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Identification of Prospective Surface Water Available Zones with Multi Criteria Decision Approach in Kushkarani River Basin of Eastern India

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Authors' contributions

This work was carried out in collaboration between both authors. Author SP initially designed the study, wrote the methodology and analysis part. Mapping design is also done by him. Author SK prepared the map and collected secondary and primary data as used here. She supported a lot to the referencing part of this work. She also contributed in the discussion part. Both authors read and approved the final manuscript.

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ABSTRACT

Present paper mainly intends to find out suitable sites for surface water harvesting in Kushkarani river basin a tributary of Mayurakshi river of Eastern India. For this multiparametric potential surface water availability model and SCS CN based runoff depth models have been prepared in soft ware environments. Both unweighted and weighted linear combination methods are used for compositing the selected parameters. Results show that 14.18% of a total basin area (172 sq. km.) characterised by very high surface water potential is mainly concentrated in the confluence segment of the river followed by high potential zone covering 22.47% area. Unweighted composting model based estimation shows that very high and high surface water potential zone cover 8.22% and 21.95% of basin area, but areal extent in these two classes is little bit lower than the results obtained from weighted composting model. Field based discharge measurement validates the surface water potential zones. Similarly, Discharge availability in the rivers of different

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potential zones are also indicating very accordant result and validating the surface water runoff models. SCS CN based runoff depth model represents that 9.32% area covers very high runoff depth (657 mm. to 693 mm). Calculated Relative error value and Nash-Sutcliffe efficiency values are respectively 53.65% and 0. 6782 which represent that runoff model is not highly optimum but it is within the range of acceptability. Correlation coefficient value between monsoon runoff depth and surface water potentiality (r=0.6453) is high and it is significant at 0.01 level of significance which does indicate both the models are highlighting result in same direction. For validating these models with field based discharge data, it is noticed that discharge data strongly controls surface water availability (R^2=0.962) and runoff depth (R^2=0.970). From the models it is proved that specifically, confluence segment and very proximate riparian low land of the rivers is selected as suitable sites for surface water harvesting.

Keywords: Surface water potentiality; runoff depth model; discharge measurement; validation of models; suitable sites and surface water harvesting.

1. INTRODUCTION

Water scarcity is likely to be one of the main haunting problems, resulting from combined effects of alterations in the hydrological cycle, anticipated under climate change, and of the increase in water demands for agriculture, urban and industries [1,2]. High population density (756/sq.km. as per Census of India, 2011) and soaring growth of population (1.57%) in the study area is the principal cause behind growing demand of agricultural goods in the study area. To meet the need, in last 40 years, agricultural growth has reached to 4-5% and cropping intensity has raised to 176% [3]. The country like India is highly characterized by seasonal and partially temporal variability of rainfall [4] and this area possesses even more seasonal variability of rainfall. Out of total rainfall, 82% rainfall occurs during June to September [5]. In this high time of rainfall only one crop can be yielded. Rest other cropping intensity is highly supported by irrigation based water supply. Out of total irrigated area 52% irrigated area is served by ground water based irrigation schemes [6] and over time ground water extraction rate for irrigation has been going rise and thereby make the ground water resource scare [7] force ground water table far below ground level (bgl) [8,9]. Events of the failure of ground water extraction by the shallow tube wells established the fact of ground water level is lowering down with very significant scale [10].

In such condition, locating suitable sites for surface water banking and harvesting are essential task for supporting surface water based irrigation projects and sustenance of agricultural production in the study area. The region possesses 234 km. stream length with stream density of 1.41/sq.km. It indicates there is a high potentiality of surface water availability as runoff. But the entire river basin is not potential for supplying surface water for irrigation. Disparity in stream concentration over space and order of stream usually make a huge difference in surface water availability. For example, stream concentration is high in the upper catchment but most of the streams are either 1st and 2nd orders and therefore water potentiality is very meager.

Present paper attempts to find out the surface water potential sites using multi criteria weighted linear combination (WCL) score in GIS and RS soft wares environment. WLC is done following different approaches as described in method section. In this study tried to validate potential surface water models with discharge data collected from different stream sites and junction sites of various potential water available zones. Apart from this Soil conservation Service Curve Number method is also applied for estimating amount of surface runoff. The SCS CN method is simple and produces better results [11-15]. For simplicity and reliability of this method many researcher used it for runoff estimation. Zhan and Huang [16], Tessema et al. [17], Awadallah et al. [18], Khare et al. [19] have performed this method in GIS environment. In India, Nayak and Jaisawal [20] developed a good correlation between measured and estimated run-off using GIS and SCS CN model. They said that GIS is an effective tool for constructing SCS CN model with maximum input data. In present study SCS CN based surface runoff model is also tried to build up in for the same purpose. Effective runoff depth is calculated from SCS CN based runoff depth model as far the evaporation loss is strongly concerned. Researcher discussed in their study impact of evapotranspiration on runoff and water availability in arid and semiarid plateau region [21].

Applications of remote sensing and GIS for the exploration of groundwater potential zones [22-27] delineation of spatial saturated areas and wetness index [28,29] land use suitability for defining suitable habitat for animal and plant species [30,31], geological favorability [32], suitability of land for agricultural activities [33-35], landscape evaluation and planning [36], environmental impact assessment [37], selecting the best site for the public and private sector facilities [38,39], and regional planning [40] including a number of criteria have been performed and they produced amazing results for concerned decision support. SCS Curve Number [41] based identification of surface water potential zone is also performed by many scholars like Rao et al. and Ramakrishnan et al. [42,43]. This attempt is also useful toward the aim set in this present paper.

2. STUDY AREA

Kushkarani river is an upper catchment tributary of Mayurakshi River situated in Birbhum district of West Bengal and Jamtara district of Jharkhand. The basin is demarcated by 23°54' 36" N. to 24° N. latitudes and 87°14'24" E. to 87°30' E. longitudes with a total area of 172 sq. km. (see Fig. 1). The east-west elongated basin of the 35 km. long river is physiographically situated in the eastern margin of the Chhotonagpur plateau, where the highest elevation (155 metres) is seen in the western side near the source of the river and lowest elevation (62 metres) is seen in the eastern side near its confluence where at present Tilpara barrage and consequent reservoir is located (23°56'46.91″N. lat. and 87°31'30.73″E long.) (see Fig. 1). Maximum area of the basin is occupied by undulated topography with an average elevation of 108 metres. On an average 120 metres contour roughly demarcates upper catchment, 80 metres contour delimits middle and lower catchments. Entire basin area comes under rarh tract [44] with secondary laterite formation [45] mainly carried by some of the rivers like Kushkarani coming from Chottanagpur plateau [46-48]. Average slope, measured as per Wentworth's method [49], is 3% to 5% whereas it is <1% in the confluence segment. Geologically 90% of the basin area is composed with granitic gneissic rock of Plesitocene age (50 lakh years old) overlain by coarse grain lateritic soil and a few isolated patches covering 08% and 02% area of the lower catchment is made with older and newer alluvium respectively of Holocene period over granitic basement (Fig. 1) (GSI 1985). Just below 4 km. below the confluence point Farakka-Midnapore fault passes through. Average annual rainfall of this basin as gauged by Suri meteorological station is 1444.432 mm. High degree of seasonality of rainfall is reflected by 82% rainfall during the months of June to September. Rainfall analysis since 1980 to 2013 focused that there is no significant trend of rainfall as also indicated by linear regression model (y -2.137x+5704) and coefficient of determination (R^2 = 0.005). This trend is identical with the general trend of rainfall in India as estimated by many a scholars. Parthasarathy et al. [50], reported that in all India scale there is no significant change of rainfall in last 110 years excepts few regional pockets. Average potential evaporation of this area since 1901 to 2014 is 73.45 mm./year [51] which indicates one of the controlling factors of surface water.

