Assessing Future hydrological response of an urban watershed using machine learning based LULC forecasting models

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Abstract
Urbanization in terms of land-use/cover (LULC) change has a long-term significant impact on the hydrological cycle as the LULC is one of the most important influencing parameters to produce curve number (CN). The drastic change in LULC changes the CN. This change directly affects surface water including peak flows. This study aims to assess the change in surface runoff due to changes in LULC. Hydrological modeling is done for the consistent long-term behavioral study of surface runoff. The area focused on the study is the Kharun river, a tributary of the Mahanadi River. For the assessment of the impact of LULC change on the catchment discharge, a daily-step conceptual model soil and water assessment tool (SWAT) was applied. Landuse maps were prepared with the Landsat Thematic Mapper satellite images.

The future land use was forecasted with the technique of spatial statistical modeling. The machine learning (ML) tool is used for quantifying the influences on the LULC change dynamics and producing the LULC map for 2024 and 2030. Remote sensing (RS) and geographic information system (GIS) analysis were coupled with hydrological SWAT modeling to investigate the connection between the LULC change and hydrologic regime. The SWAT Model's calibration efficiency is verified by comparing the simulated and observed discharge time series at the Patharidih gauge and discharge station. The monthly and daily calibrations were quite satisfactory, with Nash-Sutcliffe an efficiency coefficient of 0.86 and 0.67. This modeling provides reliable information for sustainable management of available water resources of the catchment.

Keywords: Impact of landuse Change, Hydrological Modelling, Hydrological Response, SWAT, Machine Learning.

Introduction
The understanding of insight information is essential for management actions. The growth of population, the change in climate, anthropogenic development activities are disturbing the water balance of the basin system to cause flood or drought event consequently. The hydrological processes are complex in nature and to make proper management decision, the study of integrated process has to be done through modelling[2,15,18]. There are numbers of models for the assessment of different component of hydrologic processes. Hydrological modelling is trying to simulate the natural processes by adjusting the variables in a series of mathematical equations that influence the energy and water balances of a river basin system[1]. The prime objective of modelling is to understand the river basin system in altered situation and to assess reliable information for sustainable development[17].

SWAT is an adaptable model that can be used to accommodate various environmental processes, resulting in more effective catchment management and the production of better-informed policy choices. In this study SWAT model was tested on daily time scale for simulation of the runoff[18]. The SWAT model takes an advantage of data sets both globally and spatially to simulate hydrological processes using the data such as digital elevation models (DEMs), soil types, weather variations and LULC data. The SWAT model was recognized for major work related to hydrological and environmental issues. The algorithms programmed into SWAT are simple but are derived from physical principles of hydrology. SWAT is a continuous modeling tool used to simulate runoff of smallest catchment formed in the watershed.

SCS-CN method was used for simulation of water balance components. The sub-basin and watershed boundaries, drainage networks, slope, LULC and soil maps were generated in GIS environment. GIS provides the platform to work with the complex data set of spatial and temporal resolution for hydrologic modeling[4]. This is a semi-automatic tool to support analysis, management operations and decision making. In this modeling, LULC plays a significant role as it is most emphatic parameter for hydrologic system. The SWAT-CUP was used for calibration and validation program for SWAT models. The sensitivity of parameters is estimated and those expected sensitive parameters are adjusted towards the optimal values in the catchment.

The SWAT model is being used to assess the effects of past and forecasted land use on hydrologic processes such as surface runoff, lateral movement, groundwater movement,

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water yield and evaporation and water yield in both basin and sub-basins[12,14].

The change in LULC over the time is the most influenceable factor for the disturbance in the distribution of water on the hydrological cycle. To assess the change in LULC, satellite image has to process in ERDAS Image processing software. In this study, the year 2006, 2012 and 2018 images were classified and changes in the LULC were analyzed. To assesses the future hydrological response of the basin, forecasting of LULC was done by Markov Chain (MC) which is most preferable type of machine learning technique used to produce land change map of 2024 and 2030.

Markov chain (MC) is extensively used to detect change in LULC which signify that the changes in landuse classes are random in nature[10]. The future state modeling in the MC system is based on the latest progress state and transition probability[5,21]. The transition probability matrix can be prepared by, multi-layer perception (MLP), deciduous forest (DF), logistic regression (LR) and support vector machine (SVM) methods. These modeling methods were performed for the generation of transition potential maps. In multi-layer perception (MLP), the feedforward artificial neural network creates a set of outputs from a set of inputs.

An MLP is defined by numerous layers of input nodes that are linked as a directed graph between the input and output layers. Backpropagation is used by MLP to train the network. In deciduous forest method, it works by splitting the dataset into two sections, the training set and the test set. Then select randomly multiple samples from the training set[9]. Categorical dependent variable's output is predicted using logistic regression (LR). As a result, the conclusion must be categorical or discrete. It can be yes or no, 0 or 1, true or false and so on, but instead of presenting the precise values like 0 and 1, it presents the probability values that fall between 0 and 1.

