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Evaluation of approaches for estimation of rainfall and the unit hydrograph

B. F. W. Croke, A. Islam, J. Ghosh and M. A. Khan

ABSTRACT

The impact of rainfall interpolation techniques and unit hydrograph estimation has been explored for four gauged locations in the Brahmani basin in east India. The use of ground-based and satellite-based data, coupled with testing two interpolation techniques (Thiessen polygon and inverse distance weighting), can yield improved rainfall estimates and fits to observed flows. Due to the presence of significant errors in the areal rainfall estimate it was found that identification of known errors in rainfall data can assist in focusing model calibration on catchment response, thereby reducing the uncertainty in model parameter values. Similarly, using several approaches to estimate the unit hydrograph can assist in reducing uncertainty. The resulting performance of the model for the gauged sites in the Brahmani basin gave Nash–Sutcliffe efficiency (NSE) values for the calibration period of 0.6–0.7. For this basin, the inverse distance weighting approach corrected for spatial variation in rainfall distribution generally gave the best fits to the observed streamflow. Sensitivity to errors in the rainfall surface limits the applicability for this approach in modelling the flows in ungauged basins, however.

Key words | model calibration, parameter estimation, rainfall estimation, unit hydrograph

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INTRODUCTION

Precipitation data are one of the most critical input variables in any hydrological modelling studies. Beven (2001) noted that no model, however well founded in physical theory or empirically justified by past performance, will be able to produce accurate hydrograph predictions if the inputs to the model do not characterize the precipitation inputs. Rain gauges are fundamental tools that provide an estimate of rainfall at a point. Although satellite-based precipitation data is becoming widely available, ground-based precipitation data is still used widely in modelling hydrological processes; long-term historical ground-based precipitation data are available in all parts of the world and are considered more reliable than the satellite- and radar-based data.

Generally, point measurements of rain gauge accumulations are distributed in space over the catchment by different interpolation techniques. Conversion of point rainfall data to areal estimates is especially difficult in regions where rain gauge densities are very low. Among the various sources of uncertainty affecting rainfall-runoff modelling, uncertainties in computed precipitation play a particular role. Many studies have pointed out that spatial and temporal characteristics of rainfall greatly influence runoff generation, especially in regions of highly variable convective storms. Some studies have concluded that the reliability of rainfall-runoff models is mainly associated with the ability to represent spatial and temporal rainfall characteristics. Singh (1997) observed that the shape, timing and peak flow of a stream flow hydrograph are significantly influenced by spatial and temporal variability in rainfall and watershed characteristics.

The role of rainfall data quality on model performance has been extensively studied. Examples of factors affecting the uncertainty in the modelled flow include: number of rain gauges (e.g. Faurès *et al.* 1995); rain gauge density (e.g. Hansen *et al.* 1996); and spatial variability of rainfall (Chaubey *et al.* 1999). Faurès *et al.* (1995) investigated the

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impact of rainfall variability on runoff modelling by using a dense rain gauge network on a small semiarid catchment and indicated that the uncertainty on runoff estimation for small semiarid catchments is greatly affected by spatial variability of rainfall. On the other hand, Goodrich *et al.* (1995) observed that rainfall could be considered uniformly distributed for hydrologic modelling of small basins, where a single rainfall station usually exists. In such cases, model parameters would be calibrated assuming uniform rainfall distribution within the watershed. Chaubey *et al.* (1999) found large uncertainty in estimated model parameters when detailed variations in the input rainfall were not taken into account. Bardossy & Das (2008) observed that the number and spatial distribution of rain gauges affect the simulation results, and a model might need recalibration of the model parameters when using different rain gauge networks. Specifically, a model calibrated on relatively sparse precipitation information might perform well on dense precipitation information, while a model calibrated on dense precipitation information fails on sparse precipitation information. Moulin *et al.* (2009) investigated the influence of mean areal rainfall estimation errors using lumped conceptual rainfall-runoff models to simulate the flood hydrographs of three small- to medium-sized catchments of the upper Loire River. They concluded that a large part of the rainfall-runoff modelling errors can be explained by the uncertainties in rainfall estimates, especially in the case of smaller catchments. Andréassian *et al.* (2001) studied the impact of imperfect rainfall data for three catchments on three hydrological models – GR4J (modele du Geânie Rural a 4 parametres journalier) and derivatives of IHACRES (identification of unit hydrograph and component flows from rainfall, evaporation and stream flow data) and the topography-based model TOPMODEL – and found that the models used were able to correct for imperfect rainfall input estimates. For predicting flows at ungauged locations, however, the variations in the error in rainfall estimates between catchments need to be taken into consideration.

For interpolation there are many modern methods available to optimize the available point observations, often utilizing additional information from topography, satellite data or radar information (Seo *et al.* 1990a, b; Haberlandt & Kite 1998; Grimes *et al.* 1999). Wilk *et al.* (2006) explored the combination of ground-based data and satellite-derived spatial distributions of rainfall. Creutin & Obled (1982) concluded that more sophisticated interpolation techniques might result in an improved estimation of rainfall behaviour, especially in cases of high spatial variability. Haberlandt & Kite (1998) found that better interpolation techniques and the use of combined precipitation data can improve the hydrological simulations, and that the enhancements are related to the relative size of the simulation units used. Tabios & Salas (1985) compared the applicability of various interpolation techniques for estimating annual precipitation at selected sites. Kriging and optimal interpolation techniques were found superior to the other techniques, and the multiquadric technique was almost as good as those two. The inverse distance interpolation and the Thiessen polygon gave fairly satisfactory results, while the polynomial interpolation did not produce good results.

This paper focuses on the impact of uncertainty in estimates of areal rainfall and unit hydrograph on modelling streamflow in the Brahmani basin in India. No information is available regarding the uncertainty in the gauged rainfall or streamflow, so these are ignored in this analysis. Rather, the focus is on the uncertainty in converting the point rainfall data to areal rainfall estimates and the implications this has for estimation of the unit hydrograph (total UH is considered here, not just the runoff component). Four interpolation techniques are tested (inverse distance weighted and Thiessen polygon, plus both of these weighted by a long-term rainfall surface) and these are analyzed using the jack-knife uncertainty estimator as well as cross-correlation analysis.

