Comparative evaluation of models to estimate direct runoff volume from an agricultural watershed

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ABSTRACT
Generally, runoff records are the most important input data in water resource management; however, their availability is very limited especially in developing countries as compared to rainfall records, especially under medium and small-scale catchments. In our study, we estimated runoff from ungauged agricultural watersheds with the curve number method and empirical mathematical models were compared with SCS-CN. Empirical mathematical models (Inglis and De Souza Formula (IDS); Turc relationship (TR), Indian Irrigation Department (DII) model, Coutagine relationship (CR), Khosla method (KH), Justin Equation (JE), Lacey relationship (LR), and Indian Council of Agricultural Research (ICARI)) model were used to estimate annual runoff (in cm). It was found that IDS model has capability to simulate annual runoff as very close to Soil Conservation Service Curve Number (SCS-CN) model and has lowest Root Mean Square Error (RMSE) value as 7.75, and ranking of this model (based on K factor (value of 0.001) analysis) was topmost (or 1st) in comparison to other eight models. This study suggests that empirical mathematical model has potential for annual runoff estimation from ungauged watersheds.

1. Introduction
Soil erosion is one of the most important processes that endanger the soil quality and, therefore, the agricultural production (Pásztor et al., 2016; Waltener et al., 2018). Runoff has strong relationship with the rate of erosion, as it is the consequence of the precipitation (duration, & intensity; Mohamadi & Kavian, 2015), the slope characteristics (steepness, length, & shape), soil characteristics (infiltration capacity, depth of humus layer, particle size & initial water content; Centeri et al., 2015; Szabó et al., 2015), and the vegetation/land use (management, density, leaf-area index, arboreal, or herbaceous; Jakab et al., 2013; Tadesse et al., 2017).

Simple empirical equation relates catchment characteristics and complicated physical models are available to estimate the catchment runoff. The application of conceptual hydrological model to generate runoff from ungauged watershed with limited data have been studied by researchers in past (Kaleris et al., 2015). Regional scale model can explain the variation of the model parameters with physiographic factors. These models did not fully capture the local scale process and variations. However, the certainty of the calibrated model parameters is high enough to simulate the hydrologic response of ungaged watershed. According to Wheater et al. (2008) and Devia et al. (2015), a hydrological model is a simplification of a real-world system, used mainly for the prediction of hydrological processes based on rainfall, drainage area (topography), soil properties, vegetation cover, and runoff model. It is defined as a set of equations that enable the estimation of runoff as a function of various parameters used for describing watershed characteristics.

The Universal Soil Loss Equation (USLE) is an empirical equation. The Revised Universal Soil Loss Equation (RUSLE) is a modification of USLE, especially for more complex situations of rill and inter-rill erosion in conservation planning and land uses. Both erosion-prone models calculate detachment capacity and soil loss. RUSLE model predicts soil degradation and sediment concentrations better using another soil erodibility factor (F-soil factor, based on soil texture). The soil conservation service-curve number (SCS-CN) method has been used widely (Bérod et al., 1999; Pandey & Dabral, 2004; Vaze et al., 2011). The SCS-CN method is simple, predictable, stable, and relies on only one parameter, namely the CN. The land use/land cover (LULC) class can be integrated with the hydrologic soil groups (HSG) of the sub basin in GIS, and the weighted CN can be estimated. These estimated weighted CN for the entire area can be used to compute runoff. Moore and Clarke (1981) showed...
that a variety of distributions that can be easily incorporated into this type of model structure and they derive analytical equations for the response of different distributions. Hosking and Clarke (1990) extended the work of Moore and Clarke (1981), and reported that the model can be used to derive a relationship between the frequencies of storm rainfall and flow peak magnitude in an analytical form. The UK Institute of Hydrology has shown the model for long runs to derive flood frequencies (Dorum et al., 2010; Lamb, 1999). Recently many studies have applied machine learning and soft computing approaches to study the soil properties and erosion (Jahani et al., 2016; Singh et al., 2020; Mosaffaei et al., 2020; Rahmati et al., 2020).

The earth observation datasets integration within Geographical Information System (GIS) make watershed modeling easy and accurate (Balázs et al. 2018). The capabilities of these technologies have been successfully utilized by many researchers in rainfall-runoff modeling. Earth-observing satellite provides more reliable input parameters for hydrological modeling (Rawat & Singh, 2017; Maliq & Singh, 2019). However, GIS processing has become a critical step in hydrologic modeling (Thakur et al., 2017), since it contributes to generate model parameter distribution in spatial manner.