The SVM method is used to find the optimal line or decision boundary that can divide n-dimensional space into classes so that we may simply place fresh data points in the appropriate category in the future. A hyperplane is the optimal choice boundary. SVM selects the extreme points/vectors that aid in the creation of the hyperplane. These extreme examples are referred to as support vectors and the method is known as the Support Vector Machine.

These transition probability matrix methods were revealed the expected change. Selection of transition probability method was based on accuracy of earlier LULC forecasting with all four methods. In LULC modeling, validation was done to find out the quality of forecasted LULC maps. For the validation, all the four models were used to project 2018 LULC and compared with the exiting one (supervised classified). These transitions are used to forecast future scenarios. The transitions were obtained in the form of probability matrix which has the information of expected alteration from the latest state[20]. The elements of probability matrix represent the chances of relative change from one class to another class, thereby producing the future LULC map.

The forecasted LULC map helps to understand the water distribution in hydrological cycle in changed scenario because the change in LULC will alter the volume of water flowing on the surface as well as in different compartment of hydrological system. The response of surface runoff to this change initiates imbalance of water in different compartments.

Study area

The model implemented in the watershed of Kharun river. Kharun river lies between 20°33’30” N to 21°33’38” N latitude and 81°17’51” E to 81°55’25” E longitude. The Kharun watershed is the sub-basin of Upper Seonath basin. This area falls under the planes of Chhattisgarh State in India[16]. Kharun watershed witnesses the development in last two to three decades with fast growing urbanization. The total geographical area is 4157.03 km^2. Location map of Kharun watershed is shown in figure 1 and the general characteristics of study area is listed in table 1[11].

Material and Methods

Topography: Slope of the Kharun watershed was prepared with the help of Shuttle Radar Topography Mission (SRTM) 30-m resolution data of September 2014 in the digital elevation model form. It is also used to produce basin boundary and drainage density map of the Kharun basin.

Soil Data: Soil data was collected from Water Resources Department, Chhattisgarh, India and Bhuvan Portal (GOI), Data are provided at 10 km spatial resolution soil database which is a 30 arc-second raster database contained within 1:50,000 scale of duration 2001 verified as on 2014. This data is used to produce soil map of Kharun basin. Kharun basin contains four types of soil namely clay loam, sandy loam, sandy clay loam and loamy black soil[11,15].

Table 1
General Characteristics of Study Area

S.N.	Parameter	Unit	Value
1	Area	Kilometer square	4157.03
2	Elevation Range	Meters	449 - 256
3	Mean Annual Rainfall	Millimeters	1200
4	Mean Annual Flow	Millimeters	680