Most part of the basin is characterized by coarse grain laterite soil with ferruginous nodules, feldspar nodule. In some parts older alluvium admixed with reddish laterite overlain granite gneiss regolith. These soil are very susceptible to erosion and supply substantial amount of sediment to the channel. Extreme confluence segment is characterized by newer alluvium lying over older alluvium and it is because of frequent flooding in response to the water balance to the Tilpara reservoir which is located over Mayurakshi river. Reservoir effects have created back water not only within channel but astride lowlands (see Fig. 1). Backwater effects influence up to 4 km. upstream of Kushkarani river which is the present area of interest.

Total 292 stream segments have identified out of which 224 belongs to 1st order, 55 belong to 2nd order, 12 stream segments belong to 3rd order, and 1 belongs to 4th order. Mean bifurcation ratio of this basin is 4.027. Very less form factor (F=0.268) indicates elongated river basin. Drainage frequency, density, texture are respectively 1.695/sq.km., 1.76 km/sq.km and 4.36. Index of areal asymmetry (Aa=0.754) indicates asymmetry in area distribution in two sides of the main channel is existing but its degree is very marginal. Hypsometric integral (HI) is 0.38 does indicate the basin is passing through old stage. Positive base level change due to positioning of Tilpara reservoir can shorten cyclic time of this basin.

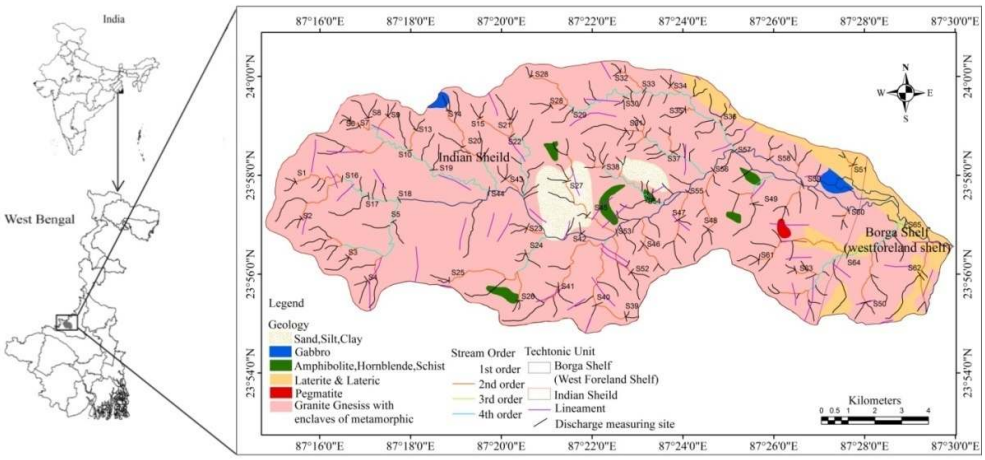

Fig. 1. Study map

3. MATERIALS AND METHODS

For constructing surface water potential zone, thirteen parameters have been considered and their concerned sources are mentioned in Table 1. Data layer used for making SCS CN based runoff model is also mentioned in same table.

3.1 Methods for Surface Water Potential Models

For nearly two decades, a number of multi-attribute (or multi-criteria) evaluation methods have been implemented in the GIS environment for land suitability evaluation, including WLC and its variants [52,53] and the analytic hierarchy process [54]. There are two fundamental classes of multicriteria evaluation methods in GIS: the Boolean overlay operations (noncompensatory combination rules) and the weighted linear combination (WLC) methods (compensatory combination rules). They have been the most often used approaches for different sorts of land-use suitability analysis [55-59]. These approaches can be generalized within the framework of the ordered weighted averaging (OWA) [60-64].

The WLC is a simple additive weighting based on the concept of a weighted average [65]. The decision maker directly assigns weights of 'relative importance" to each attribute map layer. A total score is then obtained for each alternative by multiplying the importance weight assigned for each attribute by the scaled value given to the alternative on that attribute, and summing the products over all attributes. OWA is a family of multicriteria combination procedures [66]. It involves two sets of weights: the weights of relative criterion importance and the order (or OWA) weights. Although OWA is a relatively new concept [55], there have been several applications of this approach in the GIS environment [61,67-73]. All those applications use the conventional (quantitative) OWA. Specifically, research into GIS, OWA has so far focused on the procedures that require quantitative specification of the parameters associated with the OWA operators.

In the present study thirteen parameters with their spatial pattern have been selected as map layers (see Table 2) Each attribute (map layer) is categorized into 10 classes ranking 1 to 10 (adopting 10 point scale) considering the fact that greater rank will reflect greater potentiality of getting surface water. To fulfill this purpose, all the attributes have been reclassified into 10 classes and ranked accordingly. The logic behind ranking to intra attribute classes from 1-10 is described in Table 2. Weightage of each attribute has been defined objectively (see Table 2) considering the role of those in the study area. The logic behind this consideration is that highly correlated parameter maximally explains the spatial variation of temperature. Normalization of respective weight (values of r for respective parameters) based on dimension index has been done for frame it in a scientific scale. The result of each normalized value is called attribute weight. Weights of the parameters for different season in respective years are different due to having some dynamic variables like land use, canopy coverage etc. Therefore nine prospective models have been articulated for different seasons in the selected years.

Table 1. Spatial parameters and their sources

Parameters	Sources
Drainage frequency, drainage density, slope, sinuosity and pond frequency	Toposheets, Survey of India and Google Image
Weighted junction score	Computed from stream junction map after Pal, 2014
Land use land cover (LULC)	Sensor: Landsat 8 (OLI), Feb., 2014 (Path/Row:139/43; Band used: G, R, NIR; Spatial resolution: 30 m.), Land use map, 2014 of Land reform Deptt., West Bengal
Seasonal and temporal ground water table (GWT)	Central Ground Water Board and State Water Investigating Directorate, 2015
Soil Texture/ soil type	Soil texture map prepared by NIC Birbhum District Centre
Junction buffer and stream line buffer	Prepared from base maps using GIS
Relief parameter	Derived from SRTM data (USGS)
Rainfall	Directorate of Agriculture West Bengal

Expression of weight calculation is as follows:

$$w_j = \frac{a_{j_r}}{\sum_{j=1}^{n} j_r}$$

wj=weight of jth parameter; ajr= correlation coefficient of jth attribute; Σjr = summation of correlation of all jth variable.

