Journal of Geomatics Vol 8 No. 1 April 2014

Flood estimation using advance geospatial tools

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(Received: July 26, 2013; in final form Jan 06, 2014)

Abstract: Peak flow estimation for flood forecasting as well as for real time water management with innovative use of modern technological tools has been the need of the hour. Hydrologic parameters such as rainfall, runoff etc vary both in space and time. For most of the hydrological models, one of the main components involved is rainfall-runoff process. Determination of more accurate amount of average rainfall and resulting runoff that a given storm event will produce on each hydrological unit is the technological challenge as it is the major cause of error in the applied hydrology. Considering this, an attempt has been made in this study to make innovative use of spatial tools available. To take care of the spatial variability, the hydrological unit is divided into various sub-units with hydro meteorologically homogeneous characteristics like rainfall pattern--- etc. to arrive at more accurate areal rainfall-runoff. Larger the number of sub-units better is the accuracy. Using modern tools of geospatial technology, it is possible to achieve more accurate areal rainfall and resulting runoff. This paper discusses Digital Rainfall Model- an innovative concept used for estimation of areal rainfall for the storm events for more accurate assessment of the spatial rainfall distribution in comparison with the conventional methods in vogue. For spatial runoff estimation, SCS-CN model has been applied using Arc-CN Runoff tools –of ARC-GIS to compute digital runoff. Land use and soil map of the catchment are used as inputs. The results of the model are compared with the same obtained using other tools for the observed storm events occurred in Panshet reservoir catchment within Krishna river basin in India.

Keywords: Digital Rainfall, Digital Runoff, ANN

1. Introduction

Accurate estimation of inflows during the storm event has been a crucial task for flood forecasting as well as real time water management for the storage reservoirs. Hydrologic parameters such as rainfall, runoffs etc. vary both in space and time. For most of the hydrological models, one of the main components involved is rainfall-runoff process. Determination of more accurate amount of average rainfall and resulting runoff that a given storm event will produce on each hydrological unit is the technological challenge as it is the major cause of error in the applied hydrology. To take care of the spatial variability, the hydrological unit is divided into various sub-units with hydro meteorologically homogeneous characteristics like rainfall pattern--- etc. to arrive at more accurate areal rainfall-runoff. Larger the number of sub-units better is the accuracy. Using modern tools of geospatial technology it is possible to achieve more accurate areal rainfall and resulting runoff.

2. Study area

The study area is the Panshet reservoir catchment within Krishna river basin in India. The catchment is elongated in shape having area of about 116 sq km. The region is hilly having steep slopes. The average annual rainfall is about 2.5 m. Intense storms occur in the region resulting in flash floods. The study basin has rainfall network of four stations namely at Mangaon, Koshimgarh, Shikholi & Panshet. The study area and the locations of the rainfall stations are depicted in Fig. 1. The nine number of peak storm events of different periods are as per Table 1.

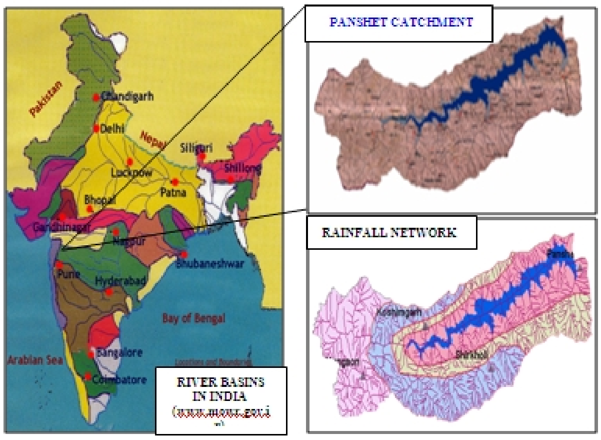


Figure 1: The study area and rainfall network

Table 1: Storm events

00.	Storm Period During	Storm Duration (Hrs)	Time step (Hrs)	Total Rainfall (mm)	Obs Runoff (mm)	Runoff factor -
1	18-20July-86	66	3	192	100	0.52
2	23-26July-89	63	3	529	307	0.58
3	26-29July-89	57	3	266	166	0.62
4	09-11Aug-90	51	3	92	55	0.60
5	11-14Aug-90	75	3	250	201	0.80
6	14-17Aug-90	75	3	362	219	0.60
7	17-19Aug-90	51	3	162	101	0.62
8	19-22Aug-90	75	3	179	126	0.70
9	22-24Aug-90	54	3	89	54	0.61