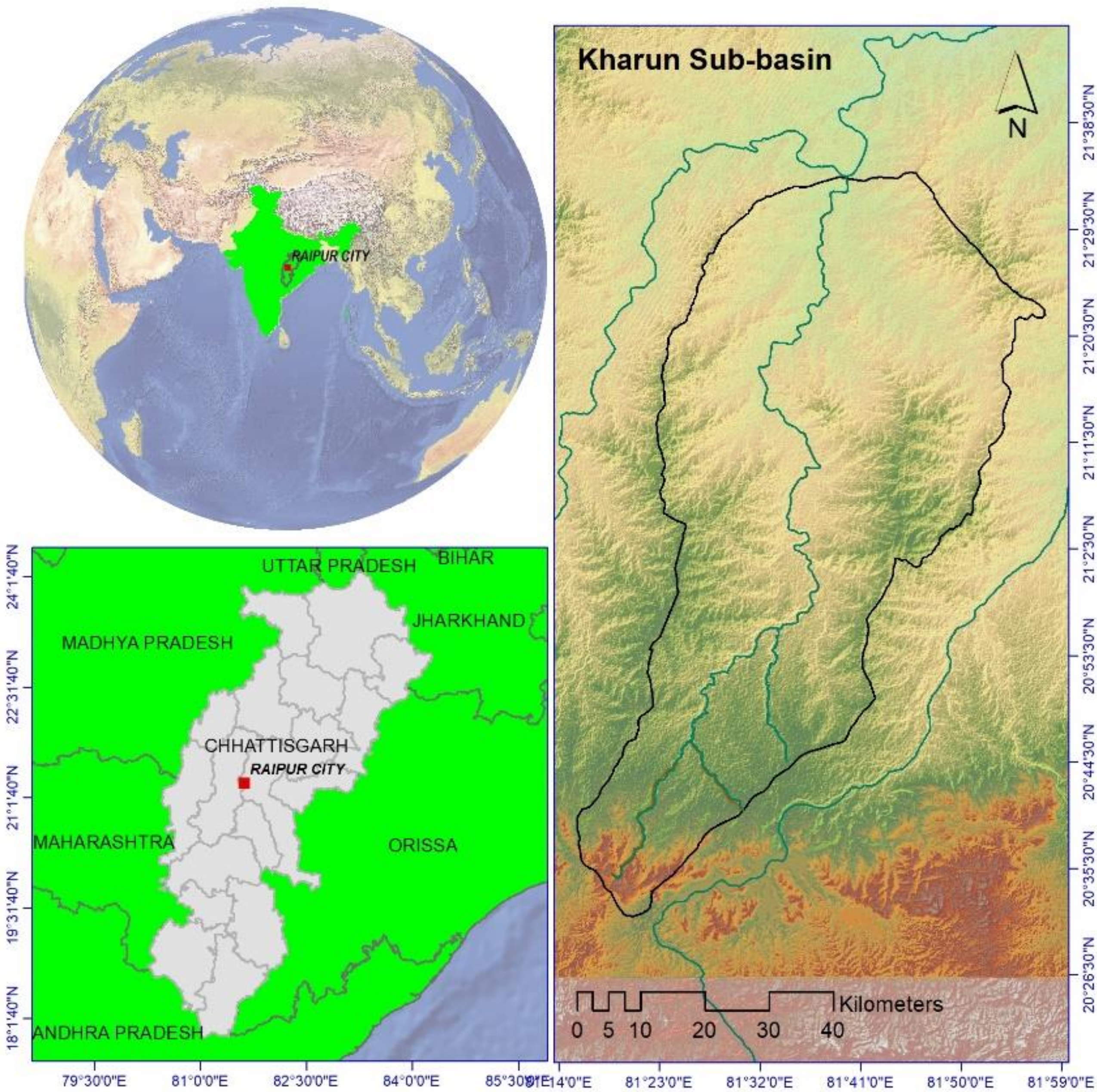


Figure 1: Location Map of Study Area[16]

Landuse data: The LULC due to developmental activity of the Kharun basin changes steadily. The LULC maps were generated with the help of satellite images of Kharun basin. The LULC is the most important parameter to quantify development of the area under consideration. It provides a window to extract the information about the changes in climate and movement of water in hydrological components of the system due to anthropogenic activities. There were three epicenters of urban sprawl in Kharun basin namely the Raipur city, Durg city and Dhamtari city.

Hydrometeorological Data: The hydrometeorological data is downloaded from the website http://www.cru.uea.ac.uk/data/ in the form of gridded climatic data with $0.5^o \times 0.5^o$ spatial resolution. This is the website of climate research unit, UK's Natural Environment Research Council. For modeling, the daily hydrometeorological data are taken for the year 2000 to 2018.

Methodology: For the settlement, human beings are dependent on land. Their developmental activities significantly alter the LULC. The pressure to meet the demand of increasing population amplified the stress on the hydrological system of nature due to change in LULC. Therefore, anthropogenic activities have to be monitored at regular interval and future prediction is to be done for the establishment of early warning system, thereby reducing the risk of environmental degradation. Figure 2 represents the working methodology adopted for the study.

The study starts with the collection of satellite imagery, DEM, rainfall data, weather data and discharge data from various sources to interpretate the satellite images digital image processing technique applied. The multispectral images are used to perform supervise classification to extract meaningful information[3]. The Landsat images were used in this study with WGS 84 datum which are georeferenced to UTM projection. Maximum likelihood method was applied to perform supervised classification in ERDAS software. The process of supervised classification is based on the probability clustering. This method is used the concept of similarity of digital number (DN) value. Pixels with same DN value clustered into an individual class.

Likewise, other classes are formed. To check the accuracy of classified image, Kappa coefficient was calculated using random stratified sampling. The corrected classified LULC map is analyzed for the temporal change of different LULC class.

The simulation tools with remote sensing data in GIS platform proved very efficient for future planning and current management of natural resources. Markov chain method is used in this study to simulate very complex pattern of LULC change with temporal resolution. In the MC method, a matrix is formed to quantify the change in various classes of LULC represented as transition potential model. The various LULC features derive its transition from driving factors. The selection of driving factors depends on the current landuse activity and the availability of the data. This transition matrix is then used to forecast the LULC pattern for the future scenario.