Rank of all sub classes under each attribute is then multiplied by the defined weight of each individual attribute. This function can be presented using the following formula.

$$\text{WLC} = \sum_{j=1}^{n} a_{ij} w_j$$

Where, aij= ith rank of jth attribute; wj= weightage of jth attribute.

This weighted linear combination has been done using raster calculator tool in Arc GIS environment.

Apart from weighted linear combination, same data layers have also used for simple linear combination. This is done for assessing the degree of variation yielded from weighted compositing.

$$\text{LC} = \sum_{j=1}^{n} a_{ij}$$

Where, aij= ith rank of jth attribute

3.2 Methods for Constructing Employed Data Layers

Each data layer has been constructed in GIS environment using the following methods i.e. drainage frequency and density after Horton [82]. Average slope and classification of relief have been constructed from SRTM data. Land use land cover (LULC) map has been constructed based on Landsat image based supervised image classification in ERDAS Imagine soft ware. The accuracy assessment for supervised technique has made through a confusion or error matrix. Kappa statistics is also calculated for assessing suitability of supervised classification. Total 100 sample sites from Google earth and ground verification are selected for accuracy assessment. The accuracy assessment generated from the supervised classification technique showed an overall classification accuracy was 86.0% with Kappa Statistic of 0.838, which indicates a good agreement between thematic maps generated from image and the reference data. This amount of agreement is generally considered a good statistical return. However, the accuracy of supervised classification is less than 85 %, which is below the acceptable level and standard of digital image classification for optical remote sensing data recommended by Jansen et al. [83]. Agriculture class shows that accuracy level of this class ranges from 77.77% to 91.66%. However, from the result it is found that all land covers classes are classified much better in this supervised approach. Junction buffer and stream line buffer layer have been made using distance mapping techniques in Arc Gis environment.

Table 2. Scaling of parameters, logic behind and their weights based on PCA

Parameters	Scaling	Logic behind scaling	Total correlation score (Xi)	Weighted score (Xi/Ximax)
1. Drainage frequency	10 rank at highest drainage frequency	Surface water potentiality is high at higher frequency class	2.93	0.59
2. Drainage density	10 rank at highest drainage density	High drainage density indicates higher surface water availability.	3.23	0.65
3. Slope	10 rank at low slope	Gentle slope is favorable for stagnating more surface water [74]	4.61	0.93
4. Weighted junction score	10 rank at maximum junction score	Maximum weighted junction is conducive of surface water availability [75]	2.39	0.48
5.LULC	10 rank at healthy water body and vegetation	Healthy vegetation retains maximum water [76]	1.71	0.35
6. GWL fluctuation (temporal)	10 rank at lowest value	Little fluctuation indicates consistency in water level; stable ground water level can support surface water availability [77]	4.32	0.87
7. GWT fluctuation (seasonal)	10 rank at lowest value	Low seasonal fluctuation indicate high level saturation of the upper layer and therefore, chance of water stagnation over surface increases [77]	4.45	0.90
8. Soil texture	10 rank at lowest value	Fine textured soil arrests maximum water [78,79]	1.74	0.35
9. Regional sinuosity	10 rank at highest value	More sinuosity indicates greater length of stream and associated with plain land [80]	2.03	0.41
10. Junction buffer	10 rank at lowest distance	Proximate junction carries high water potentiality	3.24	0.65
11. Stream line buffer	10 rank at lowest distance	Adjacent area of streams possesses high potentiality of water	3.08	0.62
12. Pond frequency	10 rank at highest value	Maximum number of ponds indicate high surface water availability	2.67	0.54
13. Relief	10 rank at lowest value	Low lying area in a basin indicates more surface water potentiality [81]	4.96	1

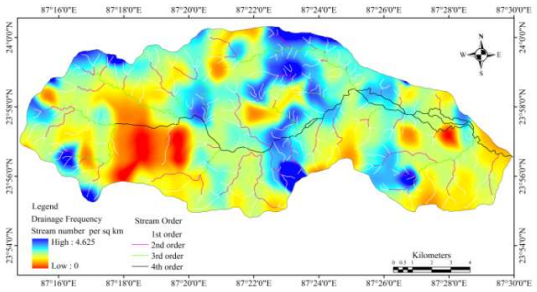

Fig. 2a. Drainage frequency

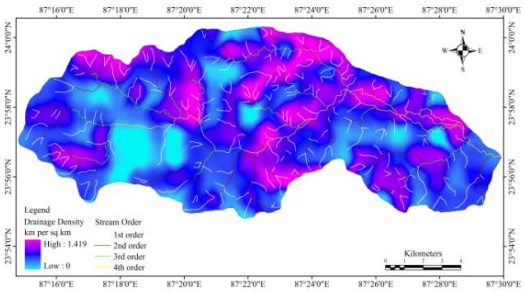

Fig. 2b. Drainage density

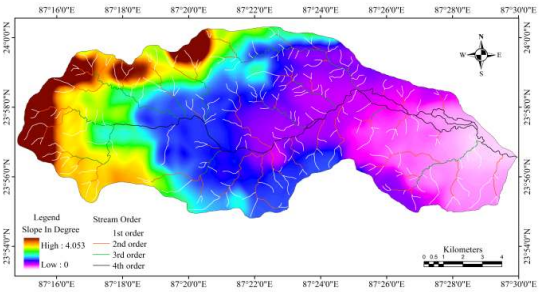

Fig. 2c. Slope map

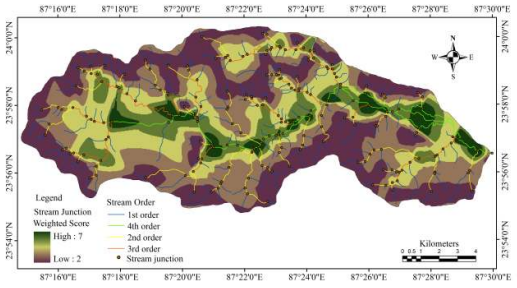

Fig. 2d. Weighted junction score

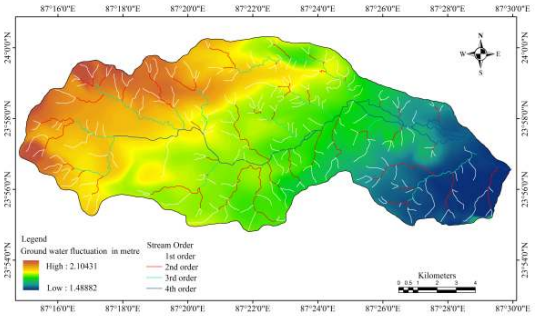

Fig. 2e. Temporal GWT fluctuation (Aug 1990-2014)

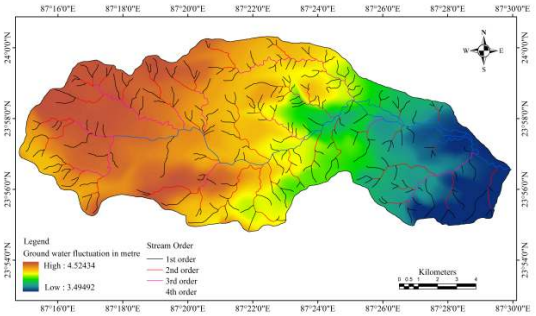

Fig. 2f. Seasonal GWT fluctuation (May-Aug 2014)