The IHACRES model has been used to test the performance of each rainfall sequence for each of the catchments included in this study. The Catchment Moisture Deficit (CMD) version of the non-linear water balance module has been used (Croke & Jakeman 2004). The CMD module has five parameters: the flow threshold d; temperature/potential evaporation conversion factor e; plant stress threshold scale factor f; drainage equation shape factor b; and dry condition response scale factor n.

STUDY AREA

The Brahmani River basin lies in eastern India between latitudes 20°30′10″ and 23°36′42″N and longitudes 83°52′55″

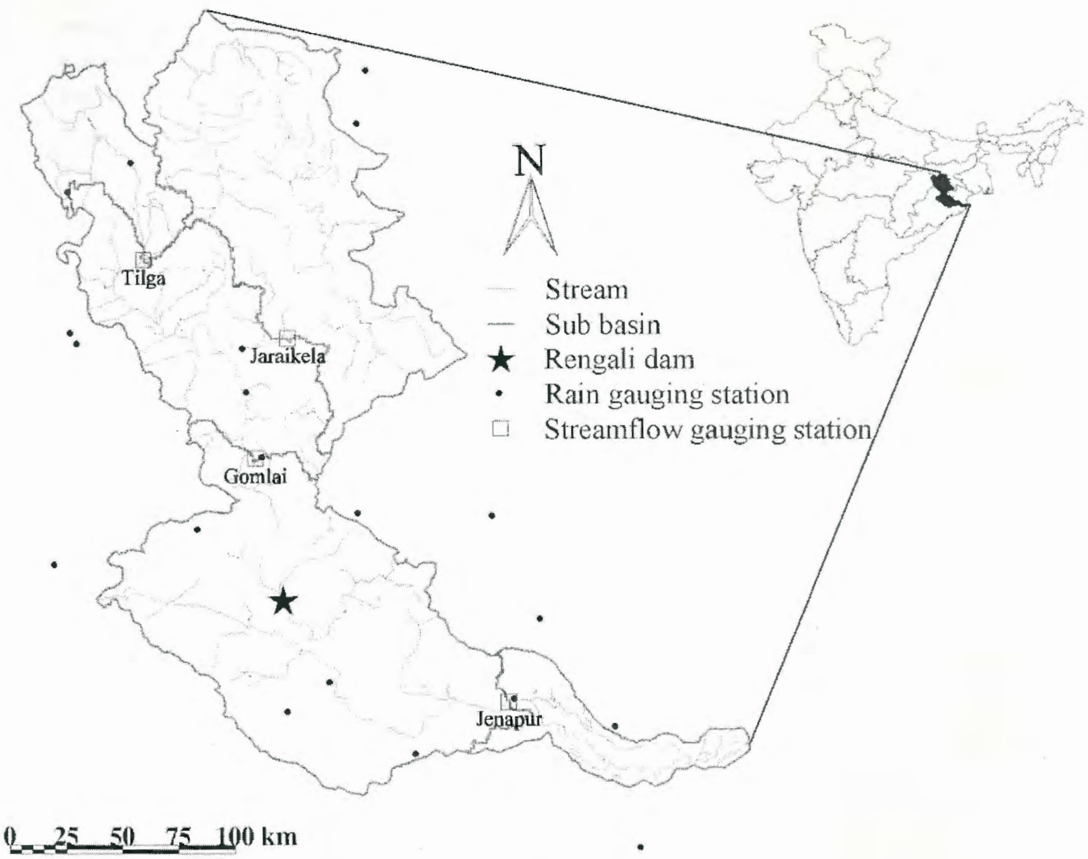

Figure 1 | Brahmani basin, showing location of streamflow and rainfall gauging sites used.

and 87°00′38″E, and is situated between Mahanadi Basin and Baitarani Basin. The basin has a total catchment area of 39,313 km^2 and is spread over the states of Orissa (57.3% of the basin area), Jharkhand (39.2%) and Chattisgarh (3.5%). There are four gauged locations in the basin: Tilga, Jaraikela, Gomlai and Jenapur (Figure 1). A large multipurpose dam (Regnali) is located upstream of Jenapur gauge and has been operational since 1985. The Rengali dam has a catchment area of 25,250 km^2 and has live storage capacity of $4 \times 10^9\,m^3$. While the presence of a large dam in the Jenapur catchment complicates the hydrological response (the behaviour of such dams is not captured by most simple rainfall–streamflow models), the catchment was included in the study because modelling such catchments is necessary for water resource management. Ideally, an approach which accounts for the impact of dam releases should be used (e.g. Payan *et al.* 2008).

The basin has a sub-humid tropical climate with an average annual rainfall of 1,305 mm, most of which is concentrated in the southwest monsoon season of mid-June to mid-October. The arable and forest land area occupy about 70 and 27% of the total area, respectively, and the remaining 3% of the basin area is urban. The basin is a key source of water supplies for different towns and industries and for irrigation in the state of Orissa. However, with rapid economic development and population growth in this region, there are increasing concerns over the adequacy of the quantity and quality of water withdrawn from the Brahmani River in the future.

HYDRO-CLIMATIC DATA

Daily streamflow and rainfall data (1979–2003) of four stream gauging stations, namely Tilga, Jaraikela, Gomlai and Jenapur, are collected from the Central Water Commission (CWC), Bhubaneswar. Daily rainfall and temperature data for 20 sites in or near the basin were collected from India Meteorological Department (IMD), Pune (Figure 1). The number of gauges with data plotted as a function of time (Figure 2) shows that the uncertainty in the estimates of areal rainfall will vary significantly through the period of record, with best estimates available from 1/1/1982 to 31/12/1999.

