

Comparative Analysis of Spatial Rainfall-Runoff Estimation Using Advance Geospatial Tools, ANN & Empirical approach

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Abstract - Hydrologic parameters such as rainfall, runoff etc vary both in space and time. For most of the hydrological models, one of the main elements involved is rainfall-runoff process. Determination of the amount of average rainfall or runoff that a given storm event will produce on each sub-basin is of prime importance as it is major cause of error in the applied hydrology. To take care of the spatial variability, the watershed is divided into various sub-basins with hydro meteorologically homogeneous characteristics like rainfall pattern to arrive at representative spatial runoff. Larger the number of sub-basins, better is the accuracy. Using modern tools of geospatial technology(SRS,GIS) as well as Artificial Neural Networks (ANN), it is possible to achieve the objectives of representative as well as more accurate spatial rainfall and concurrent runoff. This paper discusses Digital Rainfall Modelling- an innovative tool for estimation of spatial rainfall for the storm event with the objective of more accurate assessment of the spatial rainfall distribution. For spatial runoff estimation, hydrologic models such as Agricultural Non Point Source [AGNPS] model, HEC-1, HEC GEOHMS, ILWIS, SWAT, as well as Arc-CN Runoff tools of ESRI at Arc GIS are reported. Estimation of spatially varied runoff depths using Arc-CN Runoff tools -Digital Runoff modeling, is discussed. Land use and soil map of the catchment are used as inputs. The digital runoff thus obtained for the event is compared with the same obtained using ANN and rational formula with respect to the observed runoff for the events occurred in Panshet reservoir catchment within Krishna river basin in India.

Keywords - ANN, Digital Rainfall, Digital Runoff, GIS, SRS,

I. INTRODUCTION

For most of the hydrological models, one of the main elements involved are rainfall-runoff process. A watershed is usually a complex heterogeneous system. Hydrologic processes vary both in space and time.

To take care of the spatial variability, the watershed is divided into various sub-basins with hydro meteorologically homogeneous characteristics like rainfall pattern to arrive at representative spatial runoff. Larger the number of sub-basins better is the accuracy. Determination of the amount of average rainfall or runoff that a given storm event will produce on each sub-basin is of prime importance as it is major cause of error in the applied hydrology.

Using modern tools of geospatial technology as well as artificial neural networks it is possible to achieve the objectives of representative as well as more accurate spatial rainfall and concurrent runoff.

II. THE STUDY AREA

The study area is the Panshet reservoir catchment within Krishna river basin in India. The study basin has rainfall network of four stations namely at Mangaon Koshimgarh, Shikholi, & Panshet. The location of these stations is digitized & the layer is depicted at Fig.1. The rainfall events details are as per Table1.

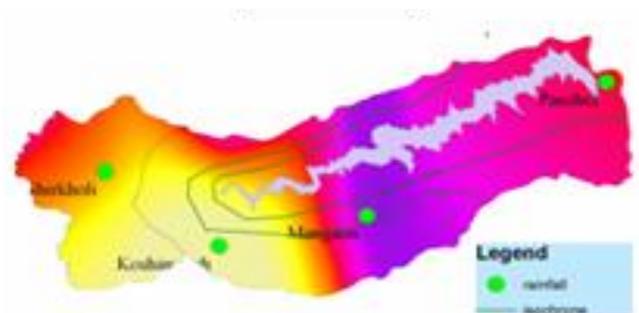


Fig.1Panshet rainfall network

Table1
Rainfall events

Sr. No.	Beginning of event		Ending of event		Time step
	Date	Time	Date	Time	Hrs
1	18 July-87	1200	20 July 87	2100	3
2	23 July-89	1800	29 July89	0900	3
3	09 Aug-90	0000	28 Aug-90	0000	3

III. DIGITAL RAINFALL ESTIMATION

Rainfall hyetographs are required for each sub basin at desirable shorter intervals. The mean areal value (R) of rainfall over a basin area A, can be algebraically expressed as

$$R = \frac{\int_A r(x, y) dx dy}{\int_A dx dy} \quad \text{---- (1)}$$

Where $r(x, y)$ is the rainfall surface function which is never known but can be approximated from the point rainfall values r_1, r_2, \dots, r_N measured by gauges. The simplified results for average areal rainfall can be obtained using geospatial tools [7][8]. D.K.Christian et al (2000) [1] tried rainfall disaggregation using Poisson cluster model. James E. Ball and Kin Chai Luk also reported modelling spatial variability of rainfall over a catchment.