3. Digital Rainfall Estimation

The estimation of areal rainfall using the observed point rainfalls at various stations can be achieved using various techniques which include conventional as well as recent tools. Ball and Luk (1998) attempted spatial variability modelling of rainfall using hydro informatics tools and found that using spline surfaces gives robust estimates of rainfall. Chen and Liu (2012) used inverse distance weighting (IDW) for spatial rainfall distribution concluding that IDW as a suitable method of spatial interpolation. In this study the point rainfall of the four stations collected for the study area is distributed spatially using the innovative concept of Digital Rainfall Model (DRM). The Digital Rainfall Model *(DRM)* concept is similar to Digital Elevation Model *(DEM)*. The pixel wise spatial distribution of the rainfall is achieved for each of the three hourly spell of the rainfall using Inverse Distance Weights *(IDW)* available in spatial analysis in *ARC-GIS* tools. The sample pixel wise distribution of rainfall in the study basin for the duration is depicted in Fig. 2 Finally the combined digital average rainfall for the event in the basin is computed. Accordingly the hyetographs computed with corresponding observed runoff hydrographs are shown in Fig. 3

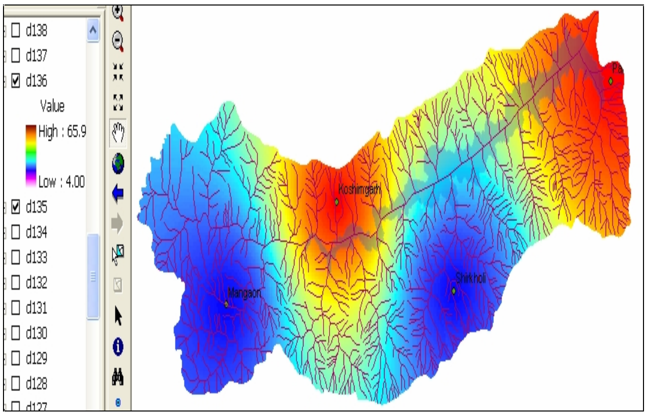


Figure 2: Digital rainfall distribution

4. Comparative Analysis

The digital rainfall distribution obtained as above has been used for computing the areal rainfall for the catchment and the same is compared with respect to the areal rainfall hyetographs obtained using Unweighted Mean (average) and Thiessen Polygon methods for the concurrent periods. The variations have been computed for following three options and the overall results for the entire nine storm events are depicted in Fig. 4.