Although researchers delineated several models, the satellite-based inputs in these models were not comparatively used and limited model performance was evaluated. Hence, objectives of work are as follows: (i) to estimate daily runoff using SCS-CN and (ii) to find an optimal empirical mathematical model with respect to SCS-CN for generating annual runoff of ungauged Jhagrabaria for the Jhagrabaria watershed using satellite data.

2. Study area and data
The Jhagrabaria watershed is located in the Allahabad district of state Uttar Pradesh, India (Figure 1). Geologically the area consists of Upper Vindhayan formation consist of mainly sandstone and shale. The elevation is ranging from 85 to 192 m above mean sea level with nearly flat to gently undulated topography and small occasional hillocks. The upland area is covered with loam, except in the south-western part of tehsil Karchhana, where the soil is a mixture of clay and marl. The area has semi-tropical climate as summer and the winter. The area receives about 91% of the total annual rainfall due to southwest monsoon from June to September. The relative humidity is high during the monsoon month (Rawat & Singh, 2017).

3. Materials and methods
3.1. Datasets used
LANDSAT7 ETM+ (path/row: 231/67) was acquired on June 27, 2006 (Table 1). The image was converted to apparent reflectance through an image-based calibration method. Atmospheric correction was performed using Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) algorithm. Image was geometrically rectified using ground control points collected from Survey of India (SOI) topographic sheets using nearest-neighborhood resampling technique and a

![Figure 1. Location of the study area (Jhagrabaria agriculture watershed), U.P., India.](image-url)
Table 1. Specifications of LANDSAT (TM and ETM+) sensors used in the present study.

| Spectral bands | TM (Spatial resolution (meters)) | ETM+ (Spatial resolution (meters)) | TM (Spectral resolution (µm)) | ETM+ (Spectral resolution (µm)) |
|----------------|----------------------------------|-----------------------------------|-------------------------------|--------------------------------|
| 1 (Blue)       | 30                               | 30                                | 0.45–0.52                     | 0.45–0.52                      |
| 2 (Green)      | 30                               | 30                                | 0.52–0.60                     | 0.53–0.61                      |
| 3 (Red)        | 30                               | 30                                | 0.63–0.69                     | 0.63–0.69                      |
| 4 (Near IR)    | 30                               | 30                                | 0.76–0.90                     | 0.78–0.90                      |
| 5 Shortwave Infrared (SWIR) 1 | 30 | 30 | 1.55–1.75 | 1.55–1.75 |
| 6 (Thermal IR)* | 120* (30) | 60 * (30) | 10.4–12.5 | 10.4–12.5 |
| 7 Shortwave Infrared (SWIR) 2 | 30 | 30 | 2.08–2.35 | 2.08–2.35 |
| 8 (Panchromatic)** | 15 | | 0.52–0.90 | |

* TM Band 6 was acquired at 120-meter resolution, but products are resampled to 30-meter pixels.
* ETM+ Band 6 is acquired at 60-meter resolution, but products are resampled to 30-meter pixels.

root-mean-square error with less than one pixel was obtained during the geometric rectification. Land use/land cover (LULC), viz. barren land, fallow land, vegetation, and water bodies/wetlands were identified in the field and their coordinates were recorded with a handheld global positioning system (GPS) device (Garmin eTrexH). The maximum likelihood classifier is a simple and easy to use classification algorithm, in which a pixel with the maximum likelihood is classified into the corresponding class (Singh et al., 2017; Lu et al., 2004). Afterward window 3 × 3 size majority filter was applied to remove the “salt and pepper” noise from classified image.

The need of satellite-estimated precipitation arises because of the non-availability or poorly distributed ground rainfall data. For the work, the daily precipitation data were downloaded from ftp://ftpprd.ncep.noaa.gov/pub/cpc/fews/S.Asia/. Resolution of rainfall estimates are of 0.1 × 0.1 degree and inputs include Global Telecommunication System (GTS) station data, as well as GOES Precipitation Index (GPI) infrared cloud top temperature fields derived from Meteosat and polar-orbiting satellite precipitation estimation data from Special Sensor Microwave/Imager (SSM/I) on board Defense Meteorological Satellite Program and Advanced Microwave Sounding Unit (AMSU-B) on board NOAA15, 16 and 17.