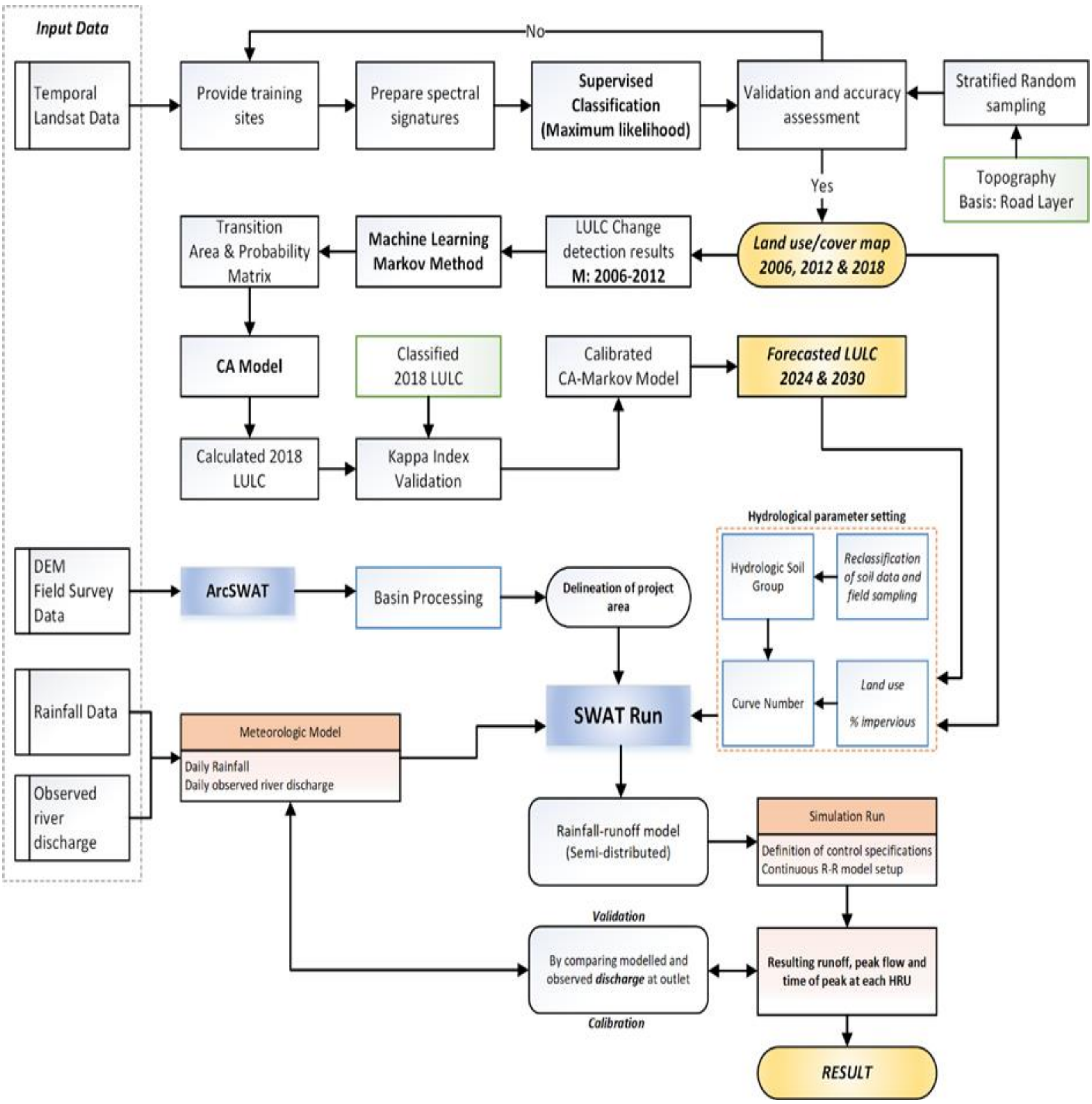


Figure 2: Flow chart of methodology adopted in the study

The driving variables selected for the LULC change detection were evaluated, based on its explanatory capacity and data availability. The driving variables have both the static and dynamic role in modelling. Four main driving parameters were recognized for the model, including "distance to road", "distance to existing Urban area", "slope" and "digital elevation model (DEM)". The transition sub models are used for preparation of transition potential model and transition probability matrix.

The transition matrix contains all the possible transition potentials which served as basics in MC, LULC change modelling. To understand and simulate a complex non-linear relationship between driving factor and land use, multi-layer perception (MLP) has been used for generating accurate transition potential estimation of LULC change[8]. The selection of suitable transition method depends upon correlation matrix with 2018 Classify LULC.

The land change modeler (LCM) was used to generate future LULC scenario of 2024 and 2030 in MC modeling. In LCM, the prediction process was performed based on transition matrix[13]. The transition matrix develops the record of numbers of pixels supposed to convert into another class. The future LULC was then developed by multiplication of column of transition probability matrix by the number of pixels in a corresponding LULC type[19]. The outcome obtained is the forecasted LULC of study area. To analyze the result, relative change in LULC class was studied for assigned landuse class type and also the net change was computed and various graphs were developed.

The footprints of LULC change on the connatural status of environment are complicated. The disturbed movement of water in different medium affects the various components of the hydrologic system. The accessibility of ample amount of good quality water was steering the environmental quality as well as the economic development of the area. The SWAT is a physically based model used to simulate the hydrological cycle and its influence on the quantity of the water in different compartments of the hydrological system. The conceptual SWAT modelling for daily step has been done to simulate the hydrological cycle within the river basin. The main concern is on the assessment of change in LULC impact on movement of quantity of water as surface runoff and its associated risk. Climate in the catchment area provides inputs in the form of energy and moisture which mutually regulate the water balance.

The three fundamental files are required for delineation of sub-basins and hydrological response unit (HRU)s in SWAT. DEM, soil map and LULC map depicted in figure 3 were used for model preparation. Three models were prepared corresponding to the three LULC maps of year 2006, 2012 and 2018. All the three models were calibrated for the year 2003 to 2005, year 2009 to 2011 and year 2015 to 2017 corresponding to the LULC of years 2006, 2012 and 2018. In SWAT modelling, the catchment is divided into sub-watersheds based on a DEM. These sub-watersheds are further subdivided into hydrologic response unit (HRUs) based on topography, landuse and soil types. The HRU model is capable to differentiate evapotranspiration for different crops and soils, so the runoff can be predicted for each HRU. The total runoff generated in the catchment can be calculated and is able to correct the model's estimation[6,7].

