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AN ASSESSMENT OF THE IMPACT OF PRECIPITATION UNCERTAINTY ON THE PERFORMANCE OF A DISTRIBUTED HYDROLOGICAL MODEL

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SYNOPSIS

The aim of this study is to assess the impact of systematic and random error in precipitation data on the simulation accuracy and uncertainty of a distributed hydrological model, and to determine the sensitivity of calibration to such errors. Firstly, a true model is established and then the margin of error is applied to true precipitation. The uncertainty is analyzed by means of a Monte Carlo approach. Finally, the impact of low precipitation is assessed by neglecting different levels of low precipitation. The result of the study for a Nepalese river basin shows that a systematic error exceeding +/-10% causes significant impact on simulated flows. The impact of normally distributed random error with standard deviation is equal to 10% of observed precipitation is not substantial. The calibration of parameters can compensate for the low error, but the higher errors should not be compensated by just fitting the curve. Precipitation of less than 0.5mm measured with some error does not affect the flood discharge.

INTRODUCTION

Due to the randomness in nature and the lack of complete knowledge of the hydrological system, the results obtained from a hydrological model are always subjected to uncertainty. The uncertainty in output of the hydrological model is a function of uncertainty in input data, parameters and the structure of model. The uncertainty in model input occurs due to the measurement errors and spatial and temporal sampling errors. There is uncertainty in parameters due to the lack of accuracy with which the parameters can be estimated or due to a limited understanding of the relationship between the parameters and the hydrological processes. The model uncertainty is due to the inability of the model to truly represent a natural process. An extensive review of the causes of uncertainty in hydrological model and various methods for assessing the uncertainty can be found in the paper written by Melching (9).

In most of the hydrological modeling studies, parameter uncertainty is a major focus. Parameter calibration in hydrological modeling reduces parameter uncertainty as well as compensates data and model uncertainty to some extent. Besides calibration, additional information on parameters, good quality data of sufficient resolution, and selection of an appropriate model for a particular situation are also instrumental in improving the model results.

Precipitation is the most important input of hydrological model as it is a major driver of the hydrological process. Two causes of uncertainty influence the precipitation measured by a rain gauge. Firstly, the uncertainty is due to the systematic error (bias) or random error in measurement. The causes of systematic error include the following: human error, site error, instrumental error, evaporation error, wind error, wetting error, splashing error, drifting error. Random error occurs due to human error in observation, error in instrument and small variations in meteorological conditions. Secondly, spatial interpolation of point data to areal data adds uncertainty to the precipitation input.

The performance of any hydrological model is highly dependent on the precipitation data. For a model whose parameters have to be determined by calibration, the uncertainty in precipitation also influences the model parameters. Although errors in other input data also affect the output of hydrological model, precipitation is the main cause of uncertainty among input data. In hydrological modeling studies, a few papers have dealt with input data uncertainty, especially precipitation as one of the dominant sources of uncertainty (e.g. Storm et al. (12); Andreassian et al. (1); Maskey et al. (8)). Nandakumar and Mein (10) analyzed the impact of input data (rainfall and pan evaporation coefficients) and parameters on model predictions. Findings showed that systematic error on rainfall is the dominating error on predicted flows. Carpenter and Georgakakos (5) analyzed parameter uncertainty, radar rainfall uncertainty and combined parameter and radar rainfall uncertainty for basins of different scales by means of a distributed hydrological model. They concluded that an increase of basin scale decreases simulation uncertainty. Butts et al. (4) evaluated the performance of different model structures within MIKE11/MIKESHE modeling framework to analyze structural uncertainty and compared this uncertainty to the uncertainty arising from rainfall, parameter and discharge measurement. They found less impact of random uncertainty in precipitation than the parameter uncertainty and the discharge measurement uncertainty, but they did not consider bias in precipitation. Review of various papers mentioned above led us to conclude that research on both the systematic and random errors in precipitation for a distributed hydrological model is still inconclusive. Therefore, the objectives of this study are to analyze the impact of systematic and random errors in precipitation on the modeling results for a distributed hydrological model and to identify the extent of error beyond which it becomes more significant in modeling.

