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# Modelling the elements of flash flood hydrograph using genetic programming

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A novel approach is proposed in this work on constructing the flash flood hydrograph by modelling the elements of the hydrograph namely the time to start of the initial flood ($t_i$), the time to peak discharge ($t_p$), the peak discharge ($Q_p$) and the base time ($t_b$) using Genetic Programming (GP). The proposed method is applied to the Kickapoo River catchment in Wisconsin, USA. It is demonstrated that even under limited data scenario, for a poorly gauged station, GP is able to model the elements of hydrograph with reasonably high accuracy thereby offering considerable lead time to predict the flash flood. The mathematical models developed by GP also offer some understanding of the influence of rainfall events and the stream discharge in producing the flash floods.

[**Keywords**: Flash flood, Genetic Programming, Mathematical models, Peak discharge]

## Introduction

Flash floods are reported to cause severe causalities and damages, both socially and economically. It is predicted that increased intense rainfall events due to climate change as well as increased urbanization may lead to frequent and severe flash floods necessitating sound forecasting methods with sufficient lead time. Many attempts have already been made in the past on the forecasting of the occurrence of flash floods. Moreover, many improvements have already been achieved in the Flash Flood Forecasting (FFF) through improved modelling techniques and more notably advancements in satellite and radar observations have been integrated with these techniques[1-3]. For small basins with poorly gauged rainfall and discharge information and where it is difficult to access satellite/RADAR observations, rainfall forecasts are not reliable for flash floods due to small size basins and high intense rainfall. In such cases, simple but robust models need to be developed with available rainfall and stream flow information.

Hapuarachchi and Wang[4] have reviewed the system and methods available for FFF comparing the advantages and disadvantages of the methods and the situations for which they are reported to be best suited. The methods of FFF range from conceptual hydrological models to physically based distributed hydrological models to data driven models. Though the superiority of each of these models can be argued from their own perspective, in this study, it is proposed to focus on data driven models which have been demonstrated to offer reliable solutions for many hydrological problems. In particular, use of multisensory data and Artificial Neural Networks (ANN) are combined to forecast stream discharge under flash flood conditions[5-9]. For instance, Kim and Barros[6] reported discharge forecasts upto 24 h lead time using raingauge, radiosonde and numerical weather prediction model outputs in ANN as inputs. Chiang *et al.*[8] reported FFF upto 3 h lead time using rain gauge data and satellite derived precipitation in a recurrent neural network model. Siou *et al.*[10] proposed ANN for modelling flash flood in Lezkarstic system (France), and reported that ANN based model forecasts quite accurately matched the actual discharge for a lead time of 2 days with a high Nash criteria. Dinu *et al.*[9] presented a comparison of ANN models with inputs from both ground and radar observations for the flash floods in Bahluet catchment and specifically observed that ANN based models are capable of good extrapolated results beyond the range of training dataset.

Studies on FFF in poorly gauged or ungauged basins, however, are very limited using data driven methods. Artigue *et al.*[11] compared the performance of recurrent neural network and the feed forward neural network using antecedent estimated and observed discharge values respectively as inputs without relying on rainfall forecasts. They took the case study of the Gardon de Mialet basin in southern France and demonstrated that efficient forecasting of flash flood discharges up to 2 h lead time can be developed from a feed forward model. For poorly gauged basins or basins where it is difficult to obtain accurate rainfall estimates, it is necessary to develop more efficient models for stream flash flood discharge without relying on rainfall forecasts. Since meteorological factors are not the sole reasons for flash floods and thus hydrologic/hydraulic factors also equally play important roles, FFF models with minimal hydrologic characteristics of rainfall and stream flow discharge data need to be used to develop sound models. It is to be noted that such an approach will be more site specific.

