed and simulated monthly rainfall totals.

Station	Jhabua	Ranapur	Udaigarh	Amba	Rama
Correlation	0.94	0.96	0.88	0.99	0.96
Station	Meghnagar	Thandla	Bhabhra	Sardarpur	Petlabad
Correlation	0.99	0.96	0.98	0.91	0.85

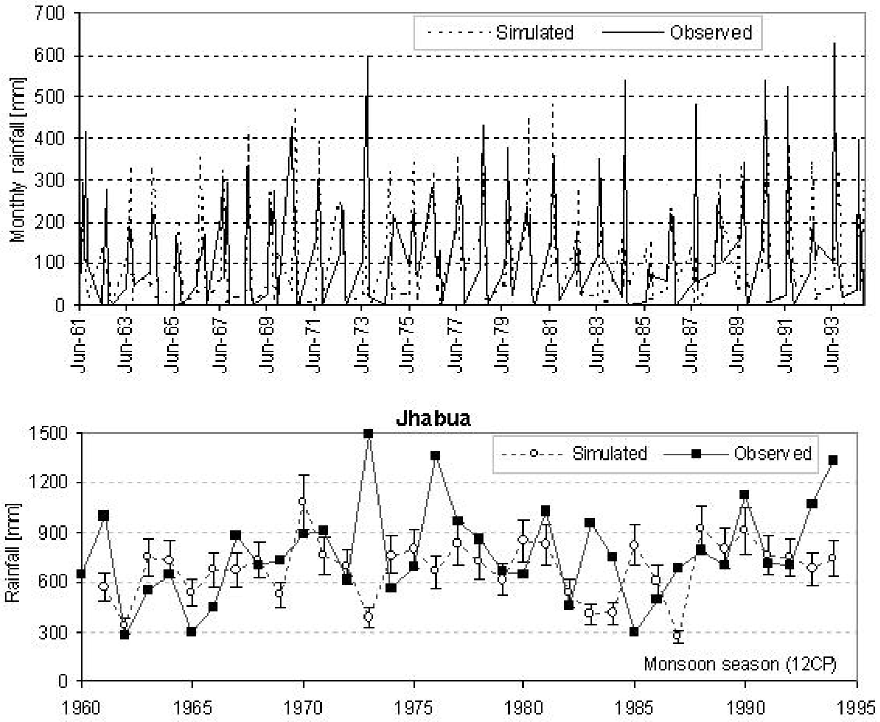

Fig. 3 Simulated and observed rainfall time series for Jhabua station during the 1961–1994 period: (a) monthly rainfall time series and (b) seasonal rainfall totals.

Prediction of long-term rainfall

The model parameters obtained from the calibration period daily rainfall time series have been used for the prediction of long-term monthly rainfall for Jhabua station during the 1961–1994 monsoon seasons. The correlation between predicted and observed time series is, at 0.40, relatively low (Fig. 3). The long-term prediction of individual monsoon season rainfall totals gives much better results, a correlation of 0.90. The deviation between predicted and observed seasonal rainfall is mostly smaller than 20%. However, in 1974 and within the period 1983–1985, the model predictions are very poor. Hence, the model is only capable of forecasting part of the inter-annual variability of total seasonal rainfall; it fails especially in predicting the extremes.

CONCLUSIONS

This research study demonstrates the benefit of using a statistical downscaling model with limited observed data records for rainfall prediction based on the daily atmospheric circulation pattern in the highly seasonal environment of India. The model calibration parameters were obtained from a daily rainfall time series limited to the 10-year period 1985–1994. A conditional weather generator, in which rainfall occurrence is conditional on the CP type of each day and the daily sequence of CP type is modelled as a fuzzy-rule based process, was used to simulate the number of rainy days for all the stations. The model overestimated the total number of rainy days for each station.

It can be stated that the rainfall downscaling model is a good starting point for seasonal predictions of monsoon rainfall. The circulation patterns give a sound explanation for the dry and wet synoptic situations through the pressure patterns over the Indian sub-continent. The model is capable of: (a) reproducing average annual rainfall, and (b) capturing parts of the inter-annual variability of total seasonal rainfall when used for long-term predictions. However, the model fails particularly fails in predicting extremes, i.e. flood or drought prone seasons. This is a clear hint that the proposed methodology does not account for all the important factors that determine the inter-annual variability of seasonal rainfall.

The future potential of the model is to test additional predictors such as sea-surface temperature (SST) or moisture flux in the atmosphere for rainfall generation. This will surely improve the model performance. Furthermore, hydrological extremes such as drought or flood are not properly addressed by the time scale of monthly or seasonal data. There is an urgent need for inter-comparison of different downscaling methods for hydrological modelling. This research work is an interesting initiative for prediction for poorly gauged catchments, or prediction under limited data availability.

REFERENCES

Bardossy, A. & Plate, E. J. (1992) Space-time model of daily rainfall using atmospheric circulation patterns. *Water Resour. Res.* **28**(5), 1247–1259.

Bardossy, A., Stehlik, J. & Caspary, H.-J. (2002) Automated objective classification of daily circulation patterns for rainfall and temperature downscaling based on optimised fuzzy rules. *Climate Res.* **23**, 11–22.

Clark, C. O, Cole, J. E. & Webster, P. J. (2000) Indian Ocean SST and Indian summer rainfall: predictive relationships and their decadal variability. *J. Climate* **13**(14), 2503–2519.

Clark, M. P., Hay, L. E., McCabe, G. J., Leavesley, G. H., Serreze, M. C. & Wilby, R. L. (2001) The use of weather and climate information in management of water resources in the western United States. In: *Proc. Climate Variability and Water Resources* (Boulder, USA).

Goodess, C. M. (2000) Rainfall scenarios for Mediterranean sites using a circulation-type approach to downscaling. PhD Thesis, University of East Anglia, Norwich, UK.

Singh, A. K. (2004) Towards decision support models for an un-gauged catchment in India. Heft 225, Institute for Water Resources Management and Rural Engineering (IWK), University of Karlsruhe, Germany.

Von-Storch, H., Bruce, H. & Mearns, L. (2000) Review of empirical downscaling techniques. In: *Proc. RegClim Spring Seminar* (Jevnaker Norway, 8–9 May 2000).

Wilby, R. L. (2001) Downscaling summer rainfall in the UK from north Atlantic ocean temperatures. *Hydrol. Earth System Sci.* **5**(2), 245–257.