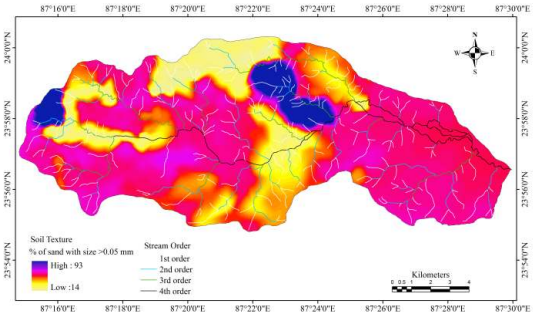

Fig. 2g. Soil texture

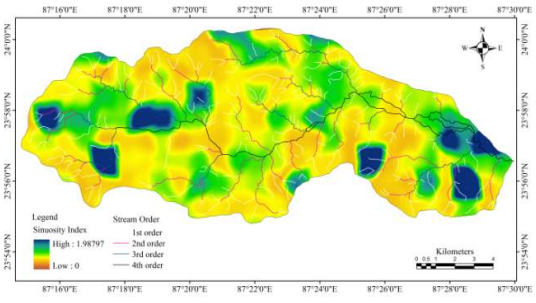

Fig. 2h. Regional sinuosity index

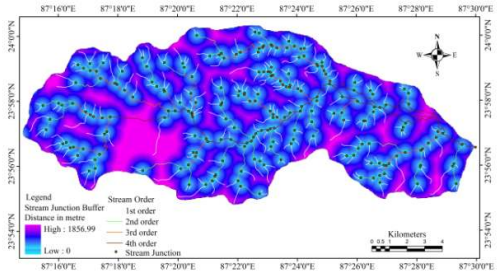

Fig. 2i. Stream junction buffer

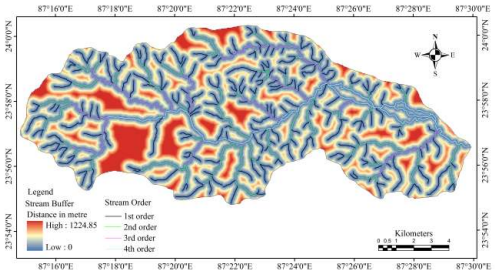

Fig. 2j. Stream line buffer

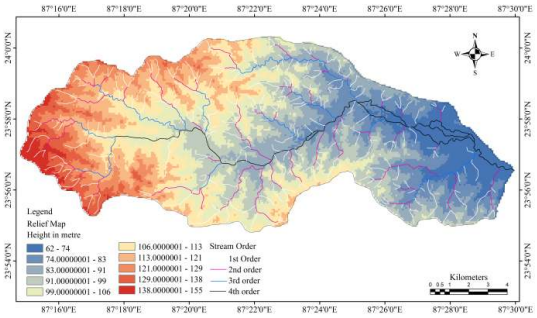

Fig. 2k. Relief map

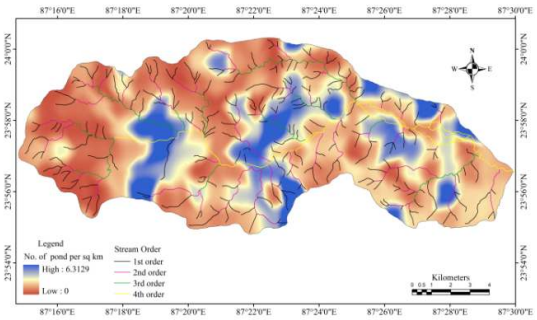

Fig. 2l. Pond frequency

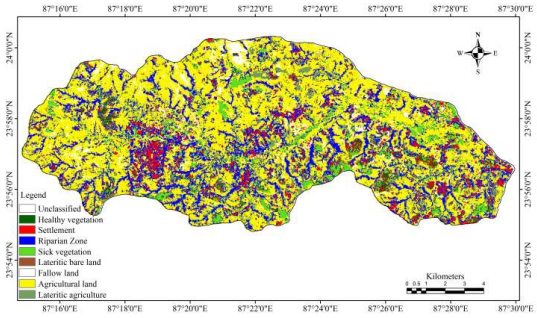

Fig. 2m. LULC

3.3 Method for Estimating Surface Runoff

The SCS model computes direct runoff through an empirical equation that required the rainfall and a watershed co-efficient as input. The watershed co-efficient is called the curve number (CN) which represents the runoff potential of the hydrologic soil cover complexes. The SCS model [84] involves relationships between land cover, hydrologic soil classes and curve number. The equation 1 is used to calculate the surface runoff of a watershed and it is aptly used for small watershed [85].

$$Q = (P - Ia)^2 / (P - Ia + S) \quad (1)$$

Where,

Q is actual surface runoff in mm,
P is rainfall in mm.

For capturing the seasonal variation of initial abstraction Ia should be considered different. Here, for annual runoff modeling, Ia is taken as 0.3S, for monsoon season it is 0.3S and for premonsoon it is 2S. following Lawrence et al. [86] annual Ia is 0.1S [Initial abstraction (mm) or losses of water before runoff begins by soil and vegetation (such as infiltration, or rainfall interception by vegetation)].

S is the potential maximum retention in mm and is calculated using the equation 2.

$$S = (25400 / CN) - 254 \quad (2)$$

Both annual and seasonal runoff depth have been calculated from annual and seasonal rainfall data layers. In earlier section it is mentioned that out of total rain more than 80% rainfall occurs during monsoon period. To capture the impact of seasonal rainfall on runoff, runoff models have been constructed season wise. In runoff model, emphasis is given only on input factors but out factors like evaporation have not considered. Considering this fact effective runoff depth has been calculated deducting evaporation from runoff model.

3.3.1 Discharge data derivation and validation of models

Discharge at different surface water potential zones at different order streams have been measured both during pre and post monsoon. Discharge is measured at 65 sites and stratified sampling technique has been applied to allocate number of sample at different potential zones. Discharge data of different surface water potential zone is corroborated and tried to capture whether discharge data is high at very high or high surface water potential zone. It is considered that if the hypothesis is valid certainly the model will also be validated.

3.3.2 Model validation and runoff predication

The measured runoff is compared with calculated runoff by the SCS-CN model. Subsequently, the applicability of the model is evaluated by testing the relative error (RE) and Nash-Sutcliffe efficiency (NSE) [87], both of which are widely used in evaluation of model performance [88].

$$RE = \frac{\left(Q_i^{cal} - Q_i^{obs}\right)}{Q_i^{obs}} \times 100\%$$

$$NSE = 1 - \frac{\sum_{i=1}^{n} (Q_i^{obs} - Q_i^{cal})^2}{\sum_{i=1}^{n} \left(Q_i^{cal} - Q_{mean}^{obs}\right)^2}$$

where $Q^{obs}{}_i$ is the ith observation of runoff, $Q^{cal}{}_i$ is the ith calculated runoff by the SCS-CN model, Q^{obs} mean is the mean value of observed runoff, and n is the total number of observations. RE value nearer to 0 indicates high optimality of the model performances. More observed value over calculated value yields negative value. NSE ranges between −∞ and 1, with NSE = 1 being the optimal value. Values of NSE between 0 and 1 are generally viewed as acceptable levels of performance, whereas a value of NSE < 0 indicates that the mean observed value is a better predictor than the simulated value, which indicates unacceptable performance [88].