STUDY AREA

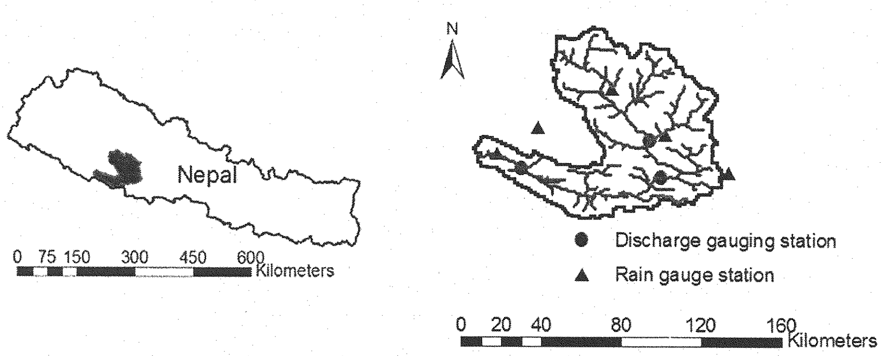

Fig. 1 Location of the West Rapti River Basin and its detailed map

The study area for the research is the West Rapti River Basin (Fig. 1), which is located in the mid-western region of Nepal. The catchment area of the basin is 5450 km^2 and the length of main stream channel is 208 km. The basin elevation ranges from 205 m to 3437 m above mean sea level. The river originates from the middle mountains of Nepal, then enters to the flat area and finally drains to India to join the Ganges River. The source of runoff is due to the monsoon rainfall and groundwater. Daily data from 5 rainfall stations and 3 discharge stations from 1980 to 1993 was available for the study. The average annual rainfall during this period is 1580mm and the mean annual discharge at Jalkundi (the most downstream station) is 113.7m^3/s. Land use, topographic, soil and potential evaporation (PET) data were obtained from freely available global data set such as topographic data from United States Geological Survey (GTOPO30), land use data from International Geosphere-Biosphere Programme, soil data from Food and Agricultural Organization, PET data from United Nations Environment Programme, Global Resource Information Database. Rainfall and discharge data were obtained from the Department of Hydrology and Meteorology, in Kathmandu, Nepal.

HYDROLOGICAL MODEL

BTOPMC

The hydrological model to be used for this study is BTOPMC (Version 1.0). BTOPMC stands for "Blockwise use of TOPMODEL with Muskingum-Cunge routing". This is a distributed hydrological model developed at the University of Yamanashi, Japan (Takeuchi et al. (13); Ao (2); Hapuarachchi et al. (7)). BTOPMC is an extension of TOPMODEL concepts (Beven et al. (3)), which was developed in order to overcome the limitations of using the TOPMODEL for large river basins. For large river basins, spatial heterogeneity and timing of flow to outlet are the important factors. For representing spatial variability in BTOPMC, a basin is composed of grid cells, which can be divided into sub-basins, where each sub-basin is considered as a block or a unit. The runoff generation at each grid cell is based on TOPMODEL concepts. To consider the timing of flow, the flow contributed from any grid cell is routed to the outlet using the Muskingum-Cunge routing method.

The flow generation mechanism of BTOPMC is based on TOPMODEL concepts. TOPMODEL is based on a saturation-excess runoff mechanism, in which the saturation zone is called the "contributing area." The difference between TOPMODEL and BTOPMC is that in the case of TOPMODEL the water table is spatially lumped over a basin, while in BTOPMC the lumping is done for a grid scale.

In BTOPMC, the soil profile of a grid cell is divided into three layers (root, unsaturated and saturated zones) as shown in Fig. 2. Rainfall on the i^{th} grid cell is first received by the root zone storage which is subjected to evaporation. The unsaturated zone receives the overflow from the root zone storage and the saturated zone receives flow from the unsaturated zone. The outflow from the saturated zone constitutes base flow. The overland flow is generated when the unsaturated zone storage exceeds the local storage deficit. The discharge in each cell is composed of both overland flow and base flow, and both are dependent on the local saturation deficit.