Land surface temperature (LST) is an important parameter in study of water resources. Data available over tile (1100 km x 1100 km) of 2003–2014; the total 495 files, emissivity and quality control (QC) files were downloaded from http://glovis.usgs.gov. LST values were retrieved based on the Split Window algorithm. Hierarchical Data Format (HDF) files of 8-day LST were stacked of each year and study area was subset from tiles and from converted sinusoidal (SIN) to Universal Transverse Mercator (UTM, WGS84) projection in EVNI software. Average 8 days images (spatial and temporal) were used to generate monthly LST. The 8-days India’s LST data for 12 years period (2003–2014) were downloaded and later it were clipped with the administrative boundary of Allahabad district’s study area, LST data were extracted.

The soil map of the Shankargarh block was collected from Soil Survey Department, Allahabad, U.P., India. The map was scanned and then registered with the help of geo-referenced Survey of India (SOI) topographical sheet no. 63 G/11 and 63 G/12, respectively. The registered soil maps were digitized and different soil attributes were assigned to the different soil groups in digital format. In present study, CN map is generated with help of LULC and HSP map, CNII is the CN for normal condition, CNI is the CN for dry condition, CNIII is the CN for wet condition and CN is assigned based on Section 2C-5 – Iowa Storm water Management 2C-5 Manual (2C-5 NRCS TR-55 Methodology) (2008).

3.2. LST role in models

LST data sets are important because five models (TR, CR, KH, JE, and ICAR) out of eight (KH, IDS, DII, TR, CR, ICAR, JE, and LR) models required LST as input data, to predict runoff. Average function was applied to calculate monthly and annual LST. In TR temperature is part of denominator, and it is also under square root function therefore its effective yield will be small, over all denominator will be a small quantity which gives a little fraction of annual rainfall, net result will come as high runoff from TR. In CR temperature is also part of denominator, and it does not has any constrain (like square root function); thus, a good yield will apply in denominator which gives small fraction of annual rainfall, resulting in the overestimation of runoff. KH model reveals a low annual runoff because a major part is subtracted from annual rainfall (T/3.74 (in °C)), and will be a big quantity. From JE model, in denominator temperature has multiple factor of 1.8 additional 32 which will give large number at denominator; therefore, a small yield in JE; Thus, this model have better result from other models being temperature-dependent (TR, CR, KH, and ICAR). ICAR model reveals that temperature is part of denominator and it is also multiplied by another factor which gives a big yield in denominator; therefore, a
less net annual runoff from ICAR. ICAR may be good for a regional area because it is directly dependent on area, slope and other factors that dominate at regional scale. Hence, annual runoff fluctuates if annual mean surface temperature slightly varies because all equations are directly linked to surface temperature.

3.3. Runoff estimation

The SCS-CN method was developed to estimate surface runoff from small agricultural watersheds (USDA-SCS, 1967). The soils have been classified into four hydrologic groups namely A, B, C, and D (USDA, 1986), based on infiltration, soil classification, and other criteria (soil’s surface condition (infiltration rate) and its horizon (transmission rate). Land use and management types have been used in the preparation of hydrological soil-cover complex, which has been utilized in estimating direct runoff. Antecedent Moisture Condition (AMC) is an indicator of watershed wetness and availability of soil moisture storage prior to a storm (Rawat & Singh, 2017). SCS has developed a guide for adjusting CN according to AMC based on total rainfall in the 5 day period preceding a storm. Three levels of AMC: AMC-I (dry), AMC-II (normal), and AMC-III (wet) conditions. The seasonal rainfall limits for these three antecedent moisture conditions (Table 2). Many hydrologists have discussed relationships of precipitation and annual surface runoff with the assumption that physical characteristics of the watershed are constant (Castiglioni et al., 2010). The brief information about the empirical models applied in this study is presented in Tables 3–4.

3.4 Performance evaluation

Model’s performance was evaluated using statistical parameters. The reference values were taken of SCS-CN model. Coefficient of Determination (R², Rawat et al., 2020) describes the dispersion of models vs. SCS-CN model. The Root Mean Square Error (RMSE, Rawat et al., 2020) values define how models overestimate or underestimate the measurements with respect to SCS-CN model. Relative Root Mean Square Error (R-RMSE; Rawat et al., 2020) is a standardization of RMSE. R-RMSE value is expressed in percent and represents the standard variation of the model. The R-RMSE assigns equal weight to any overestimation or underestimation of the statistics. Mean Absolute Error (MAE, Rawat et al., 2020) is a measure of how models are varied from SCS-CN. MAE is a more natural measure of average error and is unambiguous. Percentage Bias (PBIAS; error index for model, Rawat et al., 2019) measures the average tendency of the simulated data to be larger or smaller than their observed from SCS-CN model. Mean Difference (BIAS, Rawat et al., 2020) is difference between model’s value and value from SCS-CN, if difference is zero, it is called unbiased otherwise biased. A low Mean Bias Error (MBE, Rawat et al., 2020) is desired; ideally a zero value of MBE should be obtained. A positive value of MBE shows an over estimate with respect to SCS-CN surface runoff whereas a negative value show an under-estimate with respect to SCS-CN surface runoff.

