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Review:Rainfall Runoff Modeling

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Abstract- Hydrological modeling is a commonly used tool toestimate the basin's hydrological response due to precipitation.Therearemanylimitationsofhydrologicalmeasurementtechniques.Wehave,infact,onlyalimitedrangeofmeasurement techniques and a limited range of measurementsin space and time. We therefore need a means of extrapolatingfrom those availablemeasurements in both space and time,particularly to ungauged catchments (where measurements arenot available) and into the future (where measurements are notpossible)toassessthelikelyimpactoffuturehydrologicalchange.Modelsofdifferenttypesprovideameansofquantitative extrapolation or prediction that will hopefully behelpfulindecisionmaking.

Key words- Rainfall, Runoff , ANN, Fuzzy logic Model, SWMM,HEC-HMS,Hydrologicmodelling

I. INTRODUCTION

Rainfall is the major component of the hydrologiccycle and this is the primary source of runoff. Worldwidemany attempts have been made to model and predict rainfallbehavior using various empirical, statistical, numerical anddeterministictechniques.

Rainfall generated runoff is very important in variousactivities of water resources development and management.The method of transformation of rainfall to runoff is highlycomplex,dynamic,nonlinear,andexhibitstemporalandspatial variability. It is further affected by many parametersandofteninter-relatedphysicalfactors.Determiningarobustrelationshipbetweenrainfallandrunoffforawatershed has been one of the most important problems forhydrologists,engineers,andagriculturists.

The rainfall-runoff relationship is an important issue inhydrology and a common challenge for hydrologists. Due tothetremendousspatialandtemporalvariabilitytheimpactofrainfallonrunoffbecomesmoreintensiveandtheirproperestimateisessentialforflood management.

Sincethemiddleofthe19th century,differentmethods have been demonstrated by hydrologists to assessthe impact of rainfall on runoff whereupon many modelshave attemptedtodescribethe physicalprocessesinvolvedinit.

These rainfall-runoff models generally fall into blackbox or system theoretical models, conceptual models andphysically-basedmodels.Blackboxmodelsnormallycontainnophysicallybasedinputandoutputtransferfunctionsandtherefore,areconsideredtobepurelyempiricalmodels.

Conceptualrainfall-runoffmodelsusuallyincorporateinterconnected physical elements with simplified forms, andeach element is used to represent a significant or dominantconstituenthydrologicprocessoftherainfall-runofftransformation.
Physically basedmodel are distributedmodels consists alargenumber ofparametersasinputtothemodel.

II. LITERATURE REVIEWS

GeoffreyO'Loughlin,WayneHuber&BernardChocat(2007)[1]
Rainfall-runoff models are the backbone of almost all urbanstormwater management studies, for mitigation of floodingproblems or on alleviation of stormwaterpollution. Theseboth objectives require estimates of stormwater flows. thispaperoutlinesaboutthebasictheoryofrainfallrunoffprocess and development of modelling practice and currentuse of computer models. it also highlights about deficienciesand dilemmasofrainfall runoffmodelling.

A.R.SenthilKumar,K.P.Sudheer,S.K.Jainand
P.K.Agarwal(2005)[2]
ThispaperpresentsacomprehensiveevaluationoftheperformanceofMLP-(multi-layerperceptron)andRBF-(radial basis function) type neural network models developedforrainfall-runoffmodellingofMalaprabhacatchment,India. A comparison of the rainfall-runoff modelling skill oftwoANNconfigurations,i.e.anMLPandanRBFispresented. The results suggest that the choice of the type ofnetworkcertainlyhasanimpactonthemodelpredictionaccuracy. However, the results of the study indicate that thegeneralizationpropertiesofRBFnetworksarepoorcompared with those of MLPs in rainfall-runoff modelling.But a judgment on which is superior is clearly not possiblefromthisstudy.

AnilKumarLohani, N.K. Goel&K.K.S.Bhatia (2011)[3]Thispapercomparesartificialneuralnetwork(ANN), fuzzy logic (FL) and linear transfer function (LTF)-basedapproaches for daily rainfall-runoff modelling. This studyalso investigates the potential of Takagi-Sugeno (TS) fuzzymodel and the impact of antecedent soil moisture conditionsintheperformance ofthedailyrainfall-runoff models.
Elevendifferentinputvectorsunderfourclasses,i.e.
(i) rainfall, (ii) rainfall and antecedent moisture content, (iii)rainfall and runoff and (iv) rainfall, runoff and antecedentmoisture content are considered for examining the effects ofinputdatavectoronrainfall-runoffmodelling.Usingtherainfall-runoffdataoftheupperNarmadabasin,CentralIndia,asuitablemodellingtechniquewithappropriatemodelinputstructureissuggestedonthebasisofvarious model performance indices. The results show that the fuzzymodellingapproachisuniformlyoutperformingtheLTFandalsoalwayssuperiortotheANN-basedmodels.
Keh-HanWangandAbdusselamAltunkaynak(2012)[4]
In this paper a comparative case study betweenSWMM and a fuzzy logic model for the predictions of totalrunoff within the watershed of CascinaScala, Pavia in Italyispresented.
Adatasetof23eventsfrom2000to2003including with the total rainfall and total runoff are adoptedto train fuzzy logic parameters. Other data (1990–1995) withdetailed time variations of rainfall and runoff are availablefor the setup and calibration of SWMM for runoff modeling.Among the 1990–1995 data, 35 independent rainfall eventsareselectedtotestthepredictionperformanceoftheSWMM and fuzzy logic models by comparing the predictedtotal runoffs with measured data.The performance of the SWMM and the fuzzy logic modelwereanalyzedusingroot-mean-squarederrorandcoefficientofefficiency.
Generally,boththeSWMMandfuzzylogicmodelcanpredictrunoffsthatagreereasonablywellwiththe measured data. however, the physically based SWMMproduced the time varying hydrograph whereas the fuzzylogic model was subject to the limitation of the methodologyandwasunabletogeneratesuchanoutput.