The present work reports the application of Genetic Programming (GP) for constructing flash flood hydrograph and it differs from the previously reported works in the following ways:

(a) Previously reported works have taken the lead time of flood forecasting up to 2 to 4 h. This study suggests a different approach. Once the potential of a rainfall event to cause flash flood is identified, it is desired to forecast the time to start of the initial flood discharge in the gauging site as soon as the rainfall starts receding at the upstream rain gauge station. The time to start of the initial flash flood differs for each rainfall event. Hence, depending on the severity of the rainfall event to cause flash flood, the lead time to issue warning will be different, and in some events, the warning can be issued even 5 to 6 h in advance. So, instead of keeping a fixed lead time, we propose to predict the lead time depending on the rainfall event severity.

(b) In the earlier reported works, antecedent rainfalls from predictor rain gauges are used as inputs for the ANN model and the output is taken as hourly stream flow at a desired location[6,12]. This study proposes an alternative approach *viz*., instead of using the output as the hourly stream flow, it is proposed to construct the flash flood hydrograph by modelling the elements of the hydrograph namely, time to start of flash flood ($t_i$), the peak discharge ($Q_p$), the time to peak ($t_p$) and the base time of the flash flood hydrograph ($t_b$) as a function of rainfall and stream flow observations at a reference time. This may help to better understand the rainfall-runoff response from the basin due to flash flood events. The reference time with respect to which all these parameters are modelled is taken as the time at which rainfall starts receding and is almost 30 – 40 % of the peak rainfall value in the upstream rain gauge station.

(c) Hapuarachchi and Wang[4] also recommend the need for understanding the governing hydrological processes in FFF. In data driven models such as ANN, which are considered as black box models, generally it is difficult to reveal the physical nature of the process being modelled. Hence, in this study, GP is used which is considered more as a 'grey box' model in the sense that it has the potential to reveal the understanding of the process depending on the extent of data available for modelling. It is proposed to develop GP based mathematical models for each of the elements mentioned in (b) above as a function of the governing variables at the reference time. This may help to better understand the process of rainfall-runoff mechanism under flash flood conditions which is not attempted in the previously reported works. GP has also been reported to have many successful applications in hydrological problems, particularly under limited data conditions[13-18].

## Materials and Methods

### Study area and data description

The study area is chosen as the Kickapoo River catchment, Wisconsin, USA (Fig. 1). This basin is characterized by steep slopes (30 to 40 %), rounded ridges and steep narrow valleys and hence it is highly susceptible to flooding. Floods on the Kickapoo River are usual. An average of one destructive flood per year is being observed. The basin consists of two raingauges and three stream gauges. There are two rain gauges situated outside the basin. The scope of

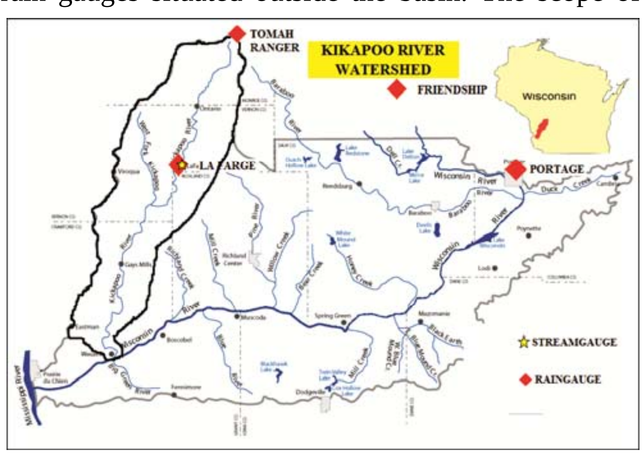


Fig. 1 — Kickapoo River, USA

this study is restricted to estimate flash flood discharge in the discharge gauge at La Farge at Kikapoo River (Q), for which the two rain gauges situated in the proximity to this discharge gauge (namely La Farge (R1) and Tomah Ranger (R2)) are considered. While the rainfall observations for Lafarge and Tomah Ranger are obtained from https://www.ncdc.noaa.gov/cdo-web/, the flashflood data are obtained from the https://blog.nssl.noaa.gov/flash/database/. The discharge data was obtained from https://nwis.waterdata.usgs.gov/nwis/rt. For the period between (Jan 1987– Dec 2013), a total of 49 events were found to have resulted in floods. These data are consolidated to get the full picture of a given flood event. It is noted that a discharge greater than or equal to 36 $m^3/s$ has been taken as the minimum threshold for defining a flash flood. Among the 49 events only 15 events (E1 to E15) are accounted into flash flood. (i.e 6 to 10 h from the decline of rain to the starting of flood). Other events are not found to have flash floods and are, therefore, not used in this study.