3.5 Ranking of empirical mathematical models

Factor K was estimated to provide proper weight (Rawat and Singh, 2018) to selected statistical index (all used statistical test) as:

$$K = \left[ \frac{1}{\sum_{n=1}^{n} \left(1/i_n\right)} \right]$$

where, $K$ is factor, $i$ is $i^{th}$ statistical index and $W$ is weight for particular statistical index. Lowest rating model will be on first rank and vice-versa.

4. Results and discussions

4.1 Land use/land cover (LULC)

LULC affects the infiltration, erosion, and evapotranspiration hence, it is an important characteristic of runoff process. Overall 90% accuracy of classified LULC map was achieved. The area of barren land (36.91 km²), fallow land (36.62 km²), and vegetation (74.71 km²) (Figure 2). The fallow and barren land together have the highest area as 48.99% whereas vegetation area is 47.81%. The area exposed for erosion offer high rate of water erosion. Several studies have demonstrated the role of LULC in hydrologic modeling and runoff estimation (Adham et al., 2014; Tedela et al., 2012; Kumar et al., 2018).

| AMC | Total 5 days Antecedent Rainfall (mm) |
|-----|--------------------------------------|
| I   | < 12.7                               |
| II  | 12.7 – 27.9                          |
| III | > 27.9                               |
Table 3. Specification of empirical mathematical models (EMM), the purpose, mathematical expression and references.

| Sr. no. | EMM                                      | Purpose/reason                                                                 | Mathematical Expression                                                                 | Reference                                                                 |
|---------|------------------------------------------|-------------------------------------------------------------------------------|----------------------------------------------------------------------------------------|--------------------------------------------------------------------------|
| 1       | SCS-CN method                            | Developed to estimate surface runoff from small agricultural watersheds      | \[ Q = \frac{P - 0.25S}{0.85 + 0.25} \] (P < 0.25) \[ Q = \text{direct runoff (mm)}, P \text{ total precipitation (mm)}, S \text{ is watershed storage} \] | SCS-CN model in USDA, (1967)                                             |
| 2       | Inglis and De Souza (IDS)                | Plains of Maharashtra region of India                                        | \[ R = \frac{P - 1.75S}{T/10} \] \[ Where, P \text{ is annual precipitation (cm), and } R \text{ is annual runoff (cm)} \] | Mutereja, (1986) Baviishi and Bhagat (2017)                               |
| 3       | Indian Irrigation Department (DII)       | Indian Irrigation Department uses the relationship equation between Rainfall and Runoff | \[ R = P - (1.17 + 0.1S) \] \[ Where, P \text{ is annual precipitation (cm), and } R \text{ is annual runoff (cm)} \] | Praveen Kumar et al. (2016)                                              |
| 4       | Turc relationship (TR)                   | Relationship for watersheds with the area less than 300 km² based on achieved results from doing a study on 254 watersheds in various climatic and weather conditions | \[ R = P - 0.1435 + 0.14T \] \[ Where, P \text{ is annual precipitation (cm), } R \text{ is annual runoff (cm)} \] | Khosravi et al. (2013)                                                   |
| 5       | Coutagne relationship (CR)               | Presented a general relationship                                             | \[ R = P - 0.1435 + 0.14T \] \[ Where, P \text{ is annual precipitation (cm), } R \text{ is annual runoff (cm)} \] | Alizade, (1999) Sadati et al. (2014)                                      |
| 6       | Khasla method (KH)                       | Amount of mean annual runoff                                                 | \[ R = P - 0.1435 + 0.14T \] \[ Where, P \text{ is annual precipitation (cm), } R \text{ is annual runoff (cm)} \] | Golshan and Ebrahimii (2014)                                             |
| 7       | Justin Equation (JE)                     | Estimate runoff with considering parameters such as mean temperature, slope and precipitation in watershed | \[ R = 0.85 + 0.1S^{0.56} - 0.05 \] \[ Where, R \text{ is annual runoff (cm), } P \text{ is mean annual precipitation (cm), } T \text{ is mean annual temperature (°C)}, S \text{ is mean slope of watershed}, H \text{ is elevations of watershed}, A \text{ is the watershed area}\] | Golshan and Ebrahimii (2013)                                             |
| 8       | Indian Council of Agricultural Research (ICAR) | Based on 17 watershed annual runoff in Nilgiri region that was conducted by Indian Council of Agricultural Research | \[ R = 0.85 + 0.1S^{0.56} - 0.05 \] \[ Where, R \text{ is annual runoff (cm), } P \text{ is mean annual precipitation (cm), } T \text{ is mean annual temperature (°C)}, S \text{ is mean slope of watershed}, H \text{ is elevations of watershed}, A \text{ is the watershed area}\] | Sadati et al. (2014)                                                    |
| 9       | Lacey relationship (LR)                  | Lacey an Indian scientist investigated several Indian watersheds to prepare a Lacey equation to estimate annual Runoff | \[ R = 0.1435 + 0.14T \] \[ Where, P \text{ is annual precipitation (cm), } R \text{ is annual runoff (cm)} \] | Baviishi and Bhagat (2017) |
Table 4. Values of F_2 coefficient.