METHOD

Areal rainfall estimation

Daily rainfall data for 20 gauges in or near the Brahmani basin were used to estimate areal rainfall for each of the four gauged catchments. Four techniques were explored for estimating the areal rainfall: inverse distance weighting (IDW), Thiessen polygons (TP) and both of these methods with rainfall spatially weighted by a long-term average rainfall surface (2000–2009) from the PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks) dataset (Sorooshian *et al.* 2000). The PERSIANN satellite-derived rainfall surface was used as there were insufficient gauges to generate a surface using spatial interpolation methods (e.g. Taesombat & Sriwongsitanon 2009).

The spatial weighting technique adopted here uses the satellite-derived rainfall surface to correct for the long-term

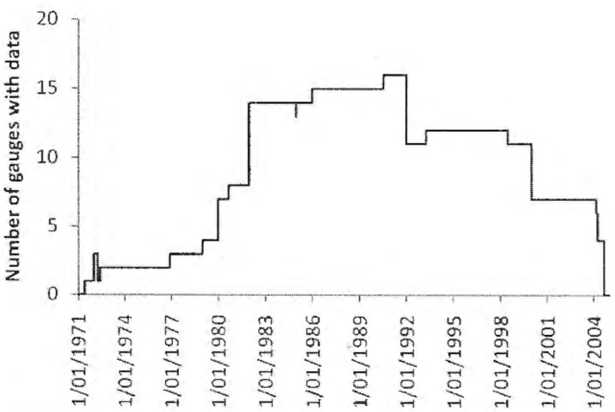

Figure 2 | Number of gauges with data as a function of time.

spatial variability in the rainfall distribution, in order to minimize the impact of gauge location on the rainfall estimates. This is achieved by dividing the data for each rain gauge by the corresponding value in the rainfall surface. This allows the use of simple interpolation techniques (such as IDW and TP) of the normalized rainfall values. The result is a normalized areal rainfall estimate. Multiplying this estimate by the mean rainfall surface value for the catchment gives an areal rainfall estimate that captures the influence of the spatial distribution of rainfall represented in the rainfall surface. Temporal variations in the rainfall surface (e.g. between events, months or years) are ignored in this application. While there is evidence of a systematic bias in the PERSIANN estimates (e.g. Hong *et al.* 2007; Boushaki *et al.* 2009), the effects of this will be reduced in this application as the decadal PERSIANN surface is only used to estimate the spatial variation in the rainfall and not the rainfall amount.

Each approach modified the contributions from each gauge for each time-step according to availability of data. The inverse distance approach used all rain gauges, relying on the weights (inverse of the distance to each gauge) to effectively remove more distant gauges from contributing to the estimate. The weights applied to each gauge were calculated on a cell by cell basis using a 1 km resolution, resampling the catchment boundaries delineated based on the Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) (90 m resolution, Smith & Sandwell 2003; Farr *et al.* 2007). The distance from a cell to a gauge was corrected for the spatial extent of a cell. This approach means that the Thiessen approach is using polygons sampled at the rate of 1 km.

The uncertainty in the daily rainfall estimate was tested in two ways. The first was based on a comparison between the different techniques, and gives a relative uncertainty between two different interpolation methods. The second approach involved the jack-knife approach for estimating the standard error in each areal rainfall estimate. In each trial, one of the ten most heavily weighted gauges was removed from the sample (depending on the number of available gauges). The jack-knife estimator gives a lower limit to the uncertainty in the areal rainfall estimates, as it only considers the scatter in the estimates from the rejection trials and ignores other factors which will influence the uncertainty (e.g. uncertainty in measured rainfall at each gauge and the under-sampling of the spatial distribution of rainfall).

Temperature interpolation

The IHACRES rainfall–streamflow model uses temperature as a surrogate for potential evaporation (as temperature data is more readily available and easier to interpolate). Daily temperature data (minimum, maximum and mean of these values) were available for five gauges in or near the Brahmani basin. Four of these had significant data gaps, and these were used to check for changes in the variations in temperature for different locations. The remaining gauge located in Ranchi (near border at the northeast extreme end of the Brahmani basin) has complete data for the period from 1980 to 2004. The Ranchi temperature data was used to estimate the areal temperature for each catchment, adjusted for elevation using a lapse rate of $7\,^{\circ}\mathrm{C\,km}^{-1}$.

Comparison between gauges showed a significant difference between all sites, with two upland sites showing evidence of systematic errors in temperature (up to 2 °C). The two sites near the coast showed significantly cooler temperatures than the inland sites in the summer, and warmer temperatures in the winter. However, since only a small fraction of the Jenapur catchment would be affected by coastal influences, this effect was ignored as it would not significantly alter the water balance.

Estimation of the unit hydrograph

Three techniques were employed to estimate the total UH which includes all flow components (surface and subsurface flow pathways): Fourier deconvolution (Croke *et al.* 2000; Croke & Littlewood 2005); direct estimation from the streamflow data (Croke 2006); and baseflow filtering (Croke *et al.* 2002). Fourier deconvolution and the direct estimation technique give non-parametric estimates of a time-invariant UH, while the baseflow filtering approach gives a parametric estimate of the UH based on a number of exponentially decaying terms as well as allowing testing of the time invariance of the UH.

Non-parametric estimates

The time-invariant UH approach assumes that the streamflow (q) is given by the convolution of the effective rainfall (u) with the UH (h):

$$q = u \times h \tag{1}$$

Taking the Fourier transform of Equation (1) gives:

$$Q = UH \tag{2}$$

where the capital letter indicates the Fourier transform of the relevant input. In theory, the Fourier transform of the UH (H) can be estimated from Q/U. However, noise in the rainfall and streamflow data, coupled with temporal variations in the UH (e.g. seasonal variations, dependence on event magnitude and intensity) make this difficult. A better estimate of the average event H can be obtained using the correlation functions as these give a signal averaged across all events, reducing the noise in the signal and removing the influence from any temporal variations in the UH.