4. RESULTS AND ANALYSIS

Both simple and weighted composite surface water availability have been constructed and presented in Figs. 3-4. Figs. 3a and 3b respectively show the simple linear combination based continuous and classified water potential models. Figs. 4a and 4b present the continuous and classified WCL based surface water potential models respectively. Figs. 5a and 6b respectively represent the raster calculators where simple and weighted compositing of the selected parameters have done for generation of models. Tables 3 and 4 depicts the absolute and proportion of area under different potential water availability classes. From the WCL model it is found that out of total area 24.44sq.km or 14.18526% area is characterized by very high potential surface water availability followed by high potentiality 22.48% to total area. 42.40% area is characterized by potential low to very low water availability zones. Potential surface water dearth zone is located at the upper catchment area or gully head zones where slope is relatively stepper (>3.5°), drainage density is low (0.4 km./ sq.km.), temporal water level fluctuation is relatively high (>1.75 m.). Confluence part of the basin where potential surface water available zone is found is characterized by low altitude (<74 m.), mild slope (<0.4°), regional sinuosity is >1.6, drainage density ranges from 0.4-0.8 km./ sq.km., temporal water level fluctuation is <1.5 m. in last 25 years and relatively finer soil texture (<45% sand with diameter greater than 0.05 mm.). A small depression is also found in this zone where at present Tilpara barrage stores water. Lower part of the basin, very adjacent part of the stream and stream junctions are highly viable areas for harvesting surface water. Agricultural viability is more in this area than upper catchment due to relatively better surface hydrological conditions prevail there on. Surface water support and high soil moisture (>16%) in the pre monsoon months are also some favourable vectors in this regard.

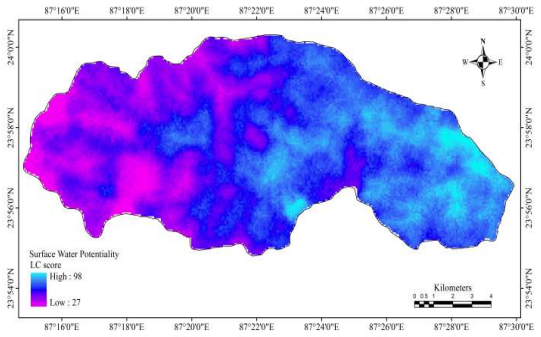

Fig. 3a. Composite surface water potentiality

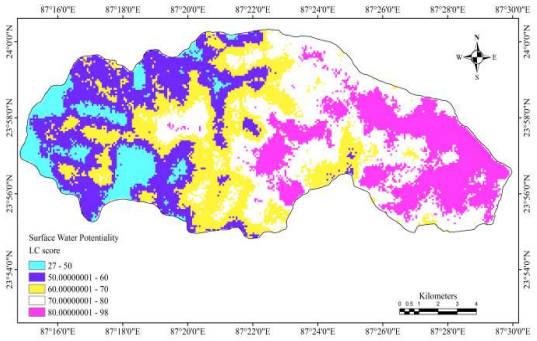

Fig. 3b. Classified surface water potentiality

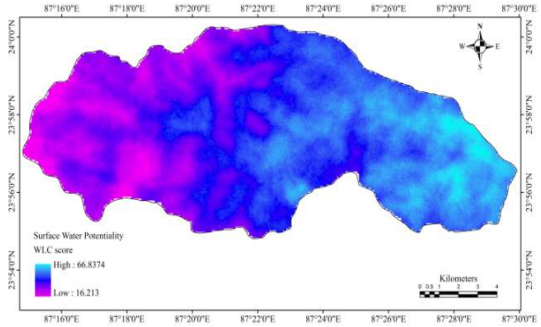

Fig. 4a. Weighted composite surface water potentiality

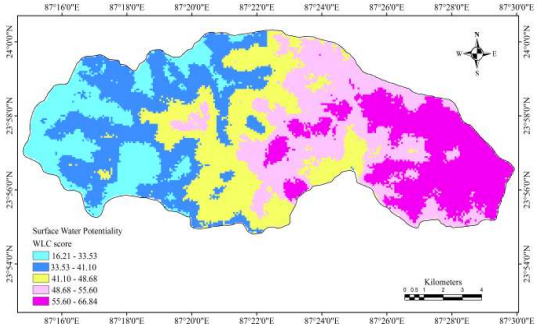

Fig. 4b. Weighted classified surface water potentiality

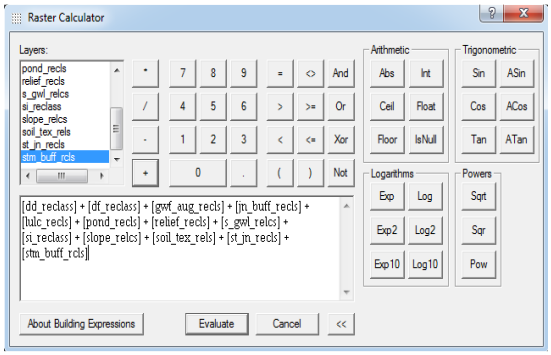

Fig. 5a. Raster calculator with LC of the parameters

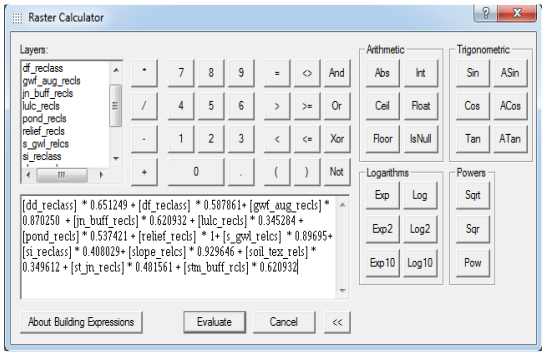

Fig. 5b. Shows the raster calculator with WCL of the parameters

Table 3. Area under different surface water suitability zones (based on un weighted composite score)

Water availability status	Classified score	Number of pixel	Area (sq.km.)	% to total area
Very low	27 - 50	20363	14.16	8.22
Low	50 - 60	17317	37.82	21.95
Moderate	60 - 70	17288	38.05	22.08
High	70 - 80	15963	48.34	28.05
Very high	80 - 98	17817	33.94	19.69

Table 4. Area under different surface water suitability zones (based on weighted composite score)

Suitability status	Weighted composite score	Area extent (sq.km)	% to total area
Very high potentiality	16.21 - 33.53	24.44	14.19
High potentiality	33.53 - 41.12	38.73	22.48
Moderate potentiality	41.12 - 48.69	36.05	20.92
Low potentiality	48.69 - 55.60	38.97	22.61
Very low potentiality	55.60 - 66.84	34.11	19.80

Comparison of results yielded from LC and WLC models it is found that only 13.5% spatial deviation is found. Areal position in LC model of any class is quite scattered than WLC model. Very high potential zone in WLC model is rather clustered than rest one but areal deviation is only 2.1%. So, application of LC model will not be so wrong.