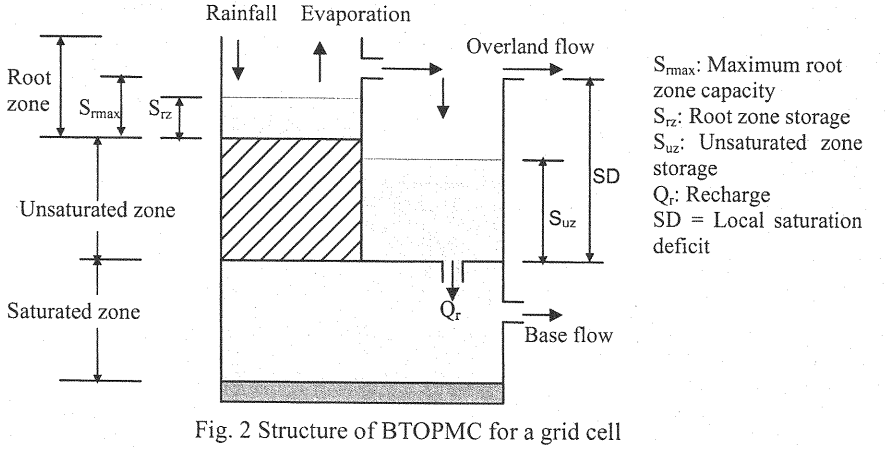

Fig. 2 Structure of BTOPMC for a grid cell

The basic equations describing the concept of BTOPMC are presented below:
Within sub-basins, groundwater is mutually shared and discharges to nearby streams within grid cell i. The groundwater flow equation is expressed as

$$q_i = T_0 \exp(-SD_i / m) \tan \beta_i \qquad (1)$$

where q_i = groundwater flow per unit contour length; T_0 = saturated transmissivity (m^2/h), namely the lateral transmissivity when the soil profile is just saturated at the ground surface; SD_i = local saturation deficit (m); m = decay factor of lateral transmissivity with respect to saturation deficit (m); β = local slope angle; and $\tan \beta_i$ = hydraulic gradient.
For each grid cell i

$$q_i = re.a_i \qquad (2)$$

where q_i = groundwater flow per unit contour length; re = recharge rate (m/h); and a_i = upstream contributing area per unit contour length (m^2/m) that drains through point i.
From eqs. 1 and 2, the distribution of local saturation deficit, SD_i is derived as

$$SD_i = \overline{SD} + m(\gamma - \gamma_i) \qquad (3)$$

where $\overline{SD}$ = average saturation deficit in the catchment; γ_i = soil-topographic index ($\gamma_i = \ln(a_i / T_0 \tan \beta_i)$); and γ = catchment average of the soil-topographic index.

Parameters of BTOPMC

The following are the parameters of BTOPMC model:
T_0: T_0 is saturated soil transmissivity, which describes the potential rate of lateral flow for a completely saturated soil for a given hydraulic gradient.
m: m is decay factor of transmissivity, which describes how the actual transmissivity decreases when the soil is not saturated.
S_{rmax}: S_{rmax} is the maximum root zone capacity, which represents the plant available soil moisture capacity as well as the interception capacity of the canopy.
n_0: n_0 is the roughness factor for a block, which is used as a scaling parameter to compute Manning's roughness for routing.

Parameters m and n_0 are specified for each sub-basin. For distributing n_0 value to each river segment, the following expression is used in BTOPMC.

$$n_i = n_0(\mathrm{k})[\tan\beta_\mathrm{i}/\tan\beta_0(\mathrm{sb})]^{1/3} \qquad (4)$$

where n_i = equivalent Manning roughness coefficient of river segment i; $\tan\beta_\mathrm{i}$ = local topographic gradient; and $\tan\beta_0$ = topographic gradient at the outlet of sub-basin sb. T_0 in BTOPMC is based on soil types, where weighted soil texture is used to represent spatial heterogeneity (Hapuarachchi et al. (6)).

$$T_0 = T_0Cl \times U_{cl} + T_0Sa \times U_{sa} + T_0Si \times U_{Si} \qquad (5)$$

where T_0Cl = saturated transmissivity for clay; T_0Sa = saturated transmissivity for sand; T_0Si = saturated transmissivity for silt; U_{cl} = percentage of clay in each grid; U_{sa} = percentage of sand in each grid; and U_{si} = percentage silt present in each grid. Calibrating T_0 for clay, sand and silt gives T_0 value of soil for each grid cell. S_{rmax} in BTOPMC is based on land use class.