In this study, the prepared SWAT Model forms 36 HRU's in five sub-basins. The LULC of sub-basin one and two contains the maximum area under built up class among the other sub-basins. In view of this consideration, the observed daily runoff at the Patharidih gauging site was analyzed with the model runoff result at the sub-basin outlet gauging site. To run the model initially at the start of simulation, three to four years as warm-up period are required to feed into the model. Modeling parameters are then adjusted for calibration. It was found that the model is very sensitive to SCS runoff curve number for antecedent moisture condition. The curves number gets changed based on the LULC of the area.

The sensitivity of the study was done for altered LULC condition and comparing the results with the observed data at Patharidih gauging stations. The SWAT CUP 2012 is used for the analysis. In this, the sensitivity is judged relative to the parameters in use in relation to hydrology. A multiple regression analysis was performed between the objective function values. The t-test is used to identify the relative importance of each parameter compared to the others on basin hydrology. Larger absolute value indicates greater sensitivity of the given parameter. The p-value is an indicator to judge the significance level of sensitivity. Smaller values indicate a higher level of statistical significance for the measured sensitivity. The calibrated SWAT model produced satisfactory reproduction of monthly and daily runoff processes over the years (2003 – 2007), (2009 – 2013) and (2015 -2019).

After the calibration and validation of SWAT model for three LULC scenario of year 2006, 2012 and 2018, the calibration parameters were fixed. Table 2 lists the 15 calibration parameters which were used in model fed with the forecasted LULC of 2024 and 2030 with a synthetic rainfall of year 2018 to run the SWAT model. In this analysis, year 2018 was considered as base period for the assessment of runoff change corresponding to LULC change of the basin. This is because year 2018 was used for the forecasting of LULC of year 2024 and 2030.

Also, year 2018 was taken for validation of LULC prepared by 2006 and 2012. So, 2018 is the year based on which LULC maps of year 2006, 2012, 2024 and 2030 were validated. Therefore, year 2018 was considered as the base year which was used to analyze model results. Runoff was then simulated and compared using the same meteorological input with five different landuse scenarios of year 2006, 2012, 2018, 2024 and 2030.