#### Genetic programming

Genetic Programming (GP) is an evolutionary algorithm based on Darwin's theory of natural selection and survival of the fittest. Using parse tree representation, the algorithm evolves computer programs/mathematical models (or equations) that relate the given input vector to the desired output. Initially, a set of population of model equations are generated by the algorithm by randomly combining what is called as terminal set (variables and constants) and function set (mathematical functions and arithmetic operators). The choice of appropriate functions (which is dependent on the understanding of the process being modelled) has significant impact on the development of physically meaningful models. The quality of the initial set of population of model equation are then improved using 'crossover', 'mutation' or 'elitistism' or a suitable combination of one or more of these operations. While the 'elitism' preserves the best fitted equation from the previous generations in the current generation, a careful selection of 'mutation' helps in broadening the scope of search space to facilitate a more optimal solution. 'Crossover' is primarily responsible for exchange of information between two parents. With the progress of the evolution process, the quality of the solution is expected to improve until the fitness criteria are met. GP is implemented using Discipulus tool[17].

### Methodology

The methodology is summarized in the flowchart shown in (Fig. 2). The first task is to ascertain if a given rainfall scenario will lead to flash flood or not in the desired discharge gauging site. Obviously, this will vary depending on the basin and the rainfall characteristics and no two basins are expected to have the same behaviour. The second step is to identify the potential predictors and to design possible models in the functional form for each of the elements of the flash flood hydrograph. The input variables of the models are unique for various catchments which can be decided based on trial and error only. Here, the current discharge at La Farge at Kikapoo River (Q) and cumulative rainfall of two rain gauges situated in the proximity to this discharge gauge (namely La Farge (R1) and Tomah Ranger (R2)) are considered as input variables. The catchment characteristics affect the rising limb of the hydrograph particularly, and though it is not included explicitly as inputs in the model, the GP model will consider its effect implicitly. The rationales for the selection of these are discussed below. Table 1 lists the possible models used in this study in functional form.

The time to start of initial flash flood (36 cumec) is basically the lead time of forecast. Depending on the rainfall intensity and the catchment response together with the discharge in the gauging station at the reference time, the $t_i$ will vary. Hence, the models are developed using $R_1$, $R_2$ and Q as the predictor variables. Forecasted rainfall using antecedent rainfalls is also taken as alternative variable for model development for modelling time to start of initial flash

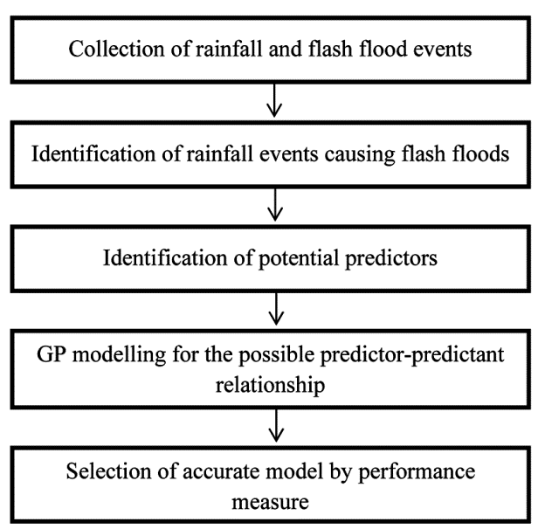


Fig. 2 — Flowchart of methodology

flood. The predictors used for the time to peak flood are taken same as that used for time to the start of the initial flood because the response of a flash flood hydrograph is expected to be very quick. In addition to this, one model incorporating predicted time to start of flood is also considered. For the modelling of peak flood discharge, it is expected that apart from the neighbouring rain gauges, the two more distant rain gauges Portage (R3) and Friendship (R4) may also contribute. Although these two stations are not located very much to the proximity of the discharge station, it is assumed that in the absence of any other rainfall information, this can be taken as representative rainfall information for the contribution from the catchment due to the nature of the Wisconsin basin. Usually, the peak in a hydrograph results when almost entire catchment is contributing. As such, the cumulative rainfalls in the four stations are taken as a variable in one of the model. The models considered for peak discharge are adopted also for modelling time base of the hydrograph.