METHODOLOGY

The approach used for uncertainty analysis is a Monte Carlo approach. The framework of the approach is presented below:

Setting up of a True Model

A set of precipitation and discharge is selected and the best set of parameters is identified by calibrating the BTOPMC model. The chosen set of precipitation is considered as true precipitation (observed precipitation assumed to be free of measurement error); the optimized parameters are considered as true parameters (error free parameters); and the simulated discharge is considered as true discharge (discharge free of measurement error).

Form of Error Models

Error model for systematic error: To determine the effect of systematic error, perturbation is applied to the observed precipitation using the following form of error model:

$$P_e = P_m + k.P_m = (1+k)P_m \qquad (6)$$

where P_e = perturbed precipitation; P_m = observed precipitation; and k = coefficient to indicate how much bias is added or subtracted from the observed precipitation. This form of equation is suitable for expressing systematic error because it is a fixed error and the equation expresses the systematic error as a fixed percentage of measured value for all measurements.

Error model for random error: In BTOPMC, spatial distribution of precipitation is obtained by means of the Thiessen polygon method, where all the grids within the polygon have the same values of precipitation as the point gauge value of precipitation. To examine the uncertainty in discharge due to the random error in precipitation, perturbation to precipitation is introduced for each gauging station data using the following form of error model:

$$P_e = P_m + \sigma.e\,; \quad \sigma = r.P_m \qquad (7)$$

where P_e = perturbed precipitation; P_m = observed precipitation; σ = assumed standard deviation of additive random error relative to the measured precipitation; r = coefficient; and e = random error component assumed normally distributed with mean equals zero and standard deviation equals one. In the above formulation, the error is assumed to be independent in time and space. With this formulation if observed precipitation is zero, the error is also zero. Thus, a zero precipitation event becomes unaffected.

Error model for very low precipitation: Trace precipitation, which is beyond the resolution of rain gauge cannot be measured and is usually neglected in modeling. To understand the effect of neglecting very low daily precipitation, the performance of BTOPMC model is assessed by neglecting different levels of low precipitation.

Assessment of the Impact of Precipitation Uncertainty on Model Results

To analyze the impact of systematic error, different values of k are taken and BTOPMC model is run keeping other inputs and parameters at true values. To examine the influence of random error, a Monte Carlo simulation is performed by taking different values of r keeping other inputs and parameters at true values. Then, uncertainty in discharge due to random error is analyzed from the outputs of n number of Monte Carlo simulations. Finally, the impact of neglecting very low precipitation is analyzed.

Assessment of the Capability of Parameters to Absorb Precipitation Uncertainty

The purpose of calibration is to bring model results as close as observed values by tuning parameters. However, if the parameters of the model are determined by using erroneous precipitation data, the parameter will also be affected. To understand to what extent the parameter calibration can absorb precipitation uncertainty, the parameters of the BTOPMC model are calibrated for different values of k and r, and the performance of the model with calibrated parameter is compared to the true model.

RESULTS AND DISCUSSIONS

True model

Digital Elevation Map (DEM) data, soil type data, land use data, precipitation data, potential evaporation data and flow data which are required for running BTOPMC, were formatted as per the requirements of BTOPMC model. The land use data was reclassified into 4 classes in order to reduce equifinality and to increase the efficiency in computation. The basin was divided into two sub basins (Fig. 3). Time series data from 1980 to 1987 was used for calibration and from 1988 to 1993 was used for validation.

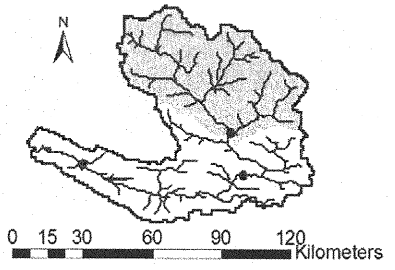

Fig. 3 Sub-basin division of the West Rapti River

The calibrated parameters of the model are: m (sub-basin 1) = 0.06m, m (sub-basin 2) = 0.04m, n_0 (sub-basin 1) =0.02, n_0 (sub-basin 2) =0.01, S_{rmax} (Deep rooted) = 0.05m, S_{rmax} (Shallow rooted) = 0.04m, S_{rmax} (Shallow rooted & Irrigated) = 0.03m, S_{rmax} (Impervious) = 0.0001m, T_0 (Clay) = 0.5m^2/h, T_0 (Sand) = 7m^2/h, T_0 (Silt) = 3m^2/h.