The Fourier transform of the cross-correlation between two series a and b is given by AB^*, where B^* is the complex conjugate of B. This means that Equation (2) can be rewritten in terms of the Fourier transforms of the cross-correlation functions:

$$H = \frac{QP^*}{UP^*} = \left(\frac{QP^*}{PP^*}\right)\left(\frac{PP^*}{UP^*}\right) \tag{3}$$

where P is the Fourier transform of the estimated areal rainfall. Since the effective rainfall is unknown, the second factor in the right-hand side of Equation (3) limits the accuracy of the estimate of h, but does not prevent valuable information from being obtained about the form of h. This approach assumes that the autocorrelation of rainfall is an adequate representation of the cross-correlation between effective rainfall and rainfall.

The direct estimation technique (Croke 2006) produces a high-resolution (one-tenth the original time-step) estimate of the decay from flow peak and is better suited than the Fourier deconvolution approach for determining the baseflow response signal. It performs best for hydrographs with well-separated flow peaks. The direct estimation technique uses only the observed streamflow data, reducing the data requirements and removing a source of uncertainty.

Parametric estimates

The baseflow filtering approach described by Croke *et al.* (2002) gives an estimate of the effective rainfall time series, the UH based on a sum of exponential terms and the baseflow (under the assumption that the exponential terms in the UH have a physical basis). In this case, the technique is used for estimating the UH as well as checking for deficiencies in the data. The baseflow filtering approach uses an iterative procedure where a first guess of the UH is used to estimate the effective rainfall time series. The effective rainfall time series is then used to update the estimate of the UH, and the procedure repeated until the change in parameter values of the UH between iterations decreases to below 10^{-6} or 40 iterations are completed. In most cases, converged solutions are obtained in approximately 20 iterations. Each exponential term in the UH has two parameters: the recession time constant τ and the volume v. For conservation of mass, the sum of the volumes for all stores is 1 (only considering parallel pathways here, not cascades of exponential stores).

Rainfall–streamflow modelling

In keeping with the top-down approach to model development (e.g. Littlewood *et al.* 2003; Sivapalan *et al.* 2003), the simplest version of the model was applied initially, with the benefit of greater complexity explored by comparing the model performance as additional parameters are optimized. The CMD version of IHACRES (Croke & Jakeman 2004) was calibrated to each catchment using a phased calibration approach where the unit bydrograph parameter values were estimated from the analysis described in the previous section. Initially, only two parameters of the CMD module were calibrated: the plant stress threshold factor f and the dry condition contribution scale factor n. The remaining parameter values were set at the values nominated by Croke & Jakeman (2004).

The CMD module parameters were calibrated using a multi-criteria approach which included: the Nasb–Sutcliffe efficiency (both the linear R^2_{NS} and logarithmic $R^2_{NS,log}$ forms); lag 1 correlation coefficients between model residual and modelled flow x_1 and effective rainfall u_1; and root mean square error (RMSE) in the flow duration curve (FDC) and the FDC for the upper 30 percentile of flows. Subsequent model runs involved increasing the number of parameters being optimized, and comparing the improvement in model performance.

RESULTS

Areal rainfall estimates

A comparison of the rainfall estimates for the Jenapur catchment using the wIDW and wTP approaches (where the prefix w indicates that the IDW and TP approaches have been weighted by a rainfall surface) is shown in Figure 3, while Figure 4 shows the variation between the two approaches as a function of the coefficient of variation (CV) of the data from all rainfall gauges on the corresponding day. The running average shown in Figure 4 clearly shows the influence of the CV. For rainfall events distributed across the region (low CV), both approaches give comparable estimates. For events that are sufficiently localized (high CV) that the rain gauge network does not adequately capture the spatial distribution, the inverse weighted approach tends to give lower estimates than the Thiessen polygon approacb due to the increased number of gauges used.

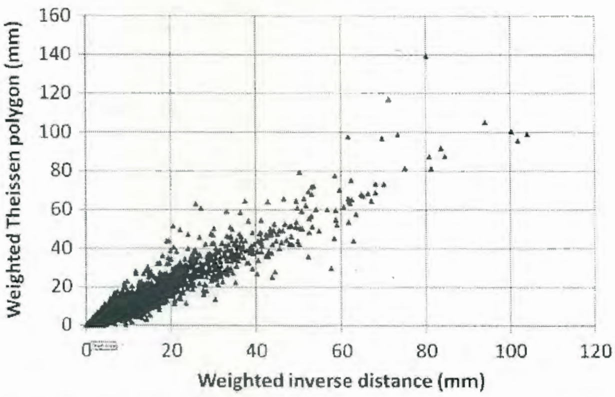

Figure 3 | Comparison of inverse distance and Thiessen polygon estimates of areal rainfall for the Jenapur catchment using the PERSIANN rainfall surface to correct for spatial variability.

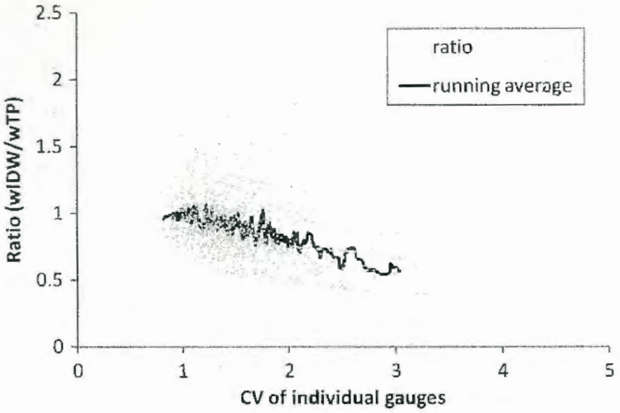

Figure 4 | Ratio of the areal rainfall estimates for the Jenapur catchment (excluding days with wTP < 10 mm) plotted against the coefficient of variation of the rainfall gauges for the corresponding day.