The 15 flash flood events has been divided into training, testing and validation data for GP training for each of the functional models described in Table 1. Of the 15 events 46 % of data has used for training, 33 % used for testing and the 20 % used for validation. The best model is selected based on Root Mean Square Error (RMSE) as the performance measure as given in Equation (1).

Table 1 — Functional form of models

| Element of the flood hydrograph | Model possibilities (in functional form) |
|---|---|
| Time to initial of flash flood ($t_i$) | (a) $t_i = f(R_1, Q)$ |
| | (b) $t_i = f(R_2, Q)$ |
| | (c) $t_i = f(R_1, R_2, Q)$ |
| | (d) $t_i = f(R_1, R_{2\,forecasted}, Q)$ |
| | (e) $t_i = f(R_1, R_2, R_{2\,wetness}, Q)$ |
| Time to peak flood discharge ($t_p$) | (a) $t_p = f(R_1, Q)$ |
| | (b) $t_p = f(R_2, Q)$ |
| | (c) $t_p = f(R_1, R_2, Q)$ |
| | (d) $t_p = f(R_1, R_2, Q, t_i)$ |
| Peak discharge ($Q_p$) | (a) $Q_p = f(R_1, R_2, Q)$ |
| | (b) $Q_p = f\left(\sum_{i=1}^{4} R_i, Q\right)$ |
| Time base ($t_b$) | (a) $t_b = f(R_1, R_2, Q)$ |
| | (b) $t_b = f\left(\sum_{i=1}^{4} R_i, Q\right)$ |

$$RMSE = \sqrt{\frac{1}{n}\sum_{i-1}^{n}[(X_m)_i - (X_s)_i]^2} \quad \dots (1)$$

Where, X is any variable subjected to modelling, 'm' is observed value and 's' is simulated/predicted value

In addition to RMSE, two more performance indices namely percentage of peak discharge (PPD) and the synchronous percentage of peak discharge (SPPD) as adopted by Artigue *et al.*[11] are used for $Q_P$:

$$PPD = \frac{(Q_p)_s}{(Q_p)_m} \quad \dots (2)$$

$$SPPD = \frac{(Q_p)_s^p}{(Q_p)_m} \quad \dots (3)$$

Where, $(Q_p)_s$ is the predicted discharge, $(Q_p)_m$ is the observed discharge and $(Q_P)^p_s$ is the predicted discharge at the time of observed discharge.

## Results and Discussion

The results obtained are discussed in detail as below:

### Identifying flash flood rainfall event

The analysis of the 15 flash flood events in this basin indicates a typical scenario associated with each rainfall event producing flash flood as shown in (Fig. 3). The flash flood is found to start after a duration of $t_i$ from the time the rainfall starts receding (region 1) in the upstream station. The cut-off rainfall

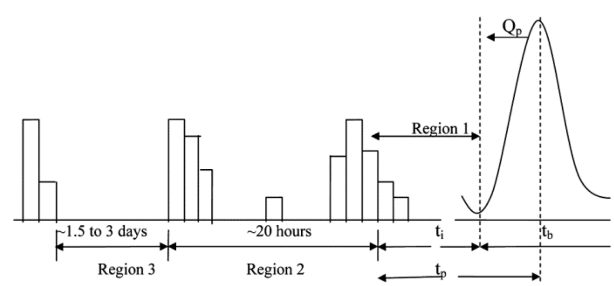


Fig. 3 — Typical scenario of flash flood

for measuring the $t_i$ is taken to be about 50 % to 60 % (on an average) of the maximum rainfall of a given rainfall event. The cumulative value of antecedent rainfalls up to duration of about 20 hours is taken (region 2). The rainfall during this window indicates the wetness index of the catchment. For the rainfall window beyond this (i.e. before 20 hours) antecedent rainfall is found to be almost nil for all the 15 events up to 2 to 3 days (region 3). This is found to be typical about this catchment. Thus, it is observed that before the flash flood can result, a high intensity rainfall creates sufficient saturation (of the catchment) resulting in increased runoff to create the flash flood during a next high intensity rainfall. A careful analysis reveals that flash flood is found to occur under any one of the two conditions (Table 2):