Table 5. Shows the Pearson's correlation coefficient between deriving factors and surface water availability zones

Parameters	Correlation value
Relief	0.90805**
Temporal ground water fluctuation	0.83075**
Seasonal ground water fluctuation	0.85051**
Slope	0.84400**
Drainage density	0.38678**
Drainage frequency	0.27564*
Weighted junction score	0.37889**
Pond	0.31093**

*** r values are significant at 0.01 level and*
** value is significant at 0.05 level*

4.1 Driving Factors

Pearson's correlation between WLC model and regulating factors has been calculated for detecting dominant driving factor. It is detected that relief parameter is most dominant regulatory factor (r= 0.908) followed by ground water fluctuation (r=0.85), slope (r=0.84) etc. (see Table 5). Drainage parameters are also significantly associated with surface water availability but degree is relatively lower than relief parameters. Stream frequency and density are high in the upper catchment but most of the streams are either 1st or 2nd order and carries water seasonally. Therefore, its degree of association with surface water availability is little bit low. Changes of forest cover and runoff modification is one of the important issues discussed by many a scholars in recent time [89,90]. From this study, it is found that sick vegetation allows more surface water potentiality runoff (52.826 mm.) than healthier vegetation (43.1914 mm.). It is quite unique but rainfall pattern compels to reflect so. From principal component analysis, it is detected that relief parameter explain 51.4% of the variability of potential surface water availability.

4.2 Estimation of Runoff Volume for Kuskarani Watershed

Figs. 6-8 respectively present the curve number, potential retention capacity and initial abstraction (Ia) which are required for constructing runoff model(s). Curve number of this basin ranges from 70-92 (Fig. 6) and weighted CN of the basin as whole is 67-87. CN is high in the lower part of the basin which is characterized by relatively finer soil, some parts are covered with vegetation, crop land and grass land. Fig. 7 illustrates the spatial maximum retention capacity of the basin where high potential retention is recorded upper part of the basin. Fig. 8 shows that average initial abstraction ranges from 6.6-30.9 mm. with an average of 18.75. Maximum initial abstraction (>24 mm.) is noticed in the upper catchment. Coarser and bare soils are the major vector for such high abstraction. Estimated average annual runoff depth in Kuskarani watershed is 1362.07 mm. and it varies from 1291.09 mm. to 1434.92 mm. over the basin (Fig. 9a) according to the nature of distribution of CN. Fig. 10a shows the continuous runoff depth model and Fig. 9b and Table 6 represents the classified runoff pattern and their respective area. From Table 6 it is clear that 11.27% and 25.58% area of the total basin area is characterized by very high (1393.36mm. to 1434.92 mm.) and high (1372.23 mm.-1393.96 mm.) runoff depth zones respectively and these are mostly located in the lower, lower middle and left wings of the main river. Spatial rainfall association is one of the main reasons behind such runoff pattern. As most of the periods of a year do not receive rain and even the intensity of

rainfall is not also equal, the antecedent soil moisture condition is not always supports to prompt runoff just after rain and runoff response is not also even. Out of total runoff, maximum runoff yields during monsoon time when rainfall is maximum. Actually, it is possible because AMC on that monsoon period favours least abstractions and supports large scale surface runoff. So, in this region, practically runoff does mean the amount of flow during monsoon and it is 1113.73 mm. (11a) which is 75% of the total rainfall. Pre monsoon period also shows 126.24 mm. runoff (12a) theoretically but practically if other outputs like evapotranspiration are taken into account, runoff will be 0 in this time. Table 7 and 8 respectively depict the spatial pattern of monsoon and pre monsoon runoff depth and their respective areal concentration. Out of total basin area 9.02% area records very high runoff depth (1,146.069 - 1,182.335 mm.) followed by high runoff depth which covers 25.19% to total area with a runoff depth of 1,124.927 - 1,146.069 mm. during monsoon time(see Table 7). Table 8 shows that 13.82% area is characterized by high runoff depth (146.353 - 163.892 mm.) during pre monsoon time.

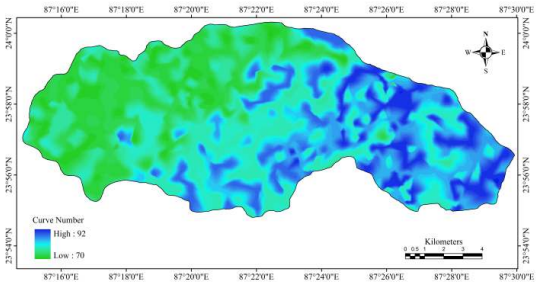

Fig. 6. Spatial pattern of curve number (CN)

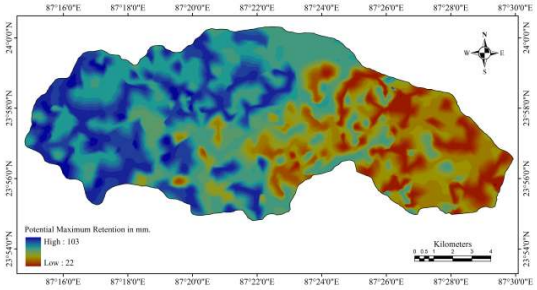

Fig. 7. Spatial pattern of potential maximum retention

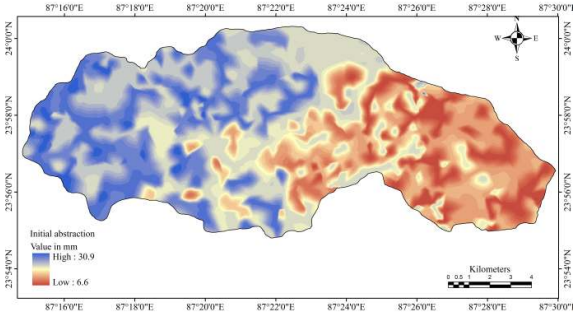

Fig. 8. Initial abstraction pattern

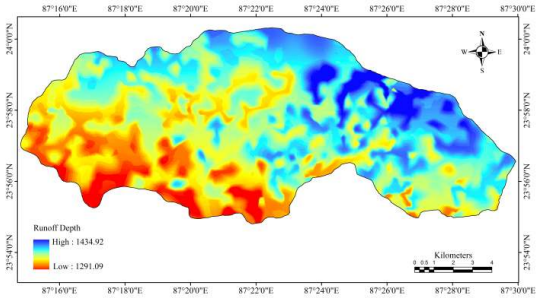

Fig. 9a. Annual average continuous surface runoff depth

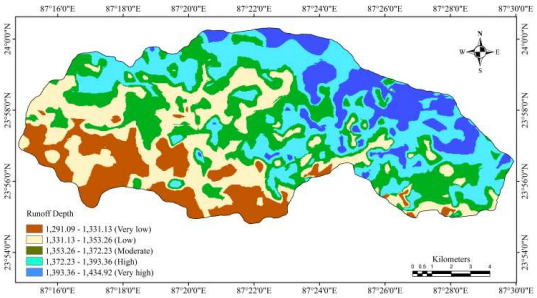

Fig. 9b. Classified average annual surface runoff depth model

Table 6. Spatial annual average runoff depth

Runoff status	Classified score (mm.)	Area extent (sq.km)	% of total area
Very low	1291.09 - 1331.13	23.22	13.48
Low	1331.13 - 1353.26	40.30	23.39
Moderate	1353.26 - 1372.23	45.27	26.27
High	1372.23 - 1393.36	44.09	25.59
Very high	1393.36 - 1434.92	19.43	11.28