Figure 5 shows the fractional uncertainty (uncertainty in mean/mean) in the TP estimate of areal rainfall obtained using the jack-knife estimator for the Jenapur, Gomlai and Jaraikela catchments (the Tilga catchment is not shown as the maximum number of gauges used by the TP approach was 2). For the Jenapur catchment, all days with more than 13 gauges having data are shown with nine gauges for the Gomlai catchment and six gauges for the Jaraikela catchment. The increase in fractional uncertainty with decreasing areal rainfall is due to the impact of more localized rainfall events which have higher CV and tend to have lower rainfall estimates when averaged over large areas. Large rainfall events covering a significant fraction of the catchment tend to have uncertainties derived from the jack-knife estimator of a little less than 10%. Smaller events can have uncertainties ranging up to 40% (slightly higher for the Jaraikela catchment due to the smaller number of available gauges).

The estimated uncertainty in the IDW-derived areal rainfall values was lower than the TP-derived values (by approximately 70% for the Jenapur catchment). This is due to the smaller number of gauges used by the TP approach. The significance of this reduction in uncertainty derived using the jack-kinfe estimator depends on the relative importance of other sources of uncertainty. However, even if there is a significant decrease in uncertainty using the IDW approach, this is offset by the bias introduced in localized events (Figure 4).

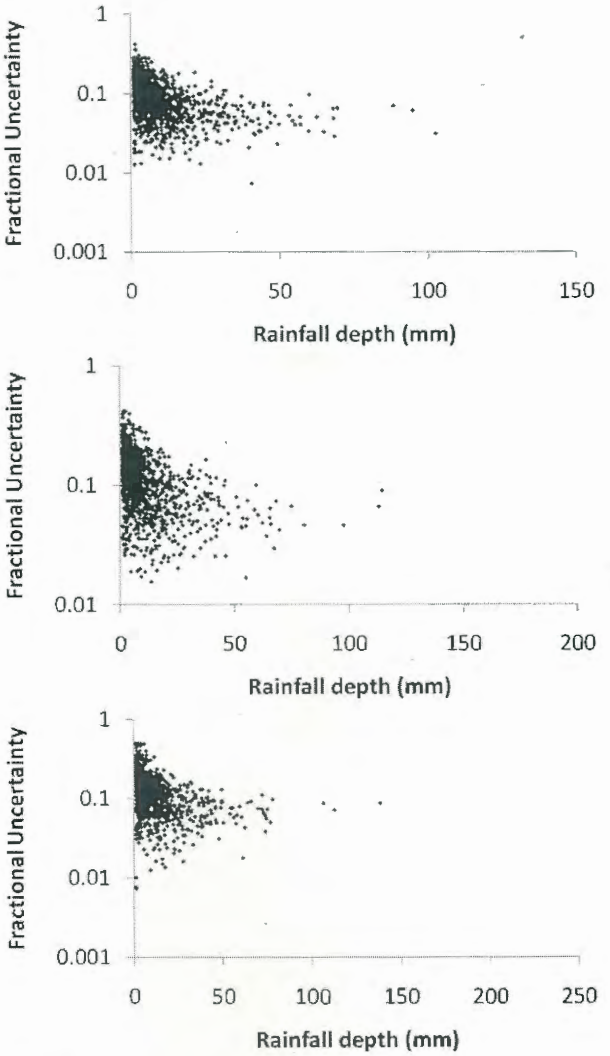

Figure 5 | Fractional uncertainty (uncertainty in mean/mean) in areal rainfall plotted against areal rainfall for Jenapur (top panel), Gomlai (middle panel) and Jaraikela (bottom panel) catchments.

Correlation analysis

Figure 6 shows the autocorrelation of rainfall (wIDW estimate) and the cross-correlation of streamflow with rainfall for the Tilga catchment. The autocorrelation of rainfall gives information about the seasonality of the rainfall signal (large lags), as well as the likelihood of rainfall on consecutive days (near a lag of zero). This is emphasized in the upper panel in Figure 6 by plotting the cross-correlation functions across lags of several years, showing the stability of the seasonality of the rainfall. In

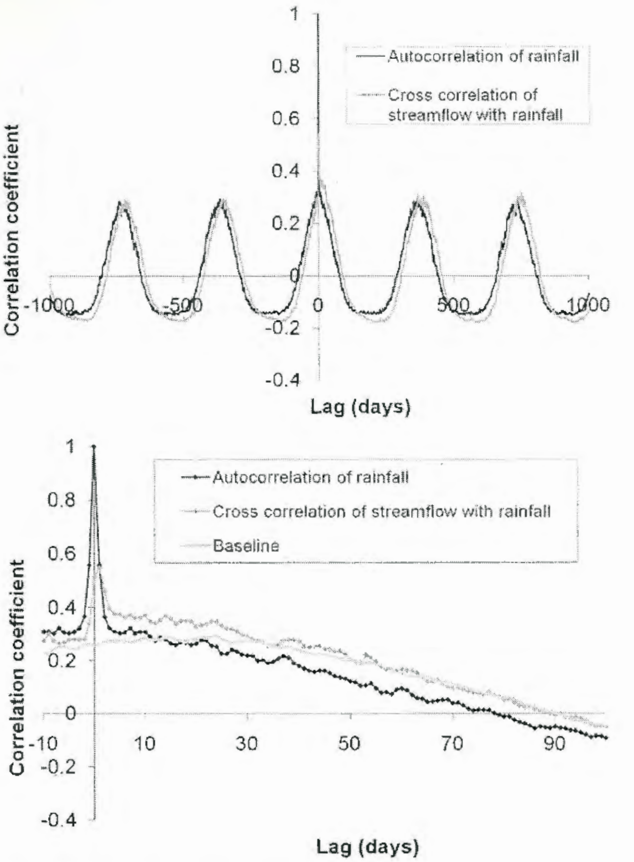

Figure 6 | Cross-correlation analysis of rainfall and streamflow data for Tilga catchment (rainfall surface adjusted inverse distance weighted).

the lower panel, the correlation functions are shown for lags between −10 and 100 in order to show the event scale rainfall and subsequent streamflow response of the catchment.