| Catchment area                                      | Duration of rainfall |
|-----------------------------------------------------|----------------------|
|                                                    | Long    | Average | Short |
| Includes shelf, flat plains with deep soils and    | 6       | 4       | 2     |
| vegetation appropriate                             |          |         |       |
| Somewhat flattened with deep soils and             | 2.5     | 1.67    | 0.83  |
| pasture vegetation                                 |          |         |       |
| Relatively high hills with shallow soils and       | 1.5     | 1       | 0.5   |
| vegetation is relatively weak                       |          |         |       |
| Sand, gravel and steep terrain with plenty of      | 0.88    | 0.58    | 0.23  |
| height                                            |          |         |       |
| High and steep rocky terrain with no               | 0.43    | 0.28    | 0.14  |
| vegetation                                        |          |         |       |

4.2. Soil map and hydrological soil group

The soil of the Jhgarbria watershed is of Devra clay soil, Jarkhori sandy loam, Lohgara silty loam, Newaria loamy and stony land (Figure 3(a)). The watershed is mainly dominated by Newaria loam (58.26 km² or 38.82%), Devra clay soils (31.92 km² or 21.27%) and Jarkhori sandy loam soils (27.99 km² or 18.65%). Presence of sand fraction in large quantities under entire watershed makes it vulnerable to soil erosion. The stoniness of the land (14.63 km² or 9.75%) will act as barrier to store water however leading to generate higher amount of runoff (Castiglioni et al., 2010; Fatkhadeh, 2008). The initial infiltration and transmission of surface water into an aquifer system is a function of soil type and its texture. From soil classes, further Hydrologic Soil Group (HSG) (Figure 3(b)) map of study area was developed with guidelines given by Chow et al. (1988).

4.3. Rainfall (2003-2014)

The daily rainfall data of 12 years are illustrated in Figure 4(a-c). These figures show accumulated rainfall over time (per day from 2003 to 2014) and low rainfall (<600 mm) in the year 2004, 2009, and 2010 was observed. This low rainfall in those years leads severe to moderate drought. After year 2004 each year one or more than one rainfall event (~80 mm) exists except year 2008 to 2011. It reveals that maximum rainfall was recorded 118.81 and 120.67 mm, respectively, during 05-Sept-2007 and 05-October-2013. Figure 4(d) (monthly rainfall) showed rainy and non-rainy months (2003–2014), it helps to understand shifting of rainfall pattern. Such types of patterns are absent during 2003 to 2014, however, some non-rainy months with low rainfall amount (April-06 (20.28 mm), May-09 (20.54 mm) and May-011 (13.33 mm) was observed. Whereas few high (Feb-07 (26.57 mm) and Feb-2013 (34.36 mm)) or high (October-2006 (47.04 mm), October-2014 (74.23 mm)) amount of rainfall is also reported. Figure 4(e), represent monsoon season rainfall pattern and year 2004, 2009, and 2010 (low rainfall with respect to average rainfall). Maximum rainfall in last 13 years was recorded for August-2013 as 532.52 mm while minimum rainfall for same year in month of September (except month of September-2008). Based on 12 years rainfall data sets, average rainfall in study area is 199.57 mm (296.1 mm, from IMD web http://www.imd.gov.in/section/climate/climateimp.pdf), which is less (97.53 mm) than from 100 year average monsoon (June, July, August and September) rainfall. Based on 12 years monsoon month rainfall, average rainfall of month of June, July, August, and September are respectively, 139.49 (88.8 mm, from IMD), 251.86 (280 mm, from IMD), 245.73 (296.1 mm from IMD) and 161.21 mm (185.0 mm from IMD). Figure 4(f), illustrates annual rainfall from 2003 to 2014, it represents drought years and particular year rainfall can correlated with particular year crop production. Figure 4(f) also explained the drought years (2004, 2009, and 2010) of study area.