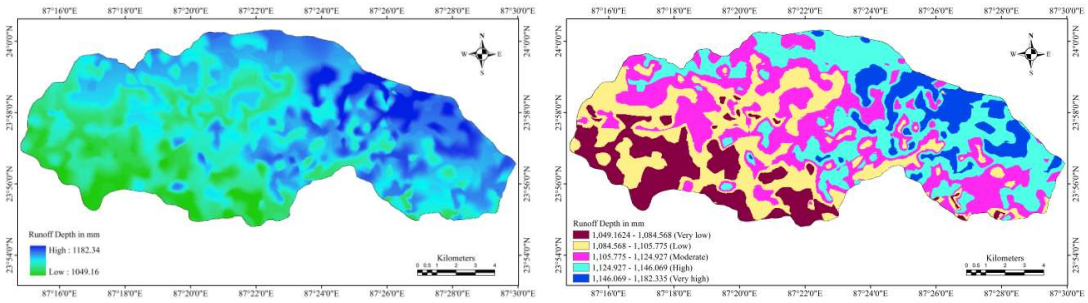

Fig. 10. Spatial runoff depth in monsoon (a) continuous model (b) classified model

Table 7. Area under monsoon runoff depth

Runoff status	Classified score (mm.)	Area extent (sq.km)	% of total area
Very low	1,049.162 - 1,084.568	23.08	13.40
Low	1,084.568 - 1,105.775	41.44	24.05
Moderate potentiality	1,105.775 - 1,124.927	48.84	28.34
High	1,124.927 - 1,146.069	43.41	25.19
Very high	1,146.069 - 1,182.335	15.54	9.02

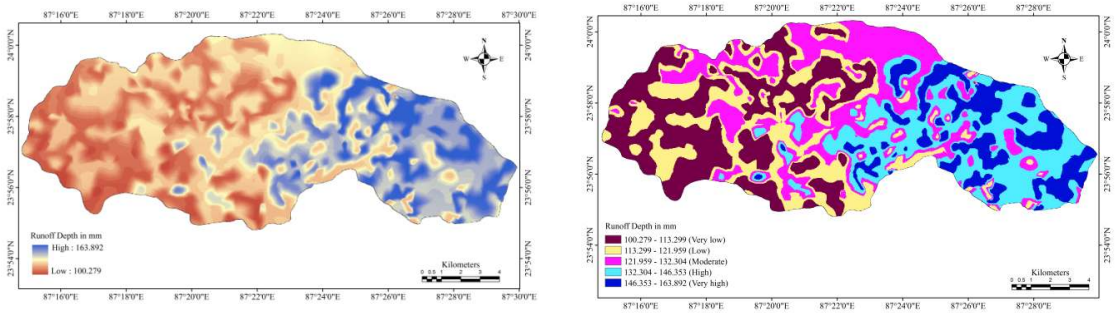

Fig. 11. Spatial runoff depth in pre monsoon (a) continuous model (b) classified model Runoff status

Table 8. Area under pre monsoon runoff depth

Runoff status	Classified score (mm.)	Area extent (sq.km)	% of total area
Very low	100.279 - 113.299	40.89	23.73
Low	113.299 - 121.959	35.94	20.86
Moderate	121.959 - 132.304	38.71	22.47
High	132.304- 146.353	34.66	20.11
Very high	146.353 - 163.892	22.10	12.83

4.3 Impact of Evapotranspiration (ET) on Runoff

Annual potential evapotranspiration (ET) in the study area is about 72cm./year which is almost 50% of the total rainfall. This rate of evaporation strongly varies over seasons, e.g. monsoon pre monsoon months (March to May) yield maximum ET which most of the cases exceeds rainfall. During monsoon time (June to October), this rate of ET is not as strong as during pre monsoon because of >90% relative humidity in air. Still, within monsoon months average ET is 53% of the total rainfall. In pre monsoon time this rate is >80% but this rate largely differs over LULC types. All these information bring another fact in forefront that the amount of runoff depth calculated as per SCS CN is devoid of considering this ET factor and if this factor is incorporated certainly the amount of runoff estimated and plotted in Figs. 12a and 12b; 13a and 13b will be reduced. Estimation and spatial runoff modeling will be more perfect if spatial ET of different periods (Monsoon and pre monsoon) is deducted from the runoff models of respective times. Keeping this unavoidable fact in mind, in this section, ET models of the monsoon and pre monsoon periods have been constructed based on some major vectors of ET like types of LULC, soil types, temperature, wind speed etc. following FAO 2010 [91]. Growing land use change specifically, change of forest land into agriculture has intensified soil moisture loss and it will negatively affect surface runoff availability.

4.4 Validation of Runoff Model

Calculated RE value and NSE value are respectively 53.65% and 0. 6782. RE value established that runoff model is not highly optimum because relative error is 53.65%. Nash-Sutcliffe efficiency (NSE) also indicates the same but the value remains within the range of acceptability (0-1) as stated by Nash and Sutcliffe [87]. Here it is to be mentioned that effective runoff model is valid but the initial model without considering evaporation is not valid in these validation reference scales.

4.4.1 Validation of potential surface water model surface runoff depth model using field based discharge data

Discharge is measured from different stream site and junction sites after constructing potential surface water available zones. Global Positioning System (GPS) based method is used for coordinating map and field site. All total 65 sites have been selected for measuring discharge representing area proportion sampling.