(a) The cumulative rainfall in the rain gauge stations (R1 and R2) are greater than 170 mm (region 2) at the reference time or

(b) The cumulative rainfall in the rain gauge stations (R1 and R2) are between 100 – 170 mm but the discharge is greater than 6 $m^3/s$ during the reference time.

The GP training is carried out for all the models in functional form listed in Table 1. For all the models, the number of generation, the population size and function set are arrived at based on trial and error. The evolved models are discussed in detail as below:

**GP model for the time to start of the initial flood ($t_i$)**

The RMSE for training, testing and validation set are shown in Table 3. It is seen that the input vector consisting of rainfalls at R1 and R2 together with the discharge in the gauging site during the reference time gives the best model. The approximate mathematical equation describing the relationship between the input vector and $t_i$ evolved by GP is given as:

$$t_i = \sqrt{\frac{8R_2 + R_1\left(Q-4\right)}{Q}} \quad \text{... (4)}$$

Where, Q is the discharge in the gauging station during the reference time.

This model reveals that with the increase in Q, the time to start of flash flood will reduce. Apparently it also appears that with increase in R1 or R2 or both, the time to start of flood will increase which is contradictory to the physics of the process. However, it can be explained that though in the model R1 and Q appear to be mutually exclusive variables, in practice it is not so, and hence all the variables in the model have to be taken as a single entity i.e. if R1 and R2 increases, it is expected that Q will also increase. The relative proportion of increase in R1 and R2 with respect to Q will decide the time to start of the flash flood. An attempt was also made to check for improvement in the model performance by introducing the ‘wetness index’ as one of the variable in the input vector which is considered as the cumulative rainfall in region 2 alone in (Fig. 2). However, the model performance didn’t show any improvement. This indicates that the cumulative rainfall in region 1 and 2 are a better indicator to reflect the catchment response than separating their effect. Sometimes such lumped approach may result in better models. The attempt to introduce the forecasted rainfall in R2 into modelling also didn’t improve the model performance.

Table 2 — Threshold range for Rainfall and Discharge

| Event No. | Rainfall at R2 at reference time (mm) | Discharge at reference time ($m^3/s$) |
|---|---|---|
| E1 | 101.6 | 7.80 |
| E 2 | 152.4 | 9.30 |
| E 3 | 152.4 | 8.15 |
| E4 | 177.8 | 6.21 |
| E5 | 177.8 | 4.41 |
| E6 | 228.6 | 4.27 |
| E7 | 228.6 | 6.98 |
| E8 | 254.0 | 4.88 |
| E9 | 254.0 | 8.16 |
| E10 | 304.8 | 11.95 |
| E11 | 355.6 | 9.38 |
| E12 | 609.6 | 7.17 |
| E13 | 635 | 24.62 |
| E14 | 863.6 | 5.58 |
| E15 | 1600.2 | 8.60 |

Table 3 — RMSE for time to initial flash flood

| Model | RMSE (in hr) | | |
|---|---|---|---|
| | Training | Testing | Validation |
| $t_i = f\left(R_1, Q\right)$ | 0.77 | 2.67 | 2.73 |
| $t_i = f\left(R_2, Q\right)$ | 0.65 | 0.78 | 3.14 |
| $t_i = f\left(R_1, R_{2,} Q\right)$ | 0.86 | 2.72 | 1.02 |
| $t_i = f\left(R_1, R_{2\,forecasted}, Q\right)$ | 1.35 | 2.28 | 3.34 |
| $t_i = f\,(R_1, R_2, R_{2wetness}, Q)$ | 1.40 | 4.13 | 5.25 |

