Landuse Change Prediction and Its Impact on Surface Run-off Using Fuzzy C-Mean, Markov Chain and Curve Number Methods

Arun Mondal, Deepak Khare, Sananda Kundu, P. K. Mishra and P. K. Meena

Abstract The landuse change has considerable impact on the surface run-off of a catchment. With the changing landuse there is reduction in the initial abstraction which results in increasing run-off. This also has effect on future because of constant change in landuse due to urbanization. The Soil Conservation Service Curve Number (SCS-CN) model was used in the study for calculating run-off in a sub-catchment of Narmada River basin for the years 1990, 2000 and 2011 which was further validated with the observed data from the gauges. Stream flow of future for 2020 and 2030 was estimated by this method to observe the impact of landuse change on run-off. The landuse classification was done by Fuzzy C-Mean algorithm. The future landuse prediction for 2020 and 2030 was performed with the Markov Chain Model with 2011 validation. Future run-off was generated on the basis of changing landuse which shows increasing rate of run-off.

Keywords Landuse change · Run-off · SCS Curve Number · Fuzzy C-Mean · Prediction · Markov Chain Model

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1 Introduction

Assessment of the impact of landuse change on the runoff dynamics of a basin is a motivating field for hydrologists. Different methods have been applied to find out the deficiency of knowledge in this field, but not much is known yet and there is a lack of any general and credible model for predicting the effect of landuse changes [1]. Many results are found, with some even opposing to the results of the others. According to [2], there is no significant rise in the yield of water due to burning of Eucalyptus. While [3] deduced that there is rising water yield because of decrease in forest cover and according to [4] there is change in yield depending on the vegetation cover. Urbanization also leads to increasing run-off and small floods [5]. Various authors who have worked on the impact of landuse change on run-off are [6–9]. Most of the physical models require large amount of data, but [10] said that there are few models which require few data and are not entirely physical models. The prediction of the effect of landuse change also largely depends on the uncertainty of the parameters used in the models [11, 12]. But the uncertainty of such models is more as they have more computation, and are not practical for large catchments.

The Soil Conservation Service Curve Number (SCS-CN) model developed by United State Department of Agriculture (USDA) [13–15] relates the run-off with rainfall parameter and soil cover through Curve Number (CN). This is a very widely used model and gives good result [16–19]. [20] deduced that landuse is an essential parameter for the SCS-CN model and it has been observed that landuse change have significant impact on the run-off and rainfall relation [21] resulted in changed run-off and soil cover [22]. There was a change in the forest catchment due to landuse change [23]. To know the hydrological response in a river basin, it is necessary to evaluate the effect of landuse change and prediction of future landuse change. It is extremely important to know this impact on future run-off.

Change in landuse is particularly important with the growing population which further affects the river basin and run-off. Change detection studies were done by number of researchers [24, 25] who have used satellite images for showing landuse changes. Markov chain model helps in prediction by developing matrix where observed transition probabilities from one state to another is used for future projection [26] and it can be utilized in large spatial scales including different types of landuse [27, 28]. Recent studies with Markov chain model for landuse prediction were performed by [29–31].

In the present study, impact of landuse change in a sub-catchment area of Narmada River basin was done for the years 1990, 2000 and 2011 to estimate the change in run-off condition. With the rising population pressure and demand, there was change in the landuse which is further influencing the total run-off from the catchment and thus affecting the water supply. Again, future landuse prediction was done to estimate the future run-off for the year 2020 and 2030. SCS-CN method was used for the run-off calculation and satellite images were taken for