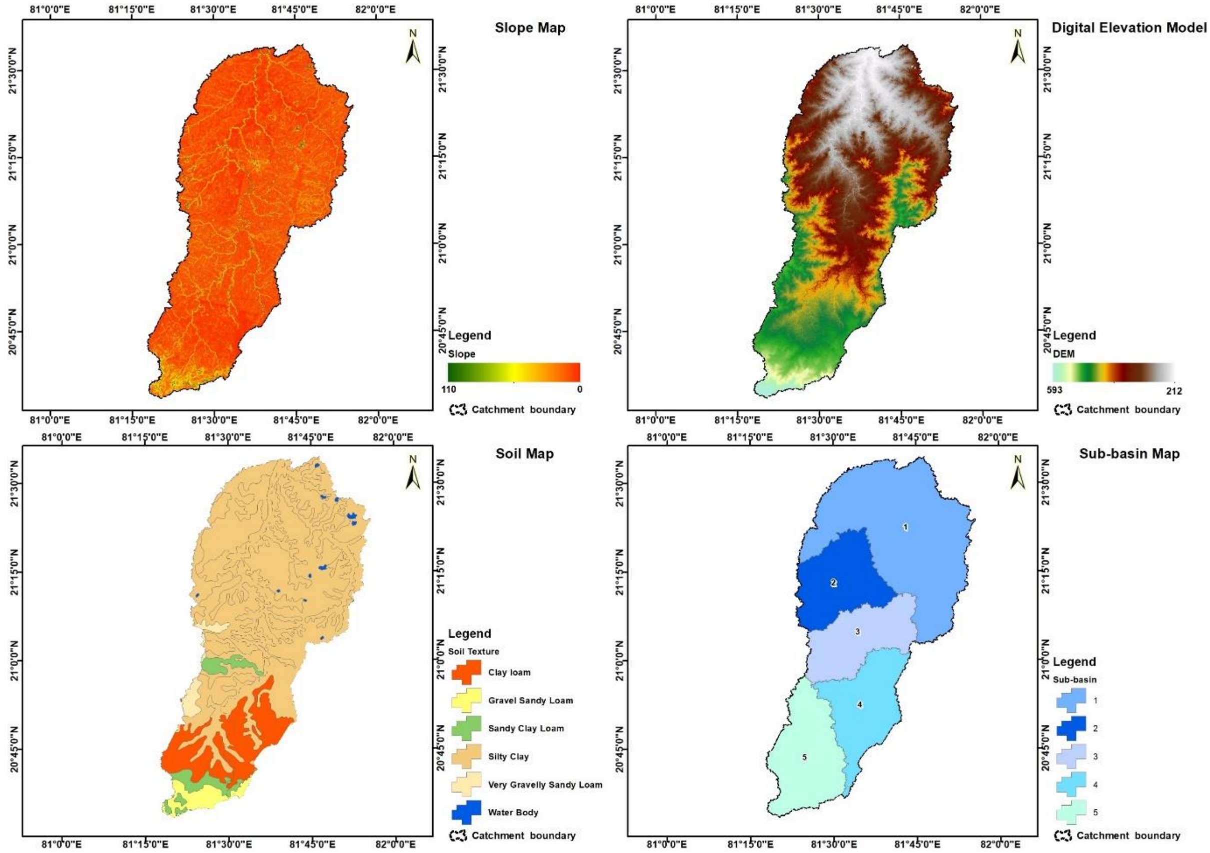


Figure 3: SWAT Input data for HRU delineation

Table 2
Calibration Parameters of SWAT model

S.N.	Parameter Name	Description of Parameters	Fitted Value	Min value	Max value
1	R__CN2.mgt	SCS Runoff curve number	0.16	-0.2	0.2
2	V__ALPHA_BF.gw	Baseflow alpha factor (days)	0.9	0	1
3	V__GW_DELAY.gw	Ground water delay (days).	72	30	450
4	V__GWQMN.gw	Threshold depth of water in the shallow aquifer	1.4	0	2
5	V__GW_REVAP.gw	Ground water revamp coefficient	0.02	0	0.2
6	V__ESCO.hru	Soil evaporation compensation factor.	0.98	0.8	1
7	V__CH_N2.rte	Manning's "n" value for the main	0.21	0	0.3
8	V__CH_K2.rte	Effective hydraulic conductivity	17.5	5	130
9	V__ALPHA_BNK.rte	Base flow alpha factor	0.9	0	1
10	R__SOL_AWC(..).sol	Available water capacity of the soil	-0.14	-0.2	0.4
11	R__SOL_K(..).sol	Saturated hydraulic conductivity.	-0.64	-0.8	0.8
12	R__SOL_BD(..).sol	Moist bulk density.	0.05	-0.5	0.6
13	R__SURLAG.bsn	Surface lag	12.025	0.05	24
14	V__RCHRG_DP.gw	Surface runoff lag time.	0.9	0	1
15	V__EPCO.bsn	Plant uptake compensation factor	0.7	0	1

Results and Discussion

Land use/ land cover change results: Increasing population demand raised the sustainability issue. Different use of land causes the change in land cover. Landsat TM and ETM+ satellite images were successfully exploited for producing LULC information of the years 2006, 2012 and 2018 and for identifying the corresponding changes. The digital image classification of remote sensing divides the pixels of an image into clusters. The principles of pixel oriented image classification (POIC) were adopted in this analysis. The accuracy estimation of classified digital image was done on the basis of selection of sample points. Each similarity based on the classified LULC map and ground truth information was counted as 1 and mismatch was counted as 0. All this information was arranged relative to an error matrix.

The Kappa coefficient was calculated according to this matrix. The Kappa coefficient is used to estimate the relationship between the modeling scenario and reality. Maximum likelihood method was executed in ERDAS image processing software with accuracy (89.45% Kappa Coefficient). Figures 6 (a), (b), (c) depicted the LULC map of years 2006, 2012 and 2018. The dynamic nature of different land use type revealed the significant changes in different LULC was class of the area under study. The LULC classified into five classes namely the water body, urban, forest, agriculture and pasture land. The developed maps reveal that the highest contribution of the agriculture landuse class was occupied within the study area. Agriculture land was estimated as 46.52% in 2006, 51.51% in 2012 and 61.47% in 2018 progressively increasing but the forest coverage decreases from 28.23% in 2006 to 21.76% in 2012 and 12.46% in 2018. Table 3 shows the areal coverage of different land use types.