**GP model for the time to peak discharge ($t_p$):**

The RMSE for training, testing and validation set are shown in Table 4. It is seen that similar to time to start of initial flash flood ($t_i$), for the time to peak also the input vector consisting of rainfalls at R1 and R2 together with the discharge in the gauging site during the reference time gives the best model. The approximate mathematical equation describing the relationship between the input vector and $t_p$ is given as:

$$t_p = \left[ 2 \left| \frac{-15.2}{(R_2 - Q)} + 16.4 - Q \right| + 3 \right] \quad \text{... (5)}$$

It is seen that although both R1 and R2 are taken as inputs, in the approximate model, R1 doesn't appear explicitly. The influence of rainfall in the station R2 (at reference time) is more pronounced as far as time to peak discharge is concerned. Once again, as discussed for $t_i$, it is the combined effect of rainfall and discharge at gauging site that affects the model.

**GP model for the peak discharge ($Q_p$):**

The RMSE for training, testing and validation set are shown in Table 5. As expected, the cumulative rainfall in all the four stations when used as input yields the best model for peak discharge as given below:

$$Q_p = \frac{\left[ \dfrac{1 - 0.0012\,R^2}{0.000027\,R^2 Q} \right]^2 + 1.92\,R}{0.037\,R} \quad \text{... (6)}$$

Where, R is the cumulative rainfall in all the four rain gauges stations with respect to the reference time. Since the peak of any hydrograph results when the entire catchment is contributing to the runoff, this model most appropriately describes this relationship. For the peak discharge, other than RMSE, the other two performance measures PPD and SPPD indicate a value greater than 0.9 for training, testing and validation data set for the best model indicating more than 90 % accuracy in prediction of peak discharge by the GP model.

**GP model for base time ($t_b$):**

The RMSE for training, testing and validation set are shown in Table 6. In this case, the best model is obtained when the input vector consisting of rainfalls at R1 and R2 together with the discharge in the gauging site during the reference time are used.

$$t_b = \left[ \frac{973.7Q - 26.7\,R_2\,Q + 2R_1R_2^2\,Q}{R_1R_2^2} \right] \quad \text{... (7)}$$

This is also expected since the end of time base represents the end of the hydrograph by which time the flash flood starts receding.

As mentioned earlier, the time to peak flood and initial time mainly depend on the catchment characteristics along with rainfall characteristics, but here the catchment characteristics are not considered explicitly in the input of model. This is because GP is a data driven approach, the dependency is implicitly taken into account. The hydrographs for the rainfall

Table 4 — RMSE for time to peak flash flood discharge

| Model | RMSE (in hr) | | |
|---|---|---|---|
| | Training | Testing | Validation |
| $t_p = f(R_1, Q)$ | 3.92 | 7.93 | 7.80 |
| $t_p = f(R_2, Q)$ | 3.07 | 8.5 | 3.4 |
| $t_p = f(R_1, R_2, Q)$ | 4.38 | 5.5 | 0.87 |
| $t_p = f(R_1, R_2, Q, t_i)$ | 5.4 | 8.48 | 2.94 |

Table 5 — RMSE, PPD and SPPD for peak flash flood discharge

| Model | RMSE (in hr) | | | PPD | | | SPPD | | |
|---|---|---|---|---|---|---|---|---|---|
| | Training | Testing | Validation | Training | Testing | Validation | Training | Testing | Validation |
| $Q_p = f(R_1, R_2, Q)$ | 5.72 | 15.67 | 35.88 | 0.99 | 0.92 | 0.67 | 0.82 | 0.89 | 0.67 |
| $Q_p = f\left(\sum_{i=1}^{4} R_i, Q\right)$ | 7.42 | 7.38 | 4.02 | 1.04 | 1.03 | 0.97 | 0.94 | 0.99 | 0.97 |