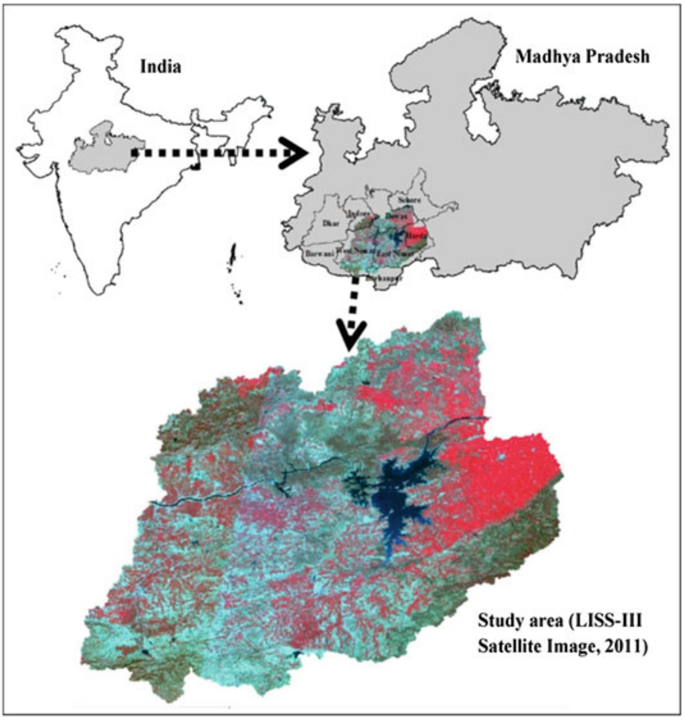

Fig. 1 Study area

landuse classification with Fuzzy C-Mean together with the Markov model to give future landuse projection and its impact on run-off.

The study area is a part of Narmada River basin in Madhya Pradesh extending from 21°23′7.7″N to 22°55′8″N and 75°21′7″E to 77°21′17″E covering about 20,561 km^2. It includes the districts of Burhanpur, Khandwa, Sehore, Barwani, Harda, Dewas, Indore, West Nimar and East Nimar. The outlet of the area is Mandaleswar gauge. The region has a subtropical climate which is a hot dry summer (April–June) through monsoon rains (July–September) to a cool and dry winter. The rainfall average is approximately 1,370 mm and it decreases from east to west (Fig. 1).

2 Data and Methods

The hydrological data for the gauging stations were used together with the daily station rainfall data for the study area from IMD. The satellite data for 1990, 2000 and 2011 were used for landuse classification from the Landsat TM and LISS-III data.

2.1 SCS-CN Method for Run-off Estimation

Run-off calculation was done with the SCS-CN [32] method at the gauge of Handia and Mandaleswar using surface run-off from Handia to Mandaleswar, total catchment area and base flow. The area was then classified into 5 landuse classes and prediction was done to observe the impact on future run-off. The overall CN (Curve Number) was taken for different landuse classes which helped in determining the run-off for the years 1990, 2000 and 2011.

2.2 Changed Run-off due to Landuse Change

The landuse data and rainfall data were used to calculate the run-off for each year. The calculated data was then validated with the observed data at the gauge points. To get the impact of landuse on run-off, rainfall of 1990 was taken as constant rainfall for 1990, 2000 and 2011, and the change in run-off was observed with respect to the corresponding landuse of these three years. For example, rainfall of 1990 and landuse of 1990 were considered to calculate run-off of 1990, rainfall of 1990 and landuse of 2000 to calculate the run-off of 2000 and so on. The future prediction of 2020 and 2030 run-off was done with the rainfall of 1990 and predicted landuse of these two years with the Markov model.

2.3 Landuse Classification with Fuzzy C-Mean

Landsat TM data sets were taken from USGS (website http://glovis.usgs.gov). Data were projected in UTM projection zone 44 and WGS 84 datum. The 1990 image was considered as the base data and 2000 and 2011 images were co-registered by first order polynomial model with the Root Mean Square Error (RMSE) of 0.5 pixel. The images were then geometrically corrected and radiometric normalization was done. All the images were classified using Fuzzy classification into 5 landuse classes. The accuracy assessment was done with all the images after classification.

[33] have described different types of existing clustering techniques. Supervised Fuzzy C-Mean is a classification technique where pixels are categorized after specifying the training sample areas. The fuzzy concept of classification represents a natural model where each pixel may have partial membership corresponding to different landuses. It assigns membership values for each sample of each class that varies from 0 to 1. In the present study following Fuzzy C-mean (FCM) algorithm was used for clustering technique:

$$J_m(U, v) = \sum_{i=1}^{C} \sum_{k=1}^{N} u_{ik}^{m} \|y_k - v_i\|_A^2 \tag{1}$$

where

Y is {Y1, Y2… YN} $\subset$ Rn = the data,

c is number of clusters in Y; $2 \leq c \leq n$,

m is weighting exponent; $1 \leq m < \infty$.

U is fuzzy c-partition of Y; U $\in$ Mfc

v is (v1, v2… vc) = vectors of centers,

vi is (vi1, vi2,…, vin) = center of cluster i,

$\|\|_A$ is induced A-norm on R'', and

A is positive-definite (n $\times$ n) weight matrix.

The membership value in each class of a sample depends on its distance to the corresponding cluster centre. The weight factor m decreases the impact of small membership values. Greater the value of m, smaller will be the influence of samples with small membership values [34].

After classification, accuracy assessment was done with the Kappa statistics [35] on the images of 1990, 2000 and 2011. Markov model was then used to predict future changes in landuse of 2020 and 2030 with validation of 2011 landuse on the basis of 1990 and 2000 landuse.