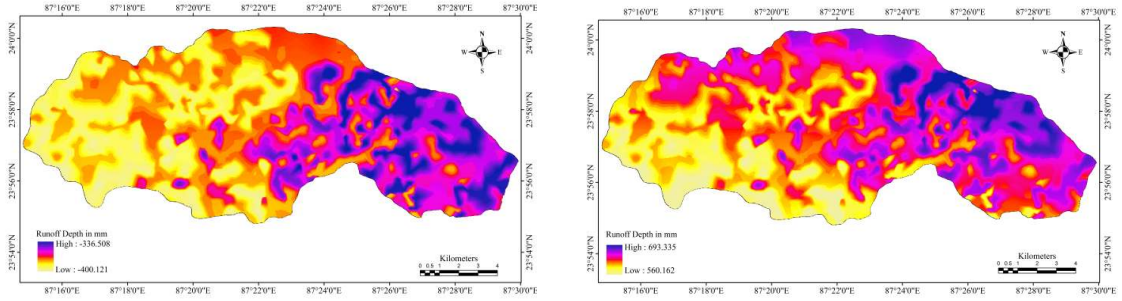

Fig. 12. Effective surface runoff depth (a) pre monsoon (b) monsoon

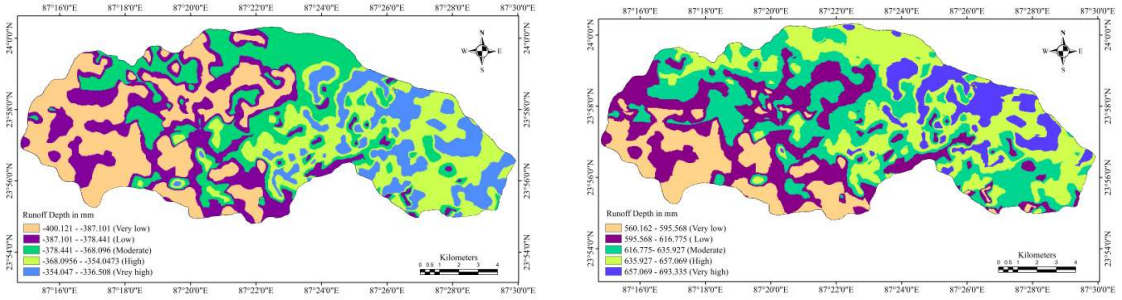

Fig. 13. Classified pattern of effective surface runoff depth (a) pre-monsoon (b) monsoon

4.5 Discharge Conditions

In Table 9, stream strength, discharge availability, level of discharge fluctuation in inter suitability zones and intra suitability zones. In most suitable zone over confluence segment, due to having high strength of streams in term of flow accumulation, both usable water and consistencies of water supply are high. In same suitability class, water availability decreases upstream segments and away from streams. Actual water supply capacity during pre monsoon period in most suitable zone varies from 61440 to 192650 m^3/day if all water is used or 43386 to 130980 m^3/day if 30% water is allowed to flow. In monsoon time, water supplying capacity is almost five times greater than premonsoon. It should be noted that estimation is also given for seven days considering the irrigation interval to the crops like pulses, oil seeds mainly cultivated in pre monsoon periods (Table 8). Therefore, estimation of irrigated area using the available water can be done based on cumulative water discharge.

Table 9. Field based measurement of the discharge of streams and accuracy assessment

Suitability status	Nature of river	Discharge (cumec.)	Remarks
Very highly potential zone	3rd and 4th order dominated at the confluence 2nd and 3rd order dominated at the middle segment	At the confluence: Monsoon: 12.5 cumec Premonsoon: 2.3 cumec. Spatial variation: CV=17.45 to 23.74% At the middle segment: Monsoon: 05.2 cumec Premonsoon: 0.9 cumec. Spatial variation: CV=18.32 to 26.45%	Water can be harvested directly from stream; pre monsoon water harvest should not exceed 61440 to 192650 m^3/day or 493530 to 1309700 m^3/7days if all water is used or 43386 to 130980 m^3/day or 316372 to 866826 m^3/ 7 days if 30% water is allowed to flow.
High potential zone	Either dominated by 2nd order with few 3rd order	Monsoon: 4-5.3 cumec Premonsoon: 0.4-1.2 cumec. Spatial variation: CV=17.42 to 29.26% Seepage water supported	Water can be harvested directly from stream or seepage tank can be prepared; premonsoon water harvest should not exceed 51200 to 110960 m^3/day if all water is used or 231640 to 562602 m^3/7 days if 30% water is allowed to flow.
Moderately potential zone	Mainly dominated by 1st and 2nd order	Monsoon: 1.92-2.2 cumec Premonsoon: 0.24-0.46 cumec. Spatial variation: CV=24.65 to 57.63% Seepage water supported	Water can be harvested directly from stream or seepage tank is necessary to capture water. Water availability: 47% to 68% of the previous class
Low potential	1st and 2nd order dominated	Monsoon: 0.16-0.57 cumec Premonsoon: 0-0.07 cumec. Spatial variation: CV=38.76 to 71.54%	Deeper water tank or shallow well can be constructed for water harvesting. High level fluctuation of water supplying potentialities and therefore less certain.
Very low potential zone	1st order stream dominates	Monsoon: 0 -0.37 cumec Premonsoon: 0 cumec. Spatial variation: CV=18.21 to 34.23%	Surface water potentiality is less, ground water based water harvesting structure can be installed.

Table 10. Regression between Effective runoff depth and actual per day discharge and WLC and discharge

Suitability status (Col 1)	Avg. discharge (cumec./day) (Col 2)	Effective surface runoff (mm.) (Col 3)	WLC (Col 4)	Regression model
Very highly potential zone	12.5	675	38.5	**Col 2vs. Col 3** $y = 8E\text{-}14e^{0.048x}$
High potential zone	4.65	646.5	55	$R^2 = 0.962$
Moderately potential zone	2.05	626.6	65	**Col 2 vs. Col 3** $y = 0.003e^{0.094x}$
Low potential	0.3	605.5	75	$R^2 = 0.953$
Very low potential zone	0.15	577.5	89	**Col 2 vs. Col 3** $y = 0.314e^{0.008x}$ $R^2 = 0.970$

So, from this actual availability of water data at different surface water potential zones it is established that high discharge is found at high or very high surface water availability zones. Table 8 clearly depicts the degree and direction of control of surface runoff depth and WLC to actual discharge. High coefficient of determination (0.953-0.962) and regression models as shown in Table 8 represent high degree of positive control. This co linearity of association between field data with constructed model states that the surface water potential model is valid.

Pearson's product moment correlation coefficient value between annual surface runoff and weighted surface water potentiality is 0.52956 which is significant at 0.01 level at one tailed test. Correlation coefficient values are also significant at the same level when it is carried out between monsoon runoff depth and surface water potentiality (r=0.6453). So, from these associations it can be inferred that surface water potential model maintains parallelism with surface runoff depth.

Table 10 represents average discharge of different surface water potential zones and their respective effective runoff depth and weighted linear combination score for deriving surface water potentiality. Regression carried out between average discharge and WLC and average discharge and effective runoff depth prove that effective runoff depth strongly control actual discharge of rivers; surface water potential area also yields high discharge in ground reality. Positive regression models and high coefficient of determination in both the cases (R^2=0.953-0.970) fortify the above statement. This analysis supports partial application of such runoff model preparation in for finding out suitable surface water potential sites and detecting water harvesting sites.

5. CONCLUSION

Surface water potential model shows more expected results than runoff depth model but discharge pattern validates both the models. For increasing the level of acceptability of SCS CN based runoff model more perfectly rainfall should be measured from adequate number of meteorological stations. Necessarily, Ia value should be refined at per present situation. Besides such limitations of this paper, the suitable sites highlighted by surface water potential model are concomitant with ground reality. Very high and high potential zones recorded maximum river discharge. So, this model can provide decision support for surface water harvesting based planning.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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