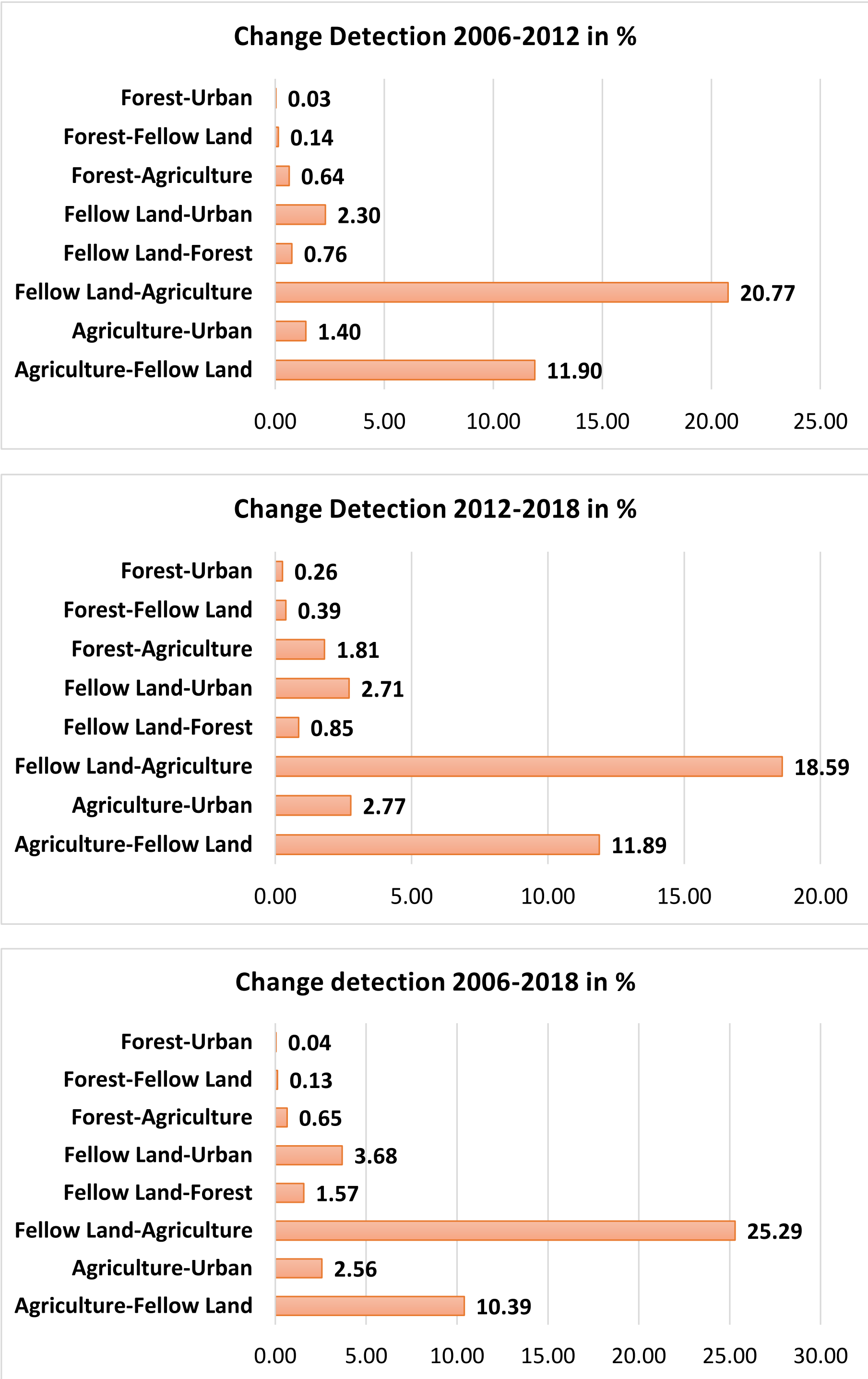


Figure 4: Relative percentage change detection in LULC between years 2006-2012, 2012-2018 and 2006-2018

Table 3
Change in Landuse/cover over from the year 2006 to 2030

S.N.	Classes	2006 Area in sq.km		2012 Area in sq.km		2018 Area in sq.km		2018 Area in sq.km		2024 Area in sq.km		2030 Area in sq.km	
1	Agriculture Land	1934.14	46.52%	2141.58	51.51%	2555.65	61.47%	2555.65	61.47%	2512.3	60.43%	2438.6	58.66%
2	Forest	1172.61	28.23%	904.72	21.76%	517.13	12.46%	517.13	12.46%	206.9	4.97%	206.9	4.97%
3	Pasture Land	849.44	20.43%	713.59	17.16%	560.942	13.49%	560.94	13.49%	771.7	18.56%	764.4	18.38%
4	Urban Land	184.28	4.43%	342.68	8.44%	413.94	9.95%	413.94	9.95%	584.3	14.05%	665.4	16%
5	Water Body	16.56	0.39%	54.45	1.31%	109.37	2.63%	109.37	2.63%	81.7	1.96%	81.7	1.96%
Total Area		4157.03	100%	4157.02	100%	4157.032	100%	4157.03	100%	4156.9	100%	4157	100%