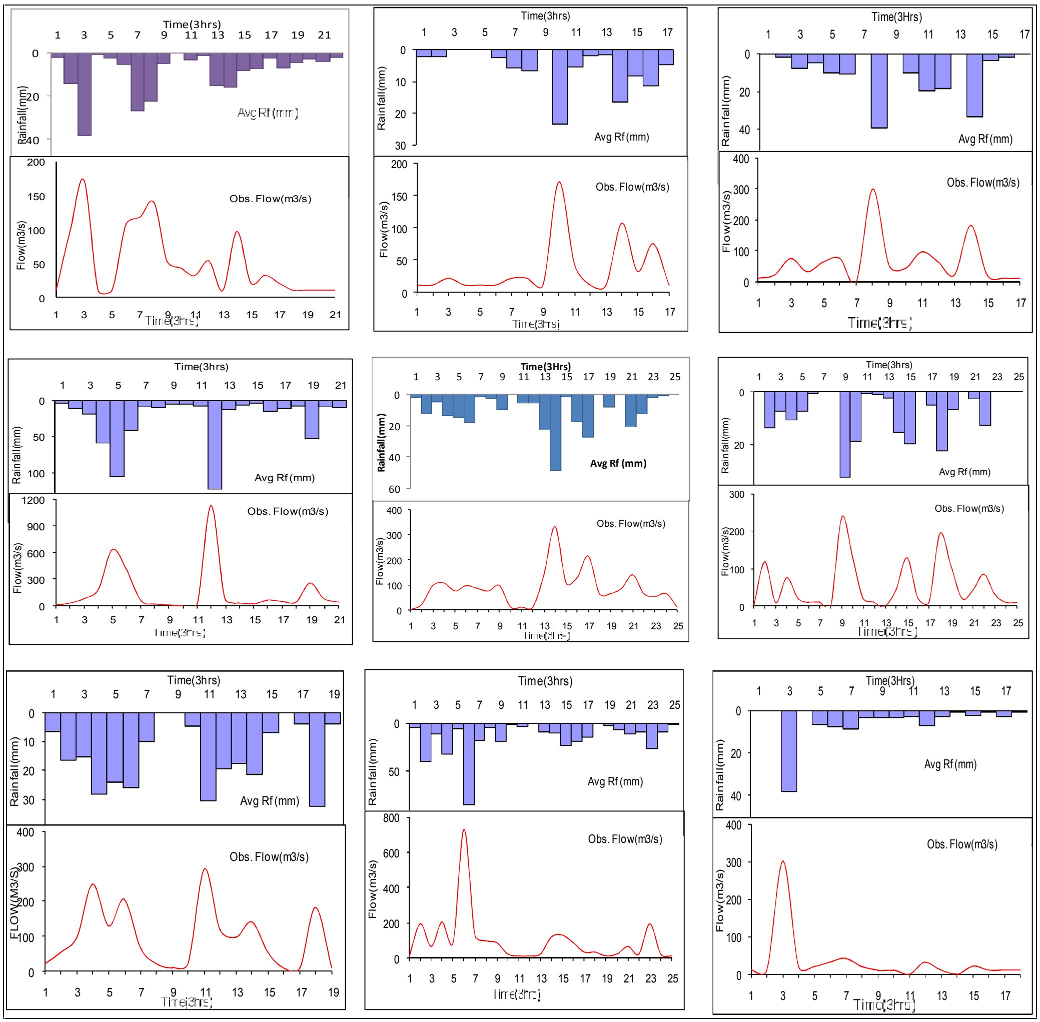


Figure 3: Digital rainfall Hyetographs with concurrent observed hydrographs for storm events

- Unweighted Mean (avg.)-Thiessen Polygon (thie.)
- Digital(dgtl)- Thiessen polygon(thie.)
- Digital (dgtl)- Unweighted Mean (avg.)

From the comparative variation analysis, it is seen that:

- For most of the event times the areal rainfall computed using unweighted mean method is under estimated when compared with the digital method (IDW) as well as that obtained using the thiessen polygon method.
- For most of the event time the areal rainfall computed using the thiessen polygon method is also under estimated when compared with digital method (IDW).
- For the variations in areal rainfall estimate using digital method (IDW) and thiessen polygon method, it is seen that the values are comparatively lower when the same is compared with unweighed means. Hence theissen polygon method results are comparatively closer to digital (IDW) method as compared to that obtained using unweighted means method.

Thus, the digital rainfall analysis (IDW) being based on pixel wise spatial variation is more accurate when compared with the results obtained using other two methods

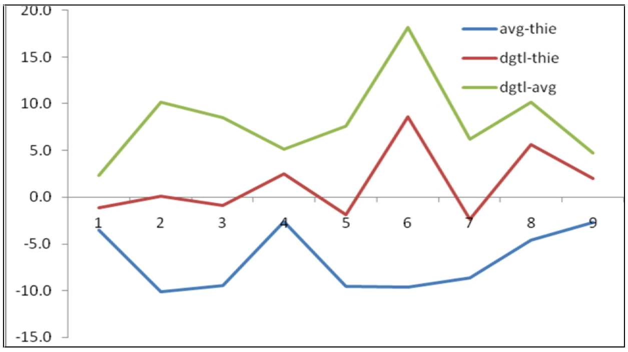


Figure 4: Comparative analysis

5. Digital Runoff Estimation

Estimation of spatially distributed runoff forms the crucial exercise in hydrologic modelling. Wide range of models which include empirical lumped mathematical models to conceptual distributed deterministic models are in vogue. Aronica and Cannarozzo (2000) studied the hydrological response using a semi distributed linear, non linear model and concluded that the variation in the spatial discretisation influences flood hydrograph. Brand et al. (1999) carried out study of rainfall – runoff process using a continuous distributed model with the conclusion that parameters like rainfall and soil variability, have major influence on peak hydrograph. Application of GIS for runoff computation has been widely attempted. Since the runoff generation depends on spatially varied catchment characteristics, climatic parameters as well as antecedent moisture conditions the estimation of its spatial variation is essential for more accurate results.