The cross-correlation of streamflow with rainfall shows the increased seasonality in the streamflow compared with the rainfall (necessitating a water balance module that has a seasonal dependence – e.g., the influence of variation in potential evaporation), the lag in streamflow response at the start of the wet season and the persistence in flow at the end of the wet season due to the baseflow component. The peak of the cross-correlation function near a lag of zero (lower panel in Figure 6) gives information on the average event response, i.e., lag in the peak with respect to rainfall, shape of UH and the strength of the dependence of streamflow on the rainfall (see earlier discussion on the non-parametric estimation of the UH).

The baseline shown in Figure 6 is the average of the values at integer year lags (therefore representing the seasonal variation in the cross-correlation function) and highlights the event response signal, where the cross-correlation function is considerably higher than the baseline near a lag of zero and merges with the baseline after about 50 days. The peak value of the cross-correlation function is higher when using the wIDW-estimated areal rainfall (0.55) than that obtained using the wTP approach (0.46), showing a stronger relationship between streamflow and wIDW-derived areal rainfall.

Non-parametric estimates of the UH

The estimated UH for the Tilga catchment derived using Fourier deconvolution of the correlation functions is shown in Figure 7 for the TP- and IDW-derived areal rainfall estimates. Generally, both rainfall estimates give similar estimated unit hydrographs. The plot extends to negative lags as this gives an indication of the noise in the UH estimates, enabling an assessment of the significance of the shape of the UH. The difference in the values at a lag of 1 day is approximately the same as the highest absolute value for negative lags (~0.05 at a lag of −9). The difference in the peak of each UH is therefore not very significant.

The resulting UHs for the four catchments are shown in Figure 8. The response curves for Jaraikela and Gomlai

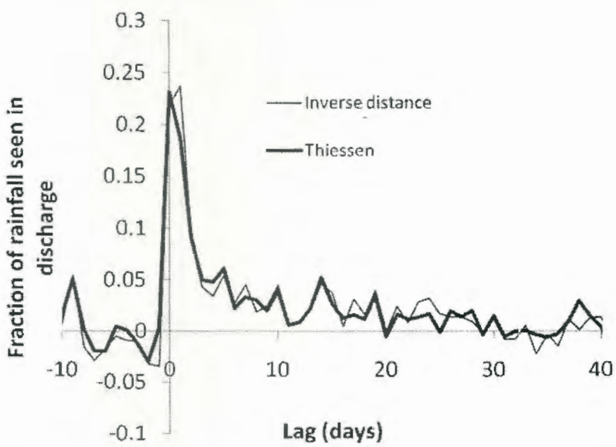

Figure 7 | Deconvolved non-parametric estimate of the unit hydrograph for Tilga catchment using the rainfall surface adjusted inverse distance, and sampled Thiessen polygon derived rainfall time series.

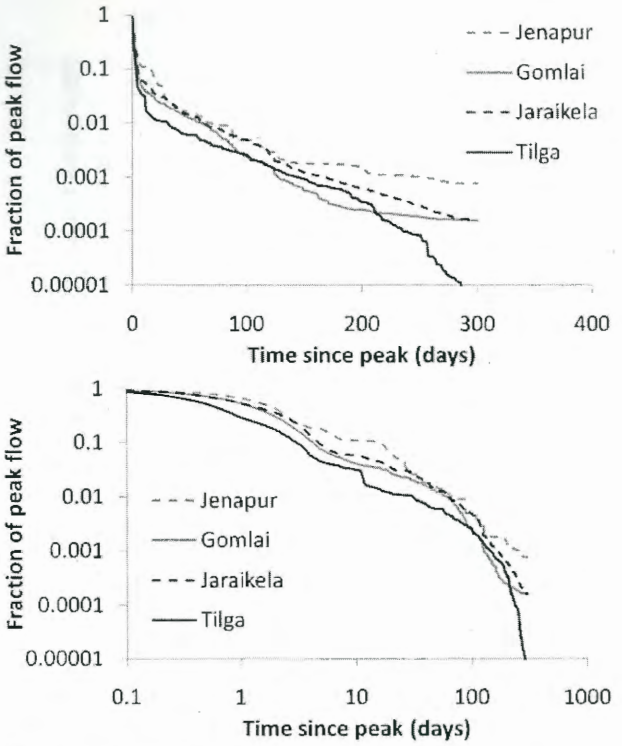

Figure 8 | UH derived for all catchments using the direct estimation technique.

are very similar, while Tilga (the smallest catchment) has a reduced baseflow volume and Jenapur (largest catchment, data from 9/4/1980 to 17/12/1993 used) has the strongest baseflow. In all catchments, the baseflow recession appears to be exponentially decaying. Both Gomlai and Jenapur catchments show evidence of a very slow low-volume baseflow component. While the significance of this is small, it is in agreement with these gauges being located lower in the Brahmani basin so the potential for such a baseflow component cannot be ruled out. The quick flow recession appears to be ordered according to catchment area, with Tilga having the most rapid decay from peak and Jenapur having the slowest. These estimates of the UH can then be compared with parametric estimates (see next section) to assess whether the adopted functional form is suitable.

Parametric estimate of the UH

The underlying assumption of the filtering approach for obtaining a parametric form of the UH is that the effective rainfall at each time-step is less than or equal to the areal rainfall. As such, this approach tests for significant underestimation in the areal rainfall but does not test for overestimation. Figure 9 shows the estimated flow obtained using the baseflow filter in comparison to the observed flow for the Tilga catchment, using the wTP estimate of areal rainfall. The top panel shows the entire period of record and the lower panel shows the observed and filter-derived flow for the years 1986 and 1987. There is a systematic underestimation of the largest flow peaks, which is due to the estimated rainfall amount on the relevant day being considerably underestimated. This problem is less severe for the other catchments, for which more rain gauges are available.