KishorChoudhari,BalramPanigrahi,JagadishChandraPau(2014)[5]
InthispaperHEC-HMSmodelisusedtosimulate rainfall-runoff process in BalijoreNala Watershedof Odisha, India. To compute runoff volume, peak runoffrate,baseflowandflowroutingmethodsSCScurvenumber, SCS unit hydrograph, Exponential recession andMuskingumroutingmethodsarechosen,respectively.Rainfall- runoff simulation is conducted using 24 randomrainstormeventscoveringfour year(2010–2013)data.
Out of these, 12 events are selected for modelcalibration and the remaining 12 for model validation. Forcalibration of model the statistical tests of error functionslike mean absolute relative error (MARE) and root meansquare error (RMSE) between the observed and simulateddata are conducted. Results shows that these obtained squarefunctionsinthevalidatedmodelindicatesatisfactoryperformanceofHEC-HMSmodelinsimulationrunoffhydrograph.

The model can help to save time and money inobtaining the runoff data rather than measurement of runoffinthewatershed.Moreover,itmayhelptosimulaterunoffin un-gauged watershed where there is no gauging station tomeasurerunoff.

M.P.Rajurkar,U.C.Kothyari& U.C.Chaube(2017)[6]InthisstudyalargesizecatchmentoftheNarmada River in Madhya Pradesh (India) is presented for modellingdaily flows during monsoon flood events by the applicationoftheArtificialneuralnetwork methodology.
DailyrainfallandrunoffdatafortheNarmadacatchment at the Jamtara gauge and discharge site located inthe central Indian State of Madhya Pradesh, are used.Alinear multiple-input single-output (MISO) model coupledwith the ANN is shown to provide a better representation ofthe rainfall-runoff relationship in such large size catchmentscomparedwithlinearand nonlinearMISOmodels.
Thepresentmodel provides asystematicapproachforrunoffestimationandrepresentsimprovementinpredictionaccuracyover theothermodelsstudied herein.

M. Kh.Askar(2014)[7]
In this paper the SCS CN method is used for thecalculation of runoff depth with Geographic InformationTechnique (GIS). The role of remote sensing in runoffcalculationisgenerallytoprovideasourceofinputdataorasanaidforestimatingequationcoefficientsandmodelparameters.
ThestudywascarriedoutintheGomalRiverwatershed about 540 km^2 catchment areas, Iraq. The areawithintheboundaryoftheKurdistanregionstartsfromnorth of Shahia to south west of Dohuk City.in this study themean annual rainfall depthfor the year 1947to 2005 isconsidered fot the calculation of runoff. Effect of slope onCN values and runoff depth was determined by using theWMS7.1program.
The result shows that the incorporation of SCS-CNmodel and GIS facilitates runoff estimation from watershedand canaugmenttheaccuracyofcomputed data.

III. CONCLUSION

- Rainfall-runoffmodelsarethebackboneofalmostallurbanstormwatermanagementstudies.
- Thechoiceofthetypeofnetworkcertainlyhasanimpactonthemodel predictionaccuracy.
- Therearevariousmodelsforrainfallrunoffmodelingdiscussedheresuchasartificialneuralnetwork,fuzzy modelingorstormwater managementmodel.
- Resultshowsthatthefuzzylogicmodelinggivescomparatively good output. the models compiled withANNcanalso beusedand givegoodresults.
- ThecomputermodelscanalsobeusedforrainfallrunoffsimulationsuchasHEC-HMS.Thismodelcan helpto save time andmoney in obtaining the runoffdataratherthanmeasurementofrunoffinthewatershed. Also, it may help to simulate runoff in un-gauged watershed where there is no gauging station tomeasurerunoff.
- Thereisanothermethodforrainfallrunoffmodeling known as SCS CN method, which is simple and easymethod and also accurate method for computation ofrunoff.
- Therefore the choice or selection of model depends ontypeofdata.

REFERENCES

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