The runoff curve number (CN) method developed by the Soil Conversation Services (SCS) with CN values for Indian conditions are used for the purpose. The method is based on the water balance equation and two fundamental hypothesizes.

The first hypothesis states that the ratio of the actual amount of direct runoff to maximum potential runoff is equal to the ratio of the amount of actual infiltration to the amount of the potential maximum retention. The second one pertains to the initial abstractions as a fraction of the potential infiltration. Using these hypothesis and water balance equation following equation for runoff depths is derived.

$$Q = [CN (P+2) - 200]^2 / CN [CN (P-8) + 800] \quad ---(1)$$

Subject to $P > (200/CN)-2$, *else* $Q = 0$

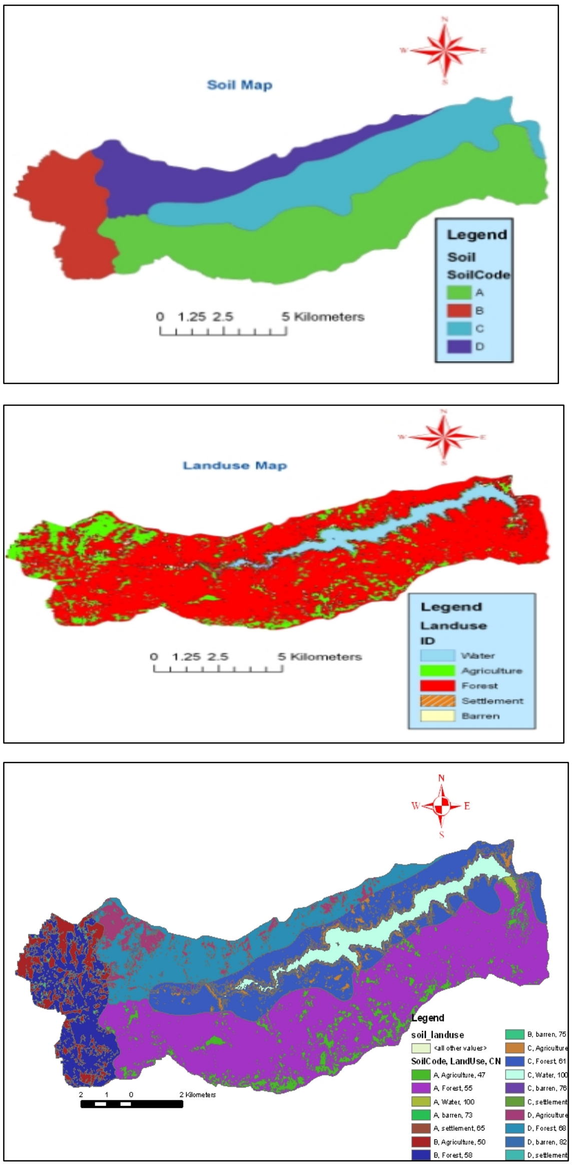
Where, P = *Total Precipitation,*

Q = *Direct runoff*

CN = *Curve Number (0-100)*

The objective is to estimate direct runoff depth from storm rainfall depth based on the parameter referred to as "Curve Number" which are estimated on the information obtained using various thematic maps of the catchment such as land use, land cover/ soils, as well as antecedent moisture condition using above equation. The *SCS* have classified various soils characteristics on the basis of infiltration rate and the runoff curve numbers for various combinations of soils and covers. The curve numbers are assessed using the clip layer obtained using land use and hydrologic soil group layer respectively with appropriate antecedent moisture conditions using ARC-CN. The satellite image (IRS -LISS-III) of the study area has been used for getting classified into land use groups using ERDAS IMAGINE. Soil map of the study area is based on the All India Soil Survey Map. The clip intersection layer of land use and soil map is obtained using ARC-CN (Fig. 5). Using these layers and the lookup table for AMC –II conditions, the CN for each land use category & in turn digital runoff layers (Fig. 6) for each rainfall depths of the storm event are computed. The areal average of the digital runoff with respect to each of the digital rainfall is computed. Since the storm event data interval(3Hrs) and the time of concentration (Tc) being near about same, the routing effect is not predominant and hence the computed digital runoff depths have been converted into flows using catchment area & the data interval and compared with the observed flows for all the nine storm events as shown in Fig. 7.