Figure 10 shows the observed rainfall (wIDW) and streamflow (both in mm) for the 1987 wet season (containing the highest observed flow for the Tilga catchment). The high flow on 28th August (81.9 mm) is not accompanied by a significant amount of rainfall (19.3 mm). Consequently, no model would be able to reproduce this flow peak. The number of flow peaks that are not captured by the baseflow filtering technique demonstrates the poor quality of the

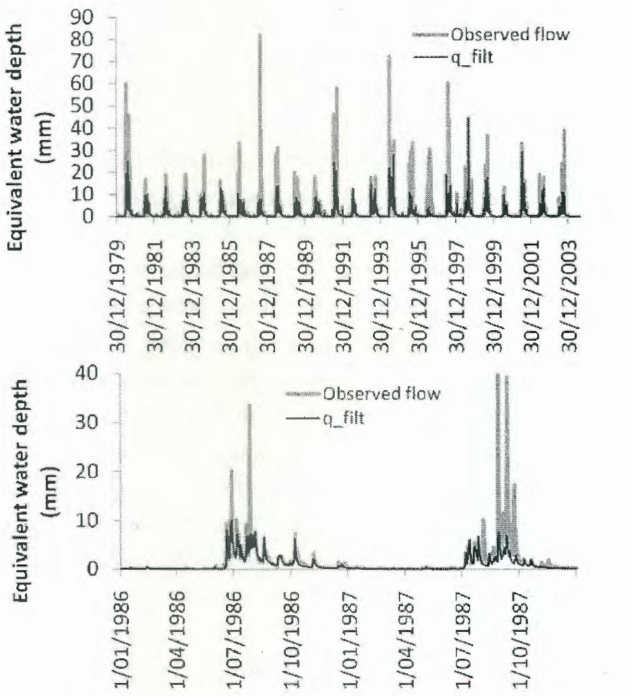

Figure 9 | Flow obtained using the baseflow filtering approach (q_filt) compared with observed flow for the Tilga catchment using wTP areal rainfall.

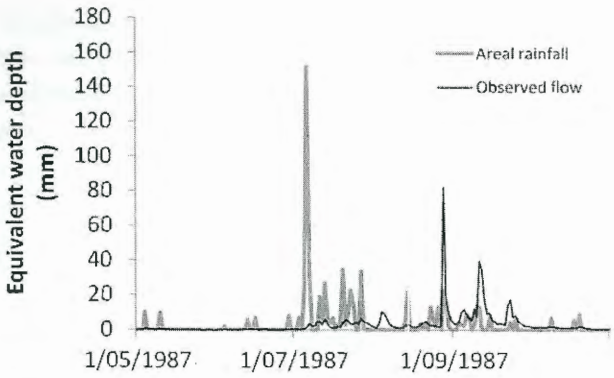

Figure 10 | Observed streamflow and estimated areal rainfall (wTP) for Tilga catchment.

estimated areal rainfall (in terms of a lower limit), and indicates that any model would give poor performance for these catchments when assessed using objective functions based on the sum of squared residuals (e.g. Nash–Sutcliffe efficiency) due to the weight given to high-flow events by such objective functions. Care must therefore be taken in evaluating model performance so that the focus is on the model rather than errors in the data.

Croke (2009) proposed a modified NSE that explicitly included the uncertainty in the observed and modelled flows. A simpler approach has been adopted here, where time-steps with significantly underestimated rainfall (if necessary, effective rainfall exceeds the estimated rainfall by more than 200%) are not included in the calculation of the objective functions.

MODEL APPLICATION

The base UH parameter set was that estimated using the baseflow filtering technique. This was then compared to the non-parametric forms of the UH obtained using the direct estimation and Fourier deconvolution techniques, and alternative parameter values and model structures developed. The calibrated parameter values and NSE (both linear and logarithmic forms) for the calibration period (16/1/1988 to 18/4/1996) for all catchments using the wIWD areal rainfall estimates are shown in Table 1. NSE (linear and logarithmic) are shown in Table 2 for all catchments and all areal rainfall estimates (UH parameters were fixed at values shown in Table 1). The baseflow filter-derived UH was adopted for the Tilga and Jenapur catchments as the departure from a simple exponential form was not significant enough to warrant a more complex UH structure. For the Jeraikela and Gomlai catchments, a rapidly decaying negative-volume component was added to the model to capture the decrease in the lag zero value of the UH due to the fraction of a day delay between rainfall and streamflow peak.

This form of the UH is simpler to estimate the parameter values compared to the more physically meaningful series of exponentially decaying stores. As the focus in this study is exploring whether the shape of the UH peak is significant in terms of reproducing the observed flows, this lack of process understanding is not critical. The relatively poor performance for the Jenapur catchment may be attributed to the presence of a large dam in this catchment.

Table 1 | Parameter values and NSE values for each catchment using the wIDW areal rainfall method

Parameter	Tilga	Jaraikela	Gomlai	Jenapur
Unit hydrograph parameter values				
τ_1	45.96	45.0	35	67.08
τ_2	1.88	1.0	1.12	2.95
τ_3	–	0.5	0.75	–
v_1	0.248	0.5	0.4	0.525
v_2	0.752	0.95	1.95	0.475
v_3	–	−0.45	−1.35	–
CMD module parameters				
F	0.44	0.78	0.52	0.68
η	0.12	0.13	0.18	0.18
Performance criteria				
R^2_{NS}	0.702	0.634	0.737	0.623
$R^2_{NS,log}$	0.835	0.839	0.798	0.579

Table 2 | NSE and NSE_log values for all catchments and all rainfall estimation techniques

	IDW	wIDW	TP	wTP
Tilga	0.693/0.854	0.702/0.835	0.591/0.813	0.628/0.804
Jaraikela	0.559/0.806	0.633/0.842	0.128/0.743	0.238/0.772
Gomlai	0.739/0.802	0.737/0.798	0.664/0.768	0.706/0.774
Jenapur	0.623/0.577	0.623/0.579	0.600/0.562	0.601/0.558

In Table 3, the various performance criteria are shown for the different areal rainfall estimates and UH for the Tilga catchment. Comparable results were obtained for the Gomlai catchment. The Jaraikela catchment gave a very poor performance using both Thiessen polygon-based approaches (NSE = 0.24) but reasonable performance using the inverse distance-weighted approaches (NSE = 0.63), suggesting at least one gauge selected by the TP and wTP approaches had significant errors.