Figure 2. (a). Land use/land cover map of 2006 of study area.
4.4. Land surface temperature (LST)

The 8-days LST was plotted (Figure 5(a-c)) and maximum temperature variation (32.8 to 41.3°C) was noted during 14-April-2010 to 25-Jun-2010 (335th to 344th 8-days). Figure 5(d) shows monthly LST and reveal that average monthly LST eight times cross 35°C limit line during different month of different years, and maximum monthly average LST was noted for during June-2010 as 37.3°C. Due to average function all peak values (in 8-days LST data sets, Figure 5(c)) all value range from 14.5 to 37.28°C, while monthly average mean value is noted as 25.3°C. Figure 5(e), represents annual LST, maximum LST 26.1°C was estimated in the year 2010 and minimum was 24.3°C in the year 2013. Hence, the maximum variation was only 1.8°C in 11 years.

4.5. Runoff from CN method

Figure 6(a-c) shows destitution of CNn at special extent and corresponding histogram showing destitution of CNn at pixel wise (n = I, II, and III) in images. Runoff calculation from SCS model mainly relied on CN value, which is a function of AMC, slope, soil type, and land use. The CN value reflects the possible runoff generation (Rawat & Singh, 2017). Under the same rainfall condition, low value of CN reflect that the land has a high possibility of water-holding capacity. While high value
of CN, precipitation can be held by the land at a small extent. Therefore, any class LULC with high value of CN can generate a high amount of runoff which will cause of flood peak. In SCS model, AMC condition has influence on CN values that’s why CN and AMC conditions are two major factors that can affect the runoff analysis in SCS modeling. Figure 7(a) represents a seasonal trend, the variability in runoff except high runoff during 05-September-07 (90.11 mm, because of high rainfall 118 mm), 05-October-2013 was noted as highest runoff (91 mm) due to highest rainfall (120 mm) during end of monsoon year of 2013. This was special month (October) of last ten years (2003 to 2012) when more rainfall in short time period (near about 135 mm within two days) and in year 2010 less runoff. Figure 7(b) represents monthly monsoon runoff during 2003 to 2014 and showed highest runoff (96 mm and 60.5% of total rainfall (159 mm)) during September-2007, because in August-2007 high amount of rainfall (309 mm) was received (total 16 days rainfall) but only 22% of total rainfall was converted into runoff, it comes as large amount of runoff (60.5% runoff) in next month (September) by 159 mm rainfall. Similarly, for high runoff (55.9% of total rainfall) during June-2005 (because high amount of rainfall receives in last days of previous month (22, 23, 25, 26, 27 29, and 30 May-2005). Figure 7(c) reveals that during year 2013 October rainfall also produces high runoff 51.9% of 293 mm rainfall, this October’s runoff is given key information that a large amount of rainfall after September becomes as runoff because of surface saturation condition. Figure 7(c) graphical representation of annual runoff with rainfall and explain rainfall and runoff yield of 12 months.

## 4.7. Runoff from surface runoff model

Annual runoff was estimated by eight different surface runoff models (KHM, IDS, TR, CR, KH, ICAR, LR and JE). Table 5
describes the comparative runoff results of these models. These eight models were independent of LULC classes, soil categories, and AMC type. These models are only based on annual rainfall and annual temperature. From Table 5, we can easily distinguished two categories, (i) predicted annual runoff was overestimated (CR and KH) and (ii) predicted annual runoff was underestimated (IDS, TR, and ICAR). Predicted runoff of CR model was always overestimated (because in each year the predicted runoff was more than the actual precipitation, like runoff of year 2013 is 34.72% of annual rainfall), therefore, in first screening this model can be discarded. In the same way, KH model also predicted high annual runoff. However, CR and IDS, the remaining models’ runoff predictions are under the acceptable limit (based on % of annual rainfall).