It is to reiterate that the runoffs as obtained above need to be routed to the outlet for better comparison with the observed flows which is further part of this study.



SOIL-LAND USE (CLIP)

Figure 5: Soil - land use intersection

6. Run off using ANN

Artificial Neural Networks (ANN) are in use for estimation of runoff for quite some time. Tokar and Johnson (1999) used ANN for Rainfall – Runoff modelling and concluded that it compared favourably with the statistical regression and a simple conceptual model techniques. Zealand et al. (1999) also attempted use of ANN for short term stream flow forecasting and concluded favourably. For comparing the results of the digital runoff model runoff estimation has been attempted using ANN. The model of an artificial neuron closely matches biological neuron. The artificial neuron is also called a processing element, a neurode, a node, or a cell. The input signals X_1, X_2, X_3....Xn are normally continuous variables instead of discrete pulses that occur in a biological neuron. The weight can be positive or negative corresponding to acceleration or inhibition respectively of the flow of electric signals. The summing node accumulates all the input weighted signals and then passes to the output through the transfer function which is usually non-linear. Using the most commonly used *sigmoidal transfer function*, the output of typical neuron can be written as follows

$$y = 1/(1+w^{-ax}) \quad ---- \quad (2)$$

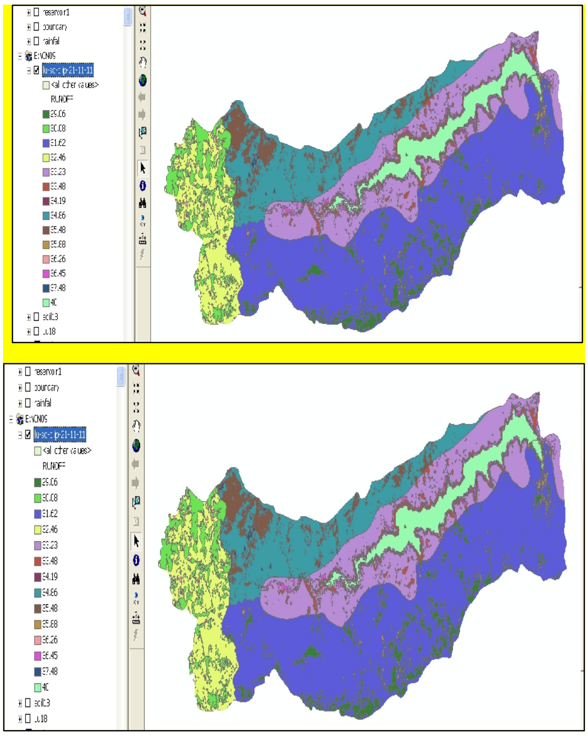


Figure. 6: Digital runoff layer

where x is the input, y is the output, w is the weight and a is the coefficient or gain which adjusts the slope of the sigmoidal function that changes between the two asymptotic values (0 and +1). Neuro-Intelligence (neural network software) is used in this study to gain the maximum productivity in preprocessing data, efficient network architecture and to analyze performance. The architecture of the model is determined through a trial and error procedure. Network with five input layers, one hidden layer and one output has been adopted for the study (Fig. 8) which has indicated highest correlation. The input parameters are rainfall depths of four rain gauge stations and the digital rainfall as obtained above for every interval of all the storm events and output target being the observed runoff depths. The model is then trained with different weight being adjusted until threshold error criteria have been achieved. Total 189 data patterns, have been used to train the network, i.e., to determine the optimal set of weights. For each neuromorphic experiment, the data are split up in to three parts; one for model training (70%), one for cross validation (to prevent model over training), and another for testing the performance of the model. The trained network has been used for the runoff outputs using the query option. The ANN model results obtained as computed runoff depths are compared with the observed runoff depths. The same are depicted in Fig. 9. The runoff results obtained are also used for comparing the results of digital runoff with respect to the observed values.