2.4 Markov Chain Model

Markov model was used here to project future landuse changes and estimation of future run-off from the changed landuse. The Markov model is given as [29]

$$\begin{aligned} P\left\{X_t = a_j \middle| X_0 = a_0, X_1 = a_1, \ldots, X_{t-1} = a_i\right\} \\ = P\left\{X_t = a_j \middle| X_{t-1} = a_i\right\} \end{aligned} \tag{2}$$

Moreover, it is proper to regard the change process as one which is uniquely distinctive with time (t = 0, 1, 2…).

$P\left\{X_t = a_j | X_{t-1} = a_i\right\}$ gives the probability where the process develops transition from state ai to state aj within one time period. When the ℓ steps are required for implementing the transition, then the $P\left\{X_t = a_j | X_{t-1} = a_i\right\}$ is called the ℓ step transition probability $P_{ij}^{(\ell)}$.

In case $P_{ij}^{(\ell)}$ is independent of time and dependent on states ai, aj and ℓ, the Markov chain is then called homogeneous;

$$P\left\{X_t = a_j \middle| X_{t-1} = a_i\right\} = P_{ij} \tag{3}$$

where Pij value is calculated from the observed data by arranging the number of times the observed data go from state i to j, nij, and total occurrences of the state ai, ni is summed up.

$$P_{ij} = n_{ij}/n_i \tag{4}$$

As the Markov chain continues with time, the probability of retaining in state j gets independent of the initial state of the chain after many steps. When this condition occurs, the chain is considered to have reached a steady state. Then Pj, which is the limit probability, is used to determine the value of $P_{ij}^{(\ell)}$,

$$\lim_{n} P_{ij}^{(n)} = P_j \tag{5}$$

Where

$$P_j = P_i P_{ij}^{(n)} \quad \mathrm{j} = 1, 2, \ldots, \mathrm{m\ (state)}$$
$$P_i = 1 \quad P_j > 0$$

3 Results and Analysis

3.1 Landuse Classification and Prediction with Markov Model

Kappa statistic was calculated for accuracy assessment given in Table 1.

Overall kappa statistics and overall accuracy for 2011 were 0.78 and 84.17 % respectively (Table 2). For the assessment of landuse change in different decades, Landsat TM and LISS-III images were taken for the years 1990, 2000 and 2011. Changes in area that have occurred in different years are provided in Table 3. Large increase in the area of water and built-up is observable from 1990 to 2011. Water area has increased from 1.01 to 4.56 % in 2011 while built-up increased from 3.61 to 10.53 % in 2011. Agricultural land area also increased from 34.87 to 40.26 % in 2011 (Table 3).

The landuse maps of 1990, 2000, 2011, 2020 and 2030 are given in Fig. 2. In 2011, water bodies increases to a great extent due to construction of Indira Sagar Dam after 2000.

The predicted results of 2020 and 2030 (Table 4) indicate rise in the water body and built-up area in next 19 years after 2011 while vegetation, agricultural land and fallow land decreases. Increase in settlement has resulted in the decrease of vegetation and fallow at the cost of built-up. Water area is increasing giving the effect of dam construction as predicted by the model.

3.2 Change in Run-off Values for Changed Landuse

The run-off calculation was done with the rainfall data by SCS-CN method for 1990, 2000 and 2011. The results of 1990 and 2000 were validated with the

Table 1 Kappa statistics

Class name	Kappa statistics (1990)	Kappa statistics (2000)	Kappa statistics (2011)
Water body	0.79	0.82	0.82
Built-up	0.87	0.80	0.83
Vegetation	0.63	0.78	0.76
Agricultural land	0.81	0.81	0.76
Fallow land	0.76	0.75	0.80

Table 2 Overall kappa statistics and overall accuracy

Category	1990	2000	2011
Over all kappa statistics	0.75	0.79	0.78
Over all accuracy (%)	81.67	84.17	84.17

Table 3 Distribution of area of different landuse

Classes	1990 (km^2)	1990 (%)	2000 (km^2)	2000 (%)	2011 (km^2)	2011 (%)
Water body	207.13	1.01	263.38	1.28	937.35	4.56
Built-up	743.25	3.61	1,307.2	6.36	2,164.64	10.53
Vegetation	6,234.55	30.33	5,879.8	28.6	4,695.65	22.84
Agricultural land	7,167.72	34.87	7,361.18	35.81	8,275.70	40.26
Fallow Land	6,205.35	30.18	5,746.44	27.95	4,484.66	21.81
Total	20,558	100	20,558	100	20,558	100

observed river flow. But the river flow became controlled after 2004 due to construction of dams, so 2011 result was not validated with the observed flow. The rainfall of three rain gauge stations was taken from the study area and computation of surface run-off was done. Base flow was used for evaluation of river run-off on daily basis. Comparison between calculated and observed run-off for the year 1990 and 2000 is shown in Fig. 3. The correlation was done with the results which show good relation between the observed and calculated flow.