4.8. Statistical performance evaluation

Comparative results of runoff estimation are obtained through statistical tests (Table 6). Statistical results for Khosla’s method ($R^2 = 0.92$, RMSE = 49.83, $R$-RMSE = 2.3, MAE = 47.64, NRMSE = 1.99, MBE = −47.64, PBIAS = −65.58, and BIAS = −2.17) with respect to SCS-CN (RS and GIS-based model) has been rejected based on rating of statistical index method, because it scored high value of 4.911 (Rank = 7) which also indicated that based on only $R^2$ test any model cannot known fully or used as good
predictor or estimator. Because despite of high value of $R^2 = 0.92$, the model comes under rank 7. Statistical results of IDS model (for plain area) with respect to SCS-CN is good because of all statistical tests ($R^2 = 0.89$, RMSE = 7.75, R-RMSE = 0.24, NRMSE = 0.31, PBIAS = 0.01, BIAS = 0.07, MAE = 0.002, and MBE = 0.002, (= 0, almost zero)) result have positive responses with respect to SCS-CN.

Figure 5. (a). Shows an example of the eight days Land SurfaceTemperature (LST) of India from MOD11A2, for 20 July 2014, (b) extracted LST for Allahabad district of Uttar Pradesh State, India. (c). 8-days LST data set of study area for year 2003 to 2014. (d). Monthly LST data set of study area for year 2003 to 2014. (e). Annual LST data set of study area for year 2003 to 2014.
model and the rating process was having the lowest value of 0.008 ($K = 0.001$ with first Rank), furthermore, it revealed that use of this model has satisfactory results compared to SCS-CN model. Similarly, statistical results for JE model showed second ranking. It can be used successfully for the prediction of surface runoff. This may be the reason for adoption of this model by JE. The performance of CR model was also found satisfactory based on $R^2$ test. Other models such as LR (model rank = 3), TR (model rank = 4), ICAR (model rank = 5) and DII (model rank = 6) have lowest value with respect to SCS-CN model. Hence, these
models have limited potential to estimate surface run-off. Significant difference was found among model with respect to SCS-CN (except IDS). Ghazavi and Abasali (2003) did not consider Coutagine method and corrected Langbin method, as suitable method in arid regions. Khosroshahi (1991) has mentioned that the estimation by ICAR is more than observed value; it is more obvious in the agricultural watersheds of more than 200 km². Also, Fatihzadeh (2008) considered classic Coutagine and Turc approaches as non-suitable methods with significant errors. In this research, according to the results of statistical tests JE method was introduced as the best method after Inglis & De Souza (IDS) method, for runoff estimation in the study area. The advantage of IDS model is as simple and not affected by any factors related to slope, type of LULC, soil hydrological group, time interval of precipitation and physical characteristics of agricultural watershed.

5. Conclusion

Runoff estimation of ungauged watershed is a challenge for hydrologists. Discharge value of ungauged catchments is important for hydrological planning and designing of various hydraulic structures. Precise knowledge about the runoff will help in better management of water resources of the local region. It is difficult to estimate the runoff more accurately from ungauged watershed with coarse resolution satellite data due to high uncertainty. SCS-CN model requires input of LULC, soil data, and rainfall that can be
obtained from satellite hence it easily provides the runoff estimation at macro level. Still there is need of some other simple alternate model for estimating annual runoff from ungauged agricultural watershed. That can provide runoff estimate close to SCS-CN model. In this context present study reveals that Inglis & De Souza (IDS) model is a simple and good alternative of SCS-CN model. It can serve the purpose of runoff estimation from ungauged watersheds. IDS model required input of annual rainfall data. This can be generated from automatic weather station or satellite-based freely available data. The major drawback of all the empirical models except SCS-CN is estimation of runoff on annual basis. Still these models provide reliable information about the runoff. This information can be utilized by the planners and policy makers for management and designing purposes.

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Disclosure statement

No potential conflict of interest was reported by the authors.