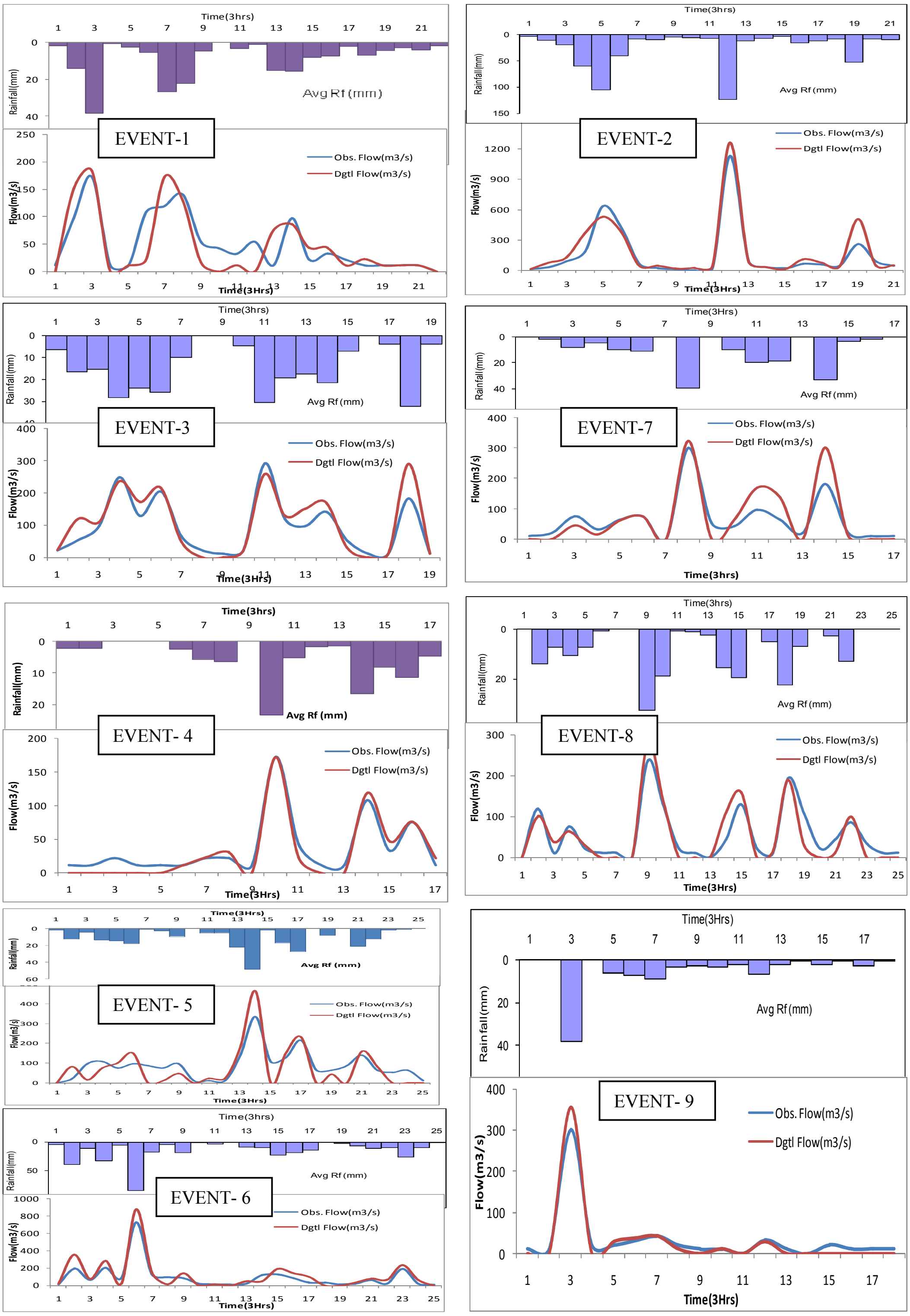


Fig. 7: Digital runoff results with observed Hydrographs

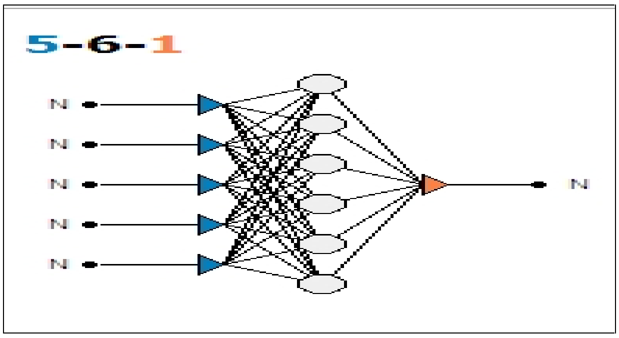


Figure 8: ANN design adopted

7. Runoff Using Conventional Tool

Use of empirical equations which give lumped values of runoff are also used for quick assessment of the flows. This method has also been used for comparing the results of digital runoff model. Determination of peak runoff for a basin can be determined using the Rational Formula. The Rational Formula states:

$$Q = CIA \qquad \text{---- (3)}$$

Where, Q= Peak runoff rate, C =Runoff coefficient I = Rainfall intensity, A = Drainage area