3.3 Change in Run-off Values for Changed Landuse

The results of the impact of landuse change on run-off show that annual total run-off of the year 1990 was 183.14 mm while total run-off of 2000 was 190.13 mm. Thus the increase is 6.99 mm. From 2000 to 2011 again, the run-off increased up to 215.80 mm with a rise of 25.67 mm. In future prediction of 2020, the annual run-off is estimated as 226.12 mm which again increases in 2030 up to 235.52 mm. Thus the total increase of run-off due to change in landuse from 1990 to 2030 is 52.38 mm if the rainfall for all these years remains same. Thus the result

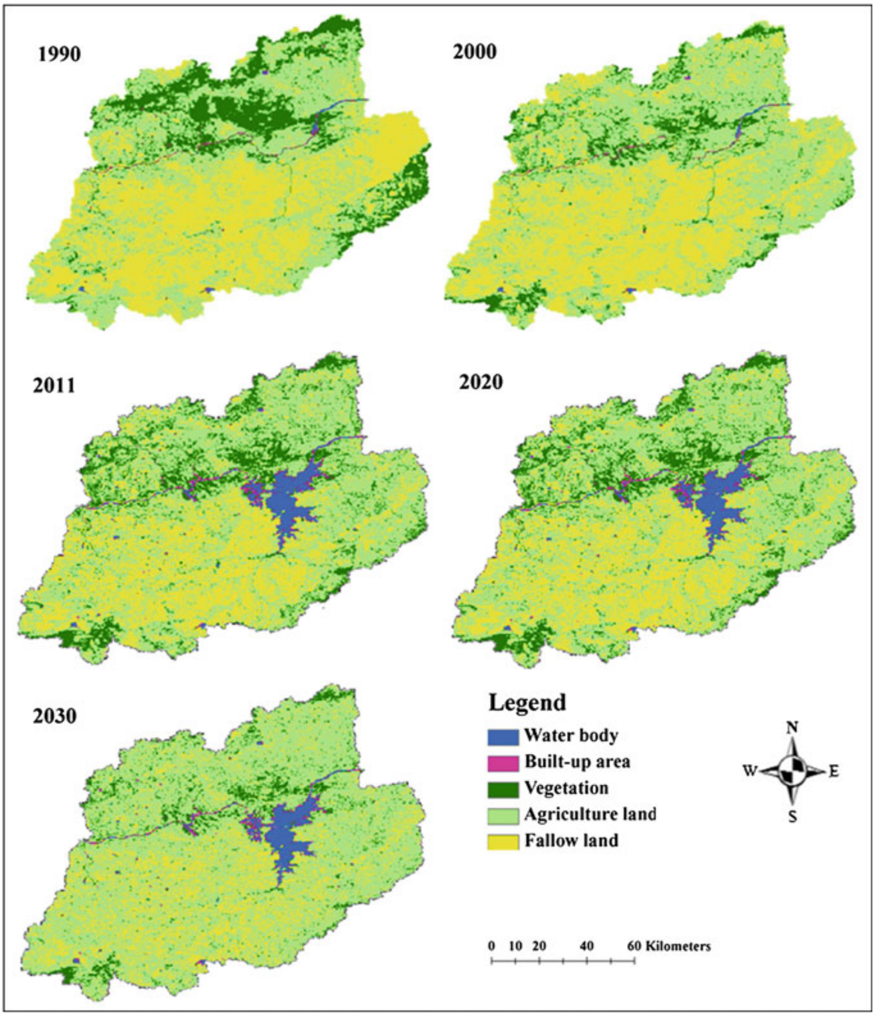

Fig. 2 Landuse map of 1990, 2000 and 2011

Table 4 Future prediction of landuse from Markov Chain for 2020 and 2030

Classes	2011 (km^2)	2011 (%)	2020 (km^2)	2020 (%)	2030 (km^2)	2030 (%)
Water body	937.35	4.56	967.8	4.71	1,009.68	4.91
Built-up	2,164.64	10.53	2,709.8	13.18	3,268.16	15.90
Vegetation	4,695.65	22.84	4,027.05	19.59	3,505.82	17.05
Agricultural land	8,275.70	40.26	9,113.09	44.33	9,445.07	45.94
Fallow Land	4,484.66	21.81	3,740.26	18.19	3,329.27	16.19
Total	20,558	100	20,558	100	20,558	100