| Table 5. Runoff estimated from different empirical model. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| S. No | Years | A. T (°C) | A. R (cm) | SCS-CN | KH | IDS | DII | TR | CR | ICAR | JE | LR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2003 | 24.79 | 93.89 | 22.58 | 81.97 | 28.13 | 35.73 | 11.26 | 2064 | 10.37 | 23.11 | 14.62 |
| 2 | 2004 | 24.71 | 56.29 | 9.04 | 44.41 | 8.53 | 18.83 | 4.34 | 744 | 4.99 | 8.32 | 5.61 |
| 3 | 2005 | 25.80 | 84.77 | 31.86 | 72.36 | 22.35 | 31.50 | 8.87 | 1629 | 8.49 | 18.40 | 12.10 |
| 4 | 2006 | 25.93 | 65.27 | 16.99 | 52.38 | 12.2 | 22.73 | 5.35 | 962 | 5.79 | 10.88 | 7.42 |
| 5 | 2007 | 24.91 | 72.32 | 20.6 | 60.34 | 15.52 | 25.85 | 6.96 | 1220 | 7.08 | 13.67 | 9.00 |
| 6 | 2008 | 24.90 | 107.64 | 36.43 | 95.66 | 38.07 | 42.22 | 14.21 | 2703 | 12.56 | 30.29 | 18.79 |
| 7 | 2009 | 25.94 | 57.20 | 14.51 | 44.72 | 8.87 | 19.22 | 4.1 | 738 | 8.35 | 8.23 | 5.78 |
| 8 | 2010 | 26.14 | 59.77 | 10.87 | 47.2 | 9.88 | 20.33 | 4.42 | 801 | 5.04 | 9.08 | 6.28 |
| 9 | 2011 | 25.44 | 112.10 | 40.61 | 99.86 | 41.62 | 44.36 | 14.82 | 2881 | 12.93 | 32.44 | 20.23 |
| 10 | 2012 | 25.13 | 89.71 | 24.5 | 77.62 | 25.4 | 33.78 | 10.2 | 1863 | 9.54 | 20.93 | 13.44 |
| 11 | 2013 | 24.34 | 146.08 | 51.63 | 134.38 | 73.78 | 61.02 | 24.29 | 5073 | 20.10 | 56.54 | 32.58 |
| 12 | 2014 | 24.79 | 72.60 | 20.42 | 60.4 | 15.66 | 25.98 | 6.82 | 1211 | 6.95 | 13.63 | 9.06 |

Annual Temperature (in °C) from MODIS, A.T; Annual Rainfall (in cm) from NOAA, A.R; KH; Khosla; IDS, Inglis & De Souza; DII, Department of Irrigation, India; TR, Turc relationship; CR, Coutagne relationship; ICAR, Indian Council of Agricultural Research; JE, Justin Equation; LR, Lacey Relationship; M, Model.

| Table 6. Statistical test values for different empirical model with respect to SCS-CN. |
|---|---|---|---|---|---|---|---|---|---|---|
| S. No | Test | IDS | JE | LR | CR | TR | ICAR | DII | KH | CR |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | R² | 0.89 | 0.89 | 0.90 | 0.90 | 0.90 | 0.92 | 0.92 | 0.90 | 0.88 |
| 2 | RMSE | 7.75 | 6.43 | 13.32 | 16.95 | 17.99 | 7.60 | 49.83 | 2158.82 |
| 3 | R-RMSE | 0.24 | 0.27 | 0.50 | 0.62 | 0.63 | 0.49 | 2.30 | 70.88 |
| 4 | MAE | 0.00 | 4.53 | 12.09 | 15.37 | 15.95 | 6.79 | 47.64 | 1799.10 |
| 5 | NRMSE | 0.31 | 0.26 | 0.53 | 0.68 | 0.72 | 0.30 | 1.99 | 86.34 |
| 6 | MBE | 0.00 | 0.53 | 12.09 | 15.37 | 15.95 | 6.79 | 47.64 | 1799.10 |
| 7 | PBIAS | 0.01 | 22.15 | 93.69 | 159.45 | 176.26 | −21.36 | −65.58 | −98.63 |
| 8 | RMSE% | 2.58 | 2.14 | 4.44 | 5.65 | 6.00 | 2.53 | 16.61 | 719.52 |
| 9 | BIAS | 0.07 | 0.21 | 0.49 | 0.62 | 0.62 | −0.38 | −2.17 | −69.33 |
| 10 | K factor | 0.00 | 0.07 | 0.13 | 0.16 | 0.16 | 0.23 | 0.61 | 0.88 |
| 11 | Rating | 0.01 | 0.35 | 1.06 | 1.29 | 1.32 | 1.88 | 4.91 | 7.04 |
| 12 | MR | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |

Note:- Coefficient of Determination, R²: Root Mean Square Error, RMSE: Relative Root Mean Square Error, R-RMSE: Mean Absolute Error, MAE: Normalized root mean square error, NRMSE; Mean bias error, MBE; RMSE%; Percentage RMSE; bias, BIAS: Mean difference bias, Model Rank, MR.

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