In comparison with the other catchments, the Jenapur catchment showed little difference in model performance for all the different areal rainfall estimates. This is due to most of the rain gauges being used in estimating the areal rainfall using the TP and wTP approaches. The influence of the dam may also have been a contributing factor. The calibrated parameter values were sensitive to the inclusion of the rainfall surface for the inverse distance technique, while the Thiessen polygon approach showed insignificant changes in parameter values. Interestingly, the parameter values obtained using rainfall derived from both the TP and wTP approaches generally agreed with the IDW estimates. This suggests there are deficiencies in the rainfall surface, particularly at large scales.

The results showed that the best UH structure and parameter values were generally obtained using a hybridization of the different techniques, with the direct estimation giving the baseflow parameter values and the Fourier deconvolution approach used to adjust the shape of the UH peak. As suggested by Wilk *et al.* (2006), the areal rainfall time series generated using the interpolation techniques investigated were tested based on the performance of the model. Results showed that the wIDW approach gave the best NSE values and fits to the FDC, while the wTP-derived values gave the best U_1 values.

DISCUSSION

For best model performance at gauged sites, the random error in the areal rainfall estimate needs to be minimized. Most systematic errors will be compensated for in the calibrated values of the model parameters (e.g. underestimation of the areal rainfall can be corrected by adjusting the model parameter values to reduce the model predicted evaporation rates). For prediction at ungauged sites, factors affecting the physical significance of the parameter values should be minimized; for example, the influence of temporal resolution (Littlewood & Croke 2008). In the case of areal rainfall estimates, the systematic errors need to be minimized (or at least, the variation in the systematic errors between sites needs to be minimized). The technique for

Table 3 | Calibrated non-linear module parameter values, source of UH parameter values and performance measures for the Tilga catchment using each rainfall estimation technique (best values are in bold)

UH	f	n	R^2_{NS}	$R^2_{NS,log}$	Bias	X_1	U_1	FDC	FDC_hi
IDW									
Baseflow	58	10	0.693	0.854	6.58	**0.02**	0.468	0.236	0.346
Corrected	59	12	0.702	**0.855**	6.71	0.056	0.46	0.238	0.35
TP									
Baseflow	58	18	0.591	0.813	−0.04	0.293	0.175	0.174	0.246
Corrected	59	19	0.598	0.81	−0.2	0.353	**0.153**	0.174	0.245
wIDW									
Baseflow	44	12	0.702	0.835	9.55	−0.117	0.567	0.237	0.342
Corrected	44	12	**0.713**	0.836	9.24	−0.075	0.553	0.235	0.341
wTP									
Baseflow	60	20	0.628	0.804	0.33	0.321	0.259	**0.172**	**0.242**
Corrected	59	18	0.617	0.803	**0.03**	0.374	0.255	0.174	0.243

estimating the areal rainfall that gives the best model performance at gauged sites is therefore not necessarily the best method for prediction at ungauged sites. While the wIDW approach generally yielded the best NSE values in this study, the dependence of the parameter values on the rainfall surface means that care should be taken in the interpretation of the parameter values, particularly in regionalization applications.

The method selected for generating the rainfall input for the model depends on modelling purpose. For best reproduction of observed streamflow, however, the wIDW approach gave the best result. This indicates that many rainfall events had a large spatial coverage, leading to reduced uncertainty in areal rainfall due to averaging of a larger number of stations. For predicting flows at ungauged sites, however, the wIDW is more sensitive to errors in the rainfall surface (due to the wider spatial distribution of gauges used), and the wTP approach should generally be preferred (or possibly the wIDW approach, with the long-term average adjusted to match the wTP-derived estimate).

CONCLUSIONS

Extra care is needed when attempting to model streamflow in data-sparse regions. It is recommended that a range of methods be used to estimate areal rainfall (including correction for spatial variations in rainfall distribution). Further, the rainfall time series generated by the different methods should be assessed through application in a rainfall–streamflow model. The performance of the different techniques depends on the distribution and density of rain gauges and the spatial variability in the rainfall distribution, and hence will vary between sites. Care should be taken, however, as the selection of the best approach may be model dependent. In the application of the approach to the Brahmani basin, it was found that the inverse distance-weighted approaches (IDW and wIDW) gave the best model performance under calibration, with preference given to the wIDW approach due to the low rain gauge density.

Comparison of observed rainfall with recorded streamflow can identify errors in rainfall data (e.g. far too little rainfall to account for a streamflow peak). Model calibration should avoid time-steps affected by such errors, as these will affect model parameter values based on the errors rather than the catchment response. Further, the physical interpretation of the parameter values (often required for prediction in ungauged basins) should take into account the likely uncertainty in the areal rainfall estimates (and streamflow, although this is not the focus of this paper), including variations between the estimated and actual (unknown) values for different catchments.

Similarly, various techniques (baseflow filtering, direct and deconvolution) were used in this paper to estimate the shape of the unit hydrograph, improving model performance in some catchments. This demonstrates the importance of using different techniques in order to separate the actual response from the errors in the data. The direct and deconvolution approaches are not model dependent, while the baseflow filtering technique is dependent only on the UH module of the IHACRES model. The most effective technique for estimating the UH when assessed using a combination of the linear- and log-transformed NSE was that derived using a combination of the techniques described in this paper.

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