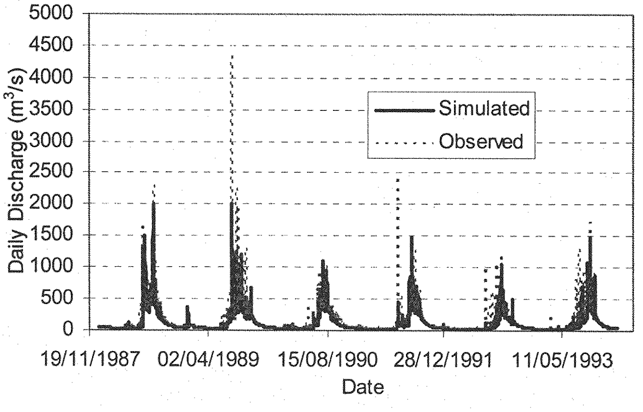

Fig. 4 Validation at Jalkundi

Nash-Sutcliffe coefficient of efficiency (NSE) at Jalkundi station is 61.55% for calibration and 66.06% for validation. The NSE in the very high range could not be obtained because there is uncertainty in the spatial and temporal distribution of precipitation (5 rainfall stations for 5450 km^2) and uncertainty in manual parameter estimation as no automatic optimization was implemented in BTOPMC. The simulated and observed hydrograph for validation at Jalkundi station is shown in Fig. 4. Findings show that the performance of the model is good for low flow as well as high flows, except some peak underestimation. For uncertainty analysis, the observed precipitation data from 1980-1987 was considered as true precipitation; the calibrated parameters were considered as true parameters; and the simulated discharge for the period of 1980-1987 was considered as true discharge.

Assessment of Precipitation Uncertainty

The impact of precipitation on model results is analyzed by using Nash-Sutcliffe coefficient of efficiency (NSE), Bias in runoff volume for overall time series and peak flow events, Normalized Root Mean Square Error (NRMSE) for low flow and high flow (normalized by average flow). Peak flow of magnitude greater than $500m^3/s$ is considered and the threshold value for separating low and high flow is set at $50m^3/s$. The results for the most downstream station are discussed in the next section.

a) Impact of Systematic Error

The magnitudes of systematic error in precipitation from various factors are (Sevruk (11)): wind error = 2%-10% for rain and 10%-50% for snow, wetting error = 2%-10%, evaporation error = 0%-4%, splashing error = 1%-2%. Including other errors, the maximum systematic error in precipitation is around 30% for rain and 70% for snow. In this study, the maximum range of systematic error is kept at +/-50% of observed precipitation, i.e. k is varied from -0.5 to 0.5.

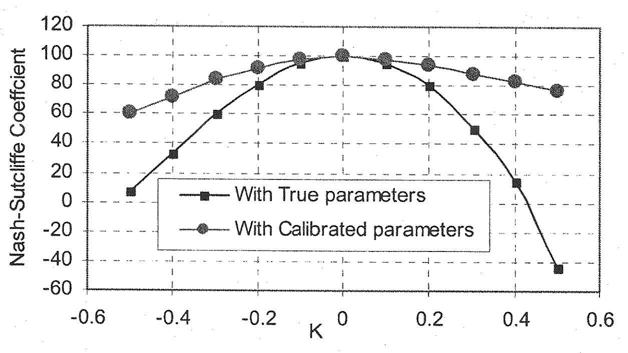

Fig. 5 Impact of systematic error on overall model performance using $P_e = (1 + k)P_m$

The results of the analysis (Fig. 5) show that for k = -0.1 and 0.1, the NSE decreases by 5.4% and 4.9% of the true model respectively. Bias in runoff volume (Fig. 6) for overall time series for k = -0.1 and 0.1 is -15.2% and 15.6% respectively, and for peak flow events, the bias is -19.1% and 19.6% respectively. Further increase of the error in either direction makes the performance of the model deteriorate.