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 four station point rainfall is distributed spatially using the innovative concept of Digital Rainfall Model (DRM). The 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 variation 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 are shown in Fig.3

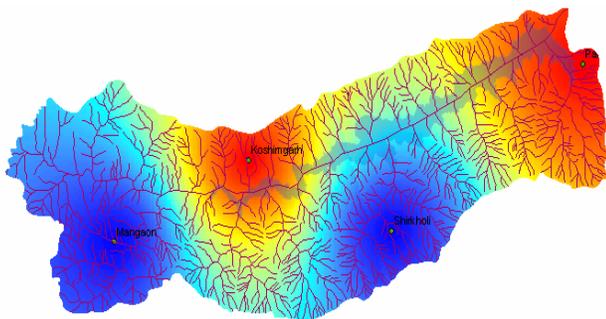


Fig.2 Digital Rainfall Model (DRM)

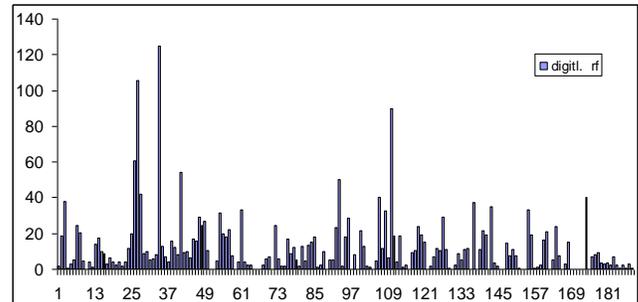


Fig.3 Event Hyetograph Using DRM

IV. DIGITAL RUNOFF ESTIMATION

For estimation of spatially distributed runoff forms the crucial exercise in hydrologic modeling.[2] The runoff curve number (CN) method developed by the Soil Conservation Services (SCS) with CN values for Indian conditions are used for the purpose. 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 from various thematic maps of the catchment such as land use, land cover/ soils, as well as antecedent moisture condition using following equation.

$$Q = \frac{[CN (P-2) - 200]^2}{CN [CN (P-8) + 800]} \quad \text{---- (2)}$$

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

Where, P = Total Precipitation

Q = Direct runoff

CN = Curve Number (0-100)

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.[3][4] 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 (Fig.4) using ERDAS IMAGINE. Soil map of the study area (Fig.5) is based on the All India Soil Survey Map.[5] [6]

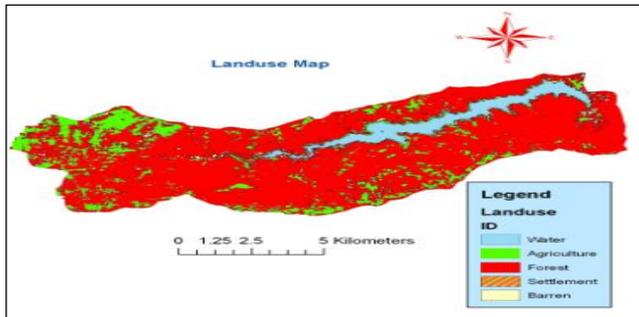


Fig. 4: Land Use Map

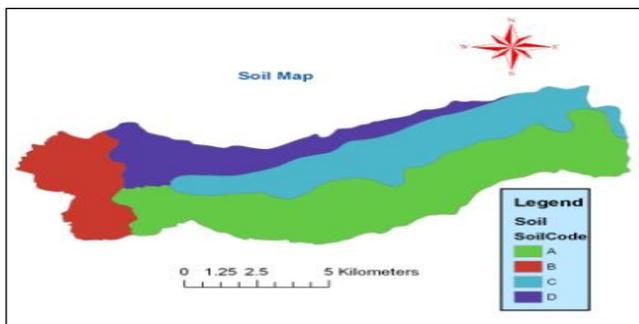


Fig. 5: Soil Map

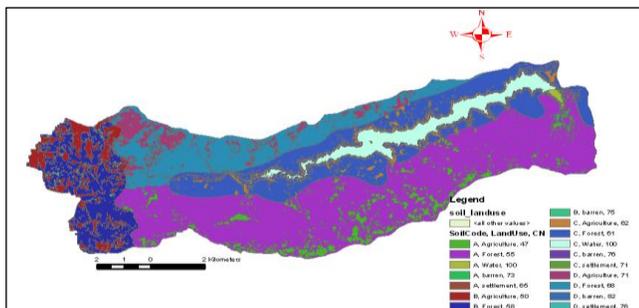


Fig.6: Soil- Land Use Intersection Map

The clip intersection layer of land use and soil map is obtained using ARC-CN (Fig.6). [9]Using these layers and the lookup table for AMC –II conditions, the CN for each land use category & in turn digital runoff depths for each rainfall depths of the storm event are computed. The Digital Runoff with respect to each of the digital rainfall are plotted. The computed value of each of the three hourly average of the digital runoff is shown in Fig. 7

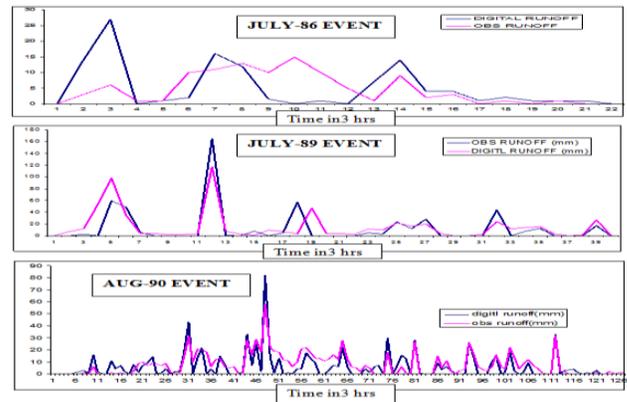


Fig.7 Digital Runoff Results

V. RUNOFF ESTIMATION USING ANN

For estimation of spatially distributed runoff has also been tried using Artificial Neural Networks (ANN). Using the most commonly used sigmoidal transfer function, the output of typical neuron can be written as follows :