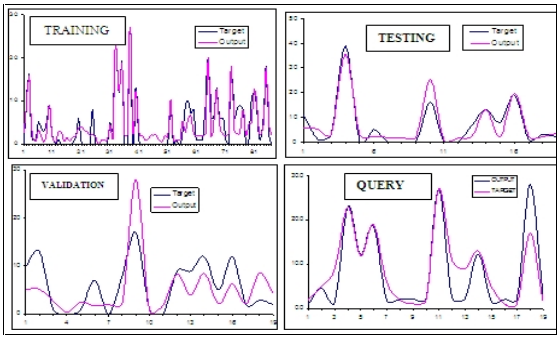


Figure 9: ANN results

It is seen that the storms in study area cover much bigger areas and of much longer durations. The rational formula is applicable for the storm durations more than the time of concentration (Tc). The Tc for the watershed is about 3 hrs and the storm events are of much larger duration. Accordingly this formula is used for computation of flows. The digital rainfall depths for three hourly durations as obtained earlier are used as input for the rational formula for the nine storm events using the runoff coefficients as per Table 1. The time duration of three hours which is approximately same as the time of concentration for the catchment, estimated using California Equation which is about three hours.. The computed runoff using rational formula are compared with the observed runoff as well as the digital runoff.

8. Comparative Analysis

For the purpose of inter comparison of results of all the above three methods i.e. digital runoff; ANN runoff & conventional runoff (Rational formula) the flows as obtained ignoring the routing effect for the reasons already cited, are compared with the observed flows. The event wise Relative Errors (RE) have been computed using

$$RE = (Qo - Qc)/Qo \qquad \text{---- (4)}$$

Where, RE = Relative Error, Qo = Observed Runoff Qc= Computed Runoff

The Relative Error results for all three methods have been plotted and depicted in Fig. 10.

From above analysis it can be inferred that:

- The results by conventional method are quite off the mark when compared to the other two methods i. e. digital runoff and ANN runoff.
- It can also be seen that, the digital runoff results are better compared to ANN runoff.
- Since the relative error being minimum it can be concluded that the results obtained using digital rainfall model can be very well used for runoff estimation with more accuracy and very short processing time.

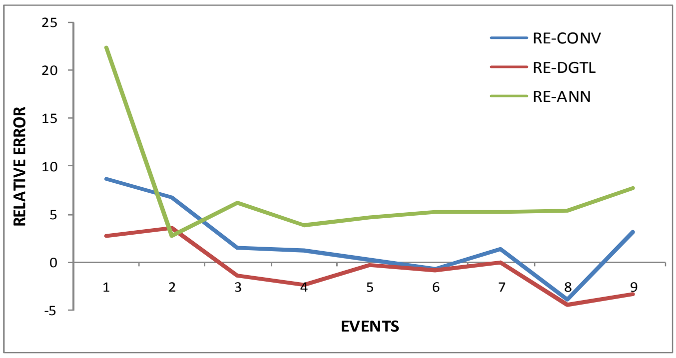


Figure 10: Relative error analysis

9. Conclusion

For real time flood forecasting as well as water management purpose, more accurate assessment of rainfall as well as runoff is essential. The satellite Remote Sensing and GIS based spatial analysis tools can be effectively used to have better assessment of spatially variable parameters such as rainfall & runoff. The results as obtained in the study indicate that the digital rainfall analysis as well as digital runoff analysis gives appreciably good results compared to conventional tools. These methods being simpler & quicker will go long way in field applications for flood /inflow forecasting as well as overall real time water management purpose. While this study demonstrated the feasibility of using GIS and ANN tools in conjunction to model flood events in the study area, there are still a number of areas of further work. For instance, in catchments where the models appear to be significantly over-or under-predicting estimated flood events, it would be worth exploring anomalies in relation to a wider set of watershed characteristics such as urban, rural etc.

Further for better comparison of the flows the routing of the flows forms further part of this study.

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