Next, for the different values of k, the model parameters were calibrated. A comparison of the model performance with true and calibrated parameters (Fig. 5) shows that for k = -0.5 to 0.5 in step of 0.1, the NSE is improved by 53.3%, 39%, 24.2%, 11.43%, 2.51%, 3.4%, 13.26%, 37.75%, 68.1%, 120.13% respectively. Though the performance of the calibrated model is better than the performance of the true parameter case due to the curve fitting procedure, the model performance becomes worse for higher errors, even for the calibrated model. Parameter calibration can compensate for some amount of error in data, but we can not adjust any amount of data. The greater the amount of error in data, the worse the performance of the model. Therefore, the NSE for recalibrated case degraded systematically.

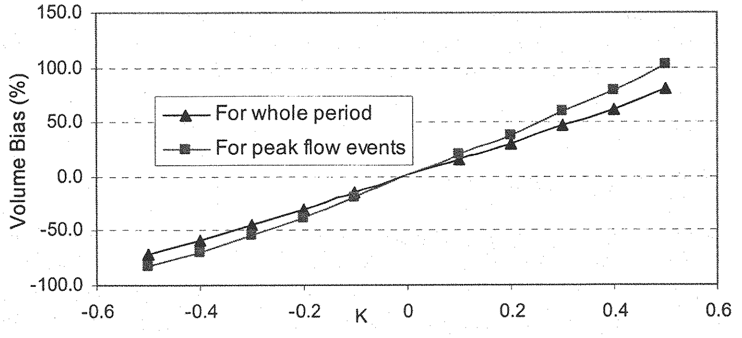

Fig. 6 Bias in runoff volume using $P_e = (1 + k)P_m$ with true parameters

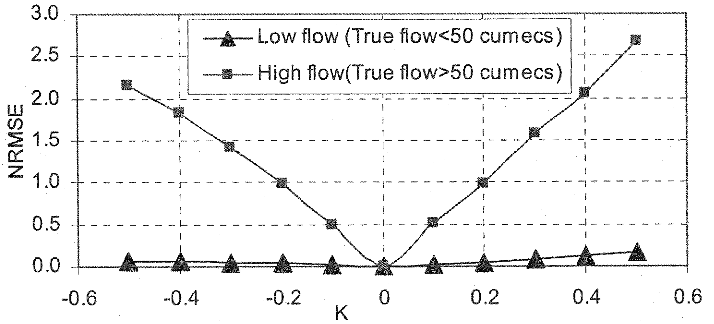

Fig. 7 Impact of systematic error on low and high flows using $P_e = (1 + k)P_m$ with true parameters

The performance of the model for high flow and low flow is shown in Fig. 7. The result shows that increasing error in rainfall during high flow makes the model performance worse. This is evident because the high flow period, which is the monsoon period, is the main rainfall period and any error on rainfall during this period propagates through the model, thus affecting its performance. The impact of error on low flow is insignificant because during low flow periods, there is no or very little rain.

It is seen from Fig. 5 that the performance curve for positive k and negative k is asymmetric. Similarly in Fig. 7, the trend of the curves is asymmetric. Increasing k in the positive side degrades the model performance rapidly, while increasing k in the negative side has less effect than the positive side. This implies that negative k is the safer side, while positive k is the risky side. For a linear model, the same bias in either direction has the same impact. However, as BTOPMC is a non-linear model, the same bias in positive direction has greater impact.

b) Impact of Random Error

Though the exact amount of the random error can not be specified, its impact on modeling results can be quantified by uncertainty analysis. Therefore, in this study we used the Monte Carlo framework for this purpose by taking r values equals to 0.1, 0.3, 0.5 and 0.7. For each case, 50 samples of precipitation data set were generated randomly according to eq. 2. If the perturbed precipitation becomes negative due to the negative random number, then it is taken as zero. The occurrence of negative values is usually low. An example of one realization shows that negative values occurrence expressed as a percentage of the total number of rainy days are: for r = 0.1, no negative value, for r = 0.3, less than 0.3%, for r = 0.5, 2%-3%, for r =

0.7, 6%-8%. For each case, the average performance indicator was computed from the performance of 50 simulations.