Table 6 — RMSE for time base ($t_b$)

| Model | RMSE (in hr) Training | Testing | Validation |
|---|---|---|---|
| $t_b = f(R_1, R_2, Q)$ | 1.67 | 21.908 | 1.93 |
| $t_b = f\left(\sum_{i=1}^{4} R_i, Q\right)$ | 9.91 | 12.55 | 3.7 |

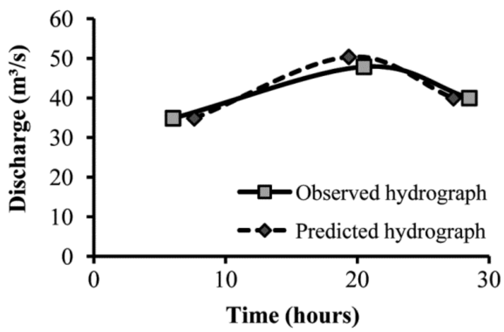


Fig. 4 — Comparison of observed and predicted hydrograph for E13

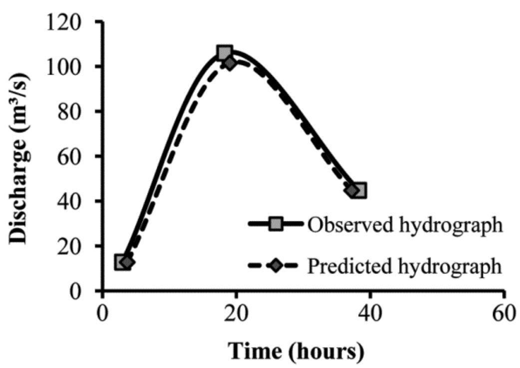


Fig. 5 — Comparison of observed and predicted hydrograph for E14

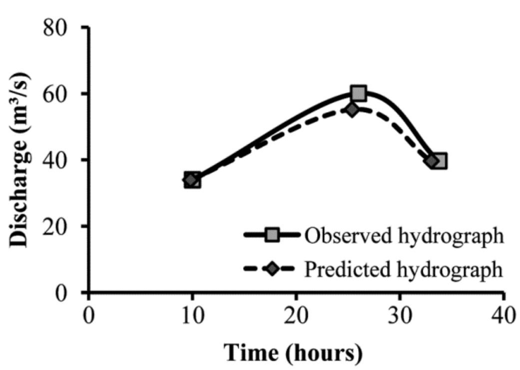


Fig. 6 — Comparison of observed and predicted hydrograph for E15

events in the validation set are compared as given in (Figs. 4 – 6). The entire shape of the observed hydrographs is very accurately predicted implying the potential of GP in hydrological modelling.

Table 7 — Comparison of RMSE for Best of GP model and the corresponding MLR model

| Parameter | RMSE GP | MLR |
|---|---|---|
| Time to initial of flash flood ($t_i$) | 1.02 | 2.23 |
| Time to peak flood discharge ($t_p$) | 0.87 | 6.37 |
| Peak discharge ($Q_p$) | 4.02 | 134.84 |
| Time base ($t_b$) | 1.93 | 15.27 |

Finally, inputs and outputs of best models of GP for all the four parameters are considered for Multiple Linear Regression (MLR) modelling. The RMSE of GP models are compared with that of MLR models for the validation set in Table 7. It is seen that the RMSE for MLR models are significantly greater than that of GP which can explained by the fact that the underlying process is essentially a non-linear process and hence a non-linear modeling is better approach than linear modeling.

## Conclusions

The alternative approach suggested in this study to model the elements of the flash flood hydrograph seems to be a potential approach for flash flood modelling without the use of forecast rainfall information. Hence, the method can be suitably used for poorly gauged basin; the models for flash flood hydrograph developed by GP are very specific to the basin for which it is developed although the method recommended can be applied in general to any basin; and GP has the potential to develop reliable models even with limited data set which is very useful for poorly gauged basins.

## Conflict of Interest

The authors have no conflicts of interest to disclose.

## Author Contributions

CS: Designed and performed experiments, analysed data, supervised the research and helped in paper writing; AM and DI: Data acquisition and performed the experiments; PS: Data analysis and helped in paper writing; and SB: Helped in paper writing.

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