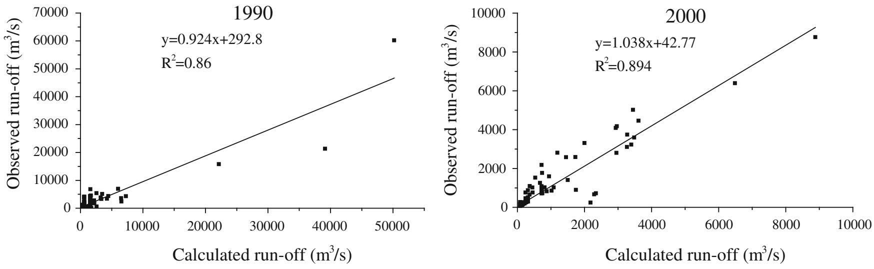

Fig. 3 Correlation of observed and simulated run-off for 1990 and 2000

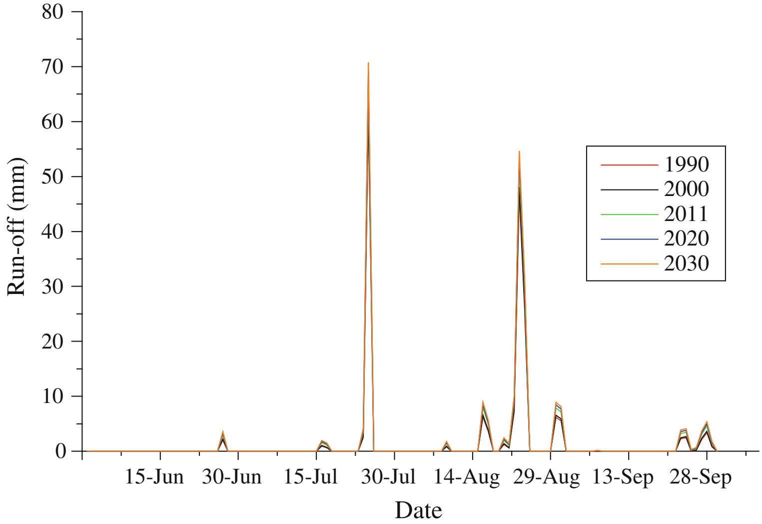

Fig. 4 Impact of landuse change on run-off

provides an estimation of future landuse and future run-off of this sub-catchment which will be useful in further studies (Fig. 4).

3.4 Future Run-off of 2020 and 2030 with Predicted Landuse

The landuse of 2011 was predicted by the landuse of 1990 and 2000 and also classified with the Fuzzy C-Mean algorithm to validate both the results. The landuse of 2020 and 2030 were predicted with the model and the results were further used to generate future run-off with the SCS-CN method. To get the change in run-off with respect to the landuse change, rainfall of 1990 was taken as a constant for all the years and run-off of 1990, 2000 and 2011 were calculated with the corresponding landuse of these years. Similarly, for 2020 and 2030, the rainfall of 1990 was taken with the predicted landuse. Thus the impact of landuse change on run-off was estimated and analysed from 1990 to 2011 for 21 years and then for next 19 years, keeping rainfall as constant (Fig. 4).

4 Conclusion

There is a constant process of increasing population resulting in rising demand and drastic changes in landuse. All these are affecting the natural resources with changing environment. Landuse change is affecting the surface run-off. This study is a combined use of hydrological methods, modeling and remote sensing together to achieve the goal. The landuse classification of 1990, 2000 and 2011 was done with the Fuzzy C-Mean algorithm which is a soft classification technique and accuracy assessment was performed with the results. The future prediction of 2020 and 2030 landuse was carried out with the Markov model and the validation was done with the 2011 landuse. There was drastic change in the landuse with increasing use of agricultural land and increasing settlement. Forest covers declines from 1990 to 2030 and this change in landuse is observable on the run-off of the study area, even in future. The SCS-CN method was applied for assessing the run-off of the region and the computed result was validated with the observed run-off of 1990, 2000 and 2011. There is a marked increase in run-off from 1990 (67.59 mm) to 2011 (84.85 mm) to 2030 (95.80 mm). These results show that with the increasing settlement and agriculture, and decreasing vegetation, there is an increasing run-off and falling rate of infiltration in near future. On the basis of these results, assessment of future landuse and change in run-off is possible for planning and management of water resource of the area.

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