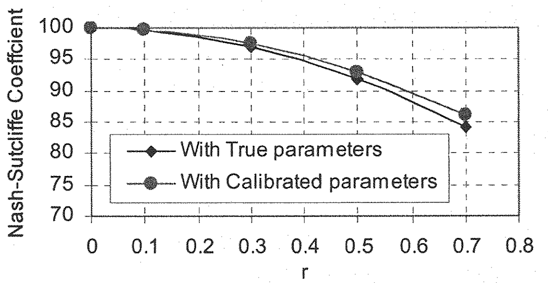

Fig. 8 Impact of random error on overall model performance using $P_e = P_m + \sigma.e$; $\sigma = r.P_m$

The results of the analysis (Fig. 8) show that the decrease in the NSE from the true model for r = 0.1, 0.3, 0.5 and 0.7 is 0.4%, 3.1%, 8.2% and 15.9% respectively. As shown in Table 1, the bias in runoff volume for r = 0.1 and 0.3 is very low; 0.071% and 0.83% for overall time series and 0.01% and 0.3% for peak flow events of value greater than 500m^3/s. This finding makes it clear that for r = 0.1, the impact is negligible and an increase in r beyond that decreases the performance of model.

Table 1 Bias in runoff volume (%) due to random error

r	0.1	0.3	0.5	0.7
For whole period	0.071	0.83	3.24	10.31
For peak flow events	0.01	0.3	2.22	10.17

Next, the parameters of the model were calibrated for different values of r. The comparison of result with true parameters (Fig. 8) shows that the calibration improves the NSE by 0.1%, 0.7%, 1.1% and 2.2% for r = 0.1, 0.3, 0.5 and 0.7 respectively. As the impact of errors on the model with true parameters is low, the difference in the performance of the calibrated model and the model with true parameters with an increase in r is not large. Similar to the systematic error case, the NSE is degraded systematically with the increase of errors even for the recalibrated case.

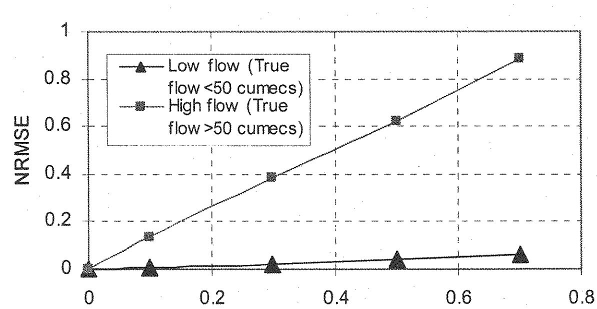

Fig. 9 Impact of random error on low and high flow using $P_e = P_m + \sigma.e$; $\sigma = r.P_m$ with true parameters

NRMSE for both high flows and low flows due to increasing standard deviation of random error is shown in Fig. 9. As in the case of systematic error, the effect on low flow is negligible because it is a period with no or very little rain. As for high flow, the performance decreases with increasing *r* due to the propagation of error imposed on rainfall.

c) Very Low Precipitation

To assess the impact of neglecting low precipitation, precipitation less than 0.5mm, 1mm, 2mm, 3mm, 4mm and 5mm were neglected respectively with other inputs and parameter same as true model. As an example, the output hydrograph for a small period with a peak is shown in Fig. 10.