$$y = 1 / (1 + w^{-ax}) \quad \text{--- (3)}$$

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). NeuroIntelligence (neural network software) is used in this study to gain the maximum productivity in preprocessing data, efficient network architecture, analyze performance. Network with four input layers, one hidden layer and one output has been adopted for the study (Fig.8). For estimation of three hourly runoff depths for the values of corresponding rainfall depths of four rain gauge stations in the study area have been used as input. Training, testing & validation have been carried out using the observed events. [10][11]

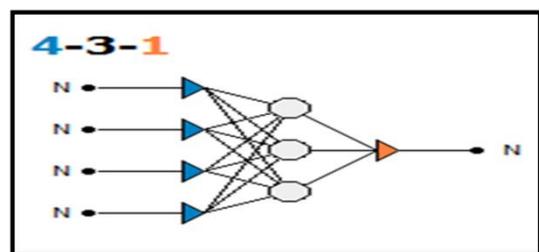


Fig.8: ANN Design Adopted

The ANN model results obtained as computed runoff depths are compared the observed runoff depths. The same are depicted in Fig. 9,

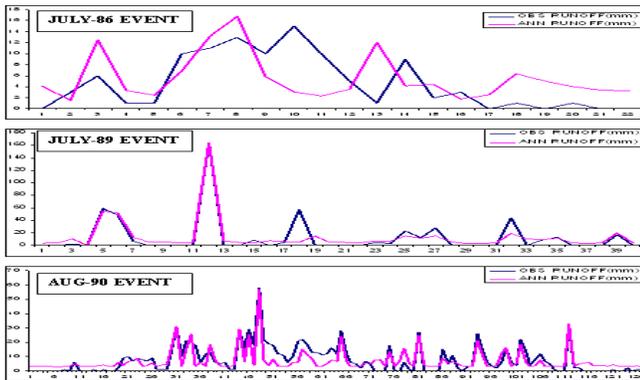


Fig.9: ANN Runoff Results

The model results as shown in Fig.9 indicate that the observed and computed runoff depths are more or less matching with respect to peaks as well as time. Hence it can be inferred that the ANN model can be very well used for runoff forecasting with more accuracy and very short processing time.

VI. RUNOFF ESTIMATION USING EMPIRICAL TECHNIQUE

Determination of peak runoff for a basin can be determined using the Rational Formula. The Rational Formula states:

$$Q = C * I * A \quad \text{----- (4)}$$

Where Q= Peak runoff rate (m³/sec), C =Runoff coefficient, I = Rainfall intensity (mm/hr), A = Drainage area (km²)

The digital rainfall depths for 3 hrly durations as obtained earlier are used as input for the rational formula. The variable runoff coefficient has been used for various events. The time duration of 3hrs, which is approximately same as the time of concentration for the catchment, estimated using *California Equation*. Since the runoff depths need to be compared, the peak discharges per unit area are computed & the results obtained are indicated in Fig.10.

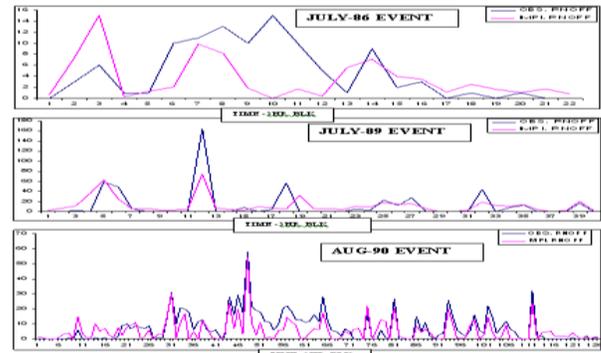


Fig.10: Empirical Runoff Results

VII. RESULTS & CONCLUSION

The digital runoff results, ANN runoff depths & empirical runoff depths are compared with the observed runoff depths. The relative error graph for all three methods have been plotted and depicted in Fig.11

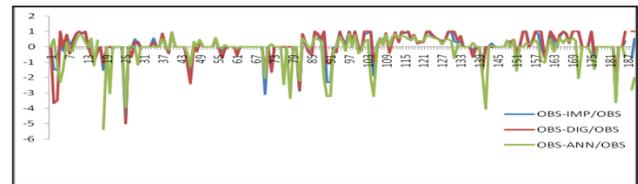


Fig.11 Relative Error Analysis

While comparing the relative errors with respect to the observed runoff depths, it is seen that the results are more or less similar for digital runoff & ANN runoff. It is seen that the during many of the event time the digital runoff depths are less estimated compared to observed values whereas it is other way in case of results obtained for ANN runoff. Relative errors are on negative side in case of empirical & ANN runoff & on positive side in case of digital runoff. 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.

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