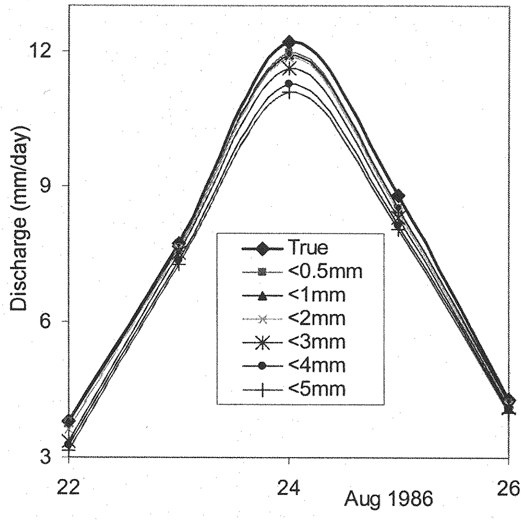

Fig. 10 A sample plot of hydrograph neglecting low precipitation

The result shows that the peak magnitude decreases with neglecting higher values of precipitation. In fact, for this peak, the peak magnitude is reduced by 1.1 mm/day for neglecting precipitation less than 5mm/day. When precipitation of less than 0.5mm/day is neglected, the peak is reduced by 0.24 mm/day. Very little rain, beyond the precision limit of the instrument (0.1 mm in most cases), can not be measured well. This study concludes that even if there is some error in measuring such low precipitation (0.5mm/day in this case), this kind of error does not affect peak discharge as most of it is lost due to evaporation.

CONCLUSIONS

In general, the impact of input data error depends on the type of model, the type of basin and the type of error model. In this study, we assessed the precipitation uncertainty for a basin in Nepal using BTOPMC as an example of a distributed model. The conclusions of the study are summarized below:

I. For a systematic error of +10% and -10%, decrease in NSE from true model is 5.4% and 4.9% respectively; bias in runoff volume is -15.2% and 15.6% respectively; and bias in runoff volume for peak events is -19.1% and 19.6% respectively. If the systematic error is very small, the effect is also small. Furthermore, if the error is very large, the effect is also very large. It was found that a systematic error exceeding 10% of observed precipitation is significant in modeling. Therefore, systematic error should be identified and reduced. The ways of reducing systematic error are as follows: implementation of quality control measures, and application of correction methodology.

II. For a random error with standard deviation that equals 10% of observed precipitation, the decrease in NSE from true model is 0.4%; bias in runoff volume is 0.071%; and bias in runoff volume for peak events is 0.01%. The random error, which is unpredictable and non-constant, might be either positive or negative, which has a long term expected value equivalent to zero. A slight increase or decrease of precipitation due to random effect acts as a compensating mechanism and hence the random errors have low impact on the model results than the systematic error. However, if the random error is larger, with standard deviation greater than 10% of observed precipitation, then its effect is detrimental to the model results.

III. The calibration of the model with a systematic error of +10% and -10% in rainfall increases NSE by 2.51% and 3.4% respectively. In case of random error in precipitation, NSE is improved by 0.1% for $r = 0.1$. For larger error, though NSE is improved due to curve fitting, the model performance is deteriorating with the increase of error. This suggests that calibration can compensate for the error of low magnitude, but errors of higher magnitude cannot be just ignored. Therefore, input data uncertainty has to be considered in hydrological modeling.

IV. The impact of neglecting precipitation of less than 0.5mm/day does not affect peak discharge. This means the small error due to resolution limit is not very significant for flood discharge.

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APPENDIX – NOTATION

The following symbols are used in this paper:

a_i	= upstream contributing area per unit contour length;
e	= normally distributed random error with zero mean and unit standard deviation;
i	= grid cell;
k	= coefficient to indicate how much bias is added or subtracted from the observed precipitation;
m	= decay factor of lateral transmissivity;
n_0	= roughness factor for a block;
n_i	= equivalent Manning roughness coefficient of river segment i;
P_e	= perturbed precipitation;
P_m	= observed precipitation;
q_i	= groundwater flow per unit contour length;
r	= coefficient;
re	= recharge rate;
sb	= sub-basin;
S_{rmax}	= maximum root zone capacity;
$\overline{SD}$	= average saturation deficit;
SD_i	= local saturation deficit;
T_0	= saturated transmissivity;
T_0Cl	= saturated transmissivity for clay;
T_0Sa	= saturated transmissivity for sand;
T_0Si	= saturated transmissivity for silt;
U_{cl}	= percentage of clay;
U_{sa}	= percentage of sand;
U_{si}	= percentage of silt;
β	= local slope angle;
β_0	= local slope angle at the outlet of sub-basin;
β_i	= local slope angle for a grid cell;
γ	= catchment average of the soil-topographic index;
γ_i	= soil-topographic index; and
σ	= assumed standard deviation of additive random error relative to the measured precipitation.

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