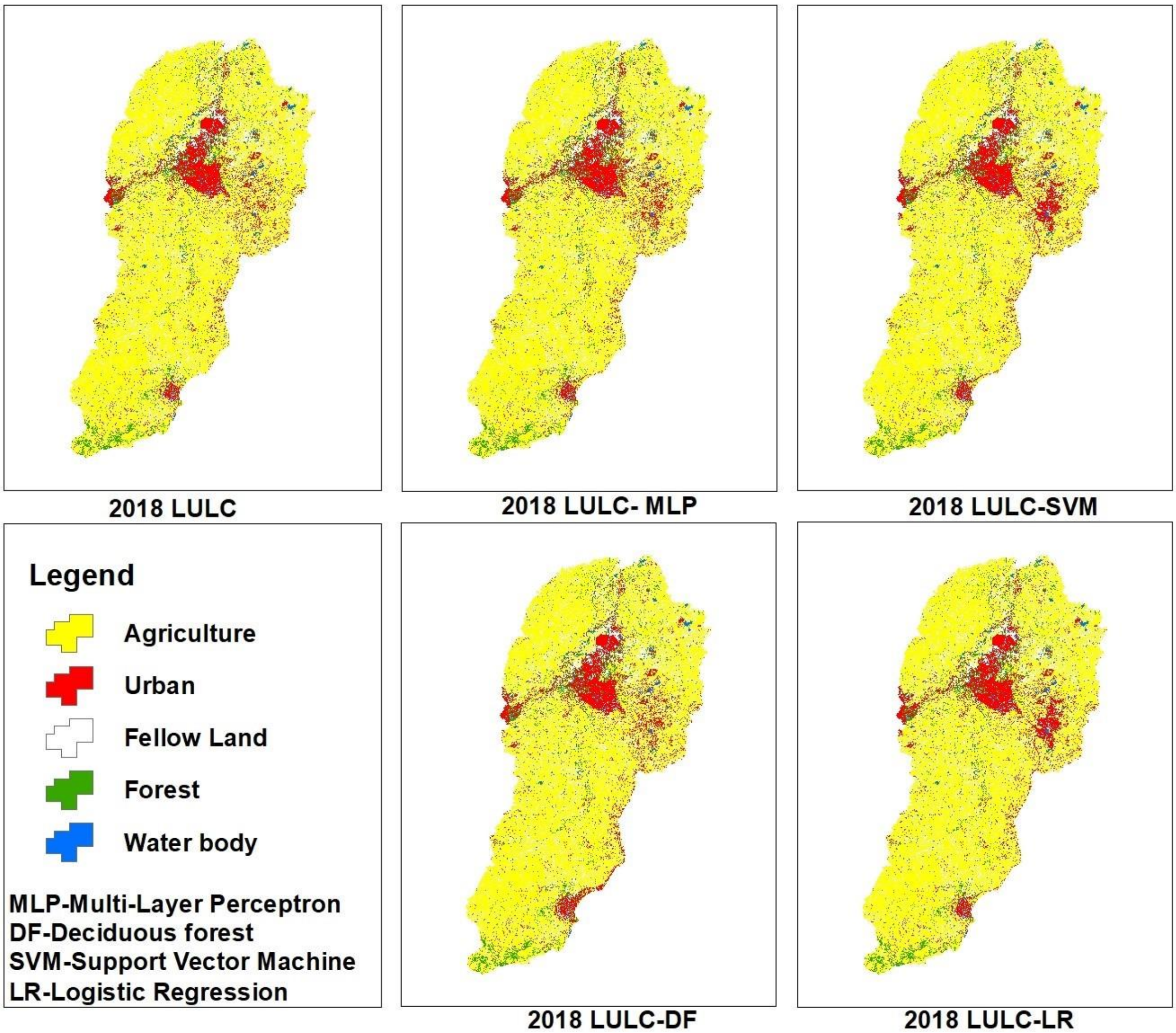


Figure 5: Forecasted LULC of the year 2018 using various forecasting methods

Forecasting Land use/ land cover results: The integration of advanced remote sensing and MC modelling was proved to be an efficient approach for landuse change identification and forecasting in Kharun river basin. LCM is a robust function in TerrSet which organizes an array to understand the static and dynamics of land use-land cover changeover and its correlated impacts in LCM modeled for transition potential using the multi-layer perceptron (MLP) neural network technique. A complex mathematical function of a non-linear neural network has ability to transform multi-variant input data into desired outputs using a backward propagation algorithm, MLP in LCM for transition prediction. A typical MLP network consists of an input layer, an output layer and one or more hidden layers, each with a number of nodes.

Validation was used to find out the quality of forecasted LULC maps. For the validation purpose, all the three models were used to project 2018 LULC and were compared with the supervised classified image. Successful run of MLP with suitable accuracy and skill measure is shown in figure 5. The probability of transition matrix was generated and fed to Markov model in LCM. The results of projected LULC of the year 2018 from all the four models were then compared with supervised classified LULC of year 2018. To understand these maps, correlation matrix was calculated in table 4 which shows correlation of year 2018 LULC and four transition probability generated LULC.

MLP was then used for the forecasting LULC of year 2024 and 2030. Figures 6 (d) and (e) show the forecasted LULC map of years of 2024 and 2030. The areal coverage of different class is listed in table 3. Percentage change of different LULC types were calculated by K-mean clustering approach. Figure 4 shows the relative change in different LULC class between the year 2006-2012, 2012-2018 and 2006-2018. Results reveal that the maximum change is detected from fellow/pasture land to agriculture land successively in 12 years with 25.29%. This change shows the steady development of the basin.

Long term continuous rainfall runoff analysis: The hydrological cycle is based on the water balance equation simulated by SWAT. The SWAT model developed in this study analyses the long-term impacts of settlements in terms of LULC change for complex system of river basin. The results of three years of changed LULC data have been used to pose surface runoff.

Table 4
Correlation matrix of 2018 Classify LULC with Multi-layer perception (MLP) Deciduous Forest (DF), Logistic Regression (LR) and Support vector Machine (SVM)

	2018 Classify	2018 MLP	2018 SVM	2018 LR	2018 DF
2018 Classify	1.00				
2018 MLP	0.93	1.00			
2018 SVM	0.92	0.91	1.00		
2018 LR	0.92	0.90	0.90	1.00	
2018 DF	0.85	0.85	0.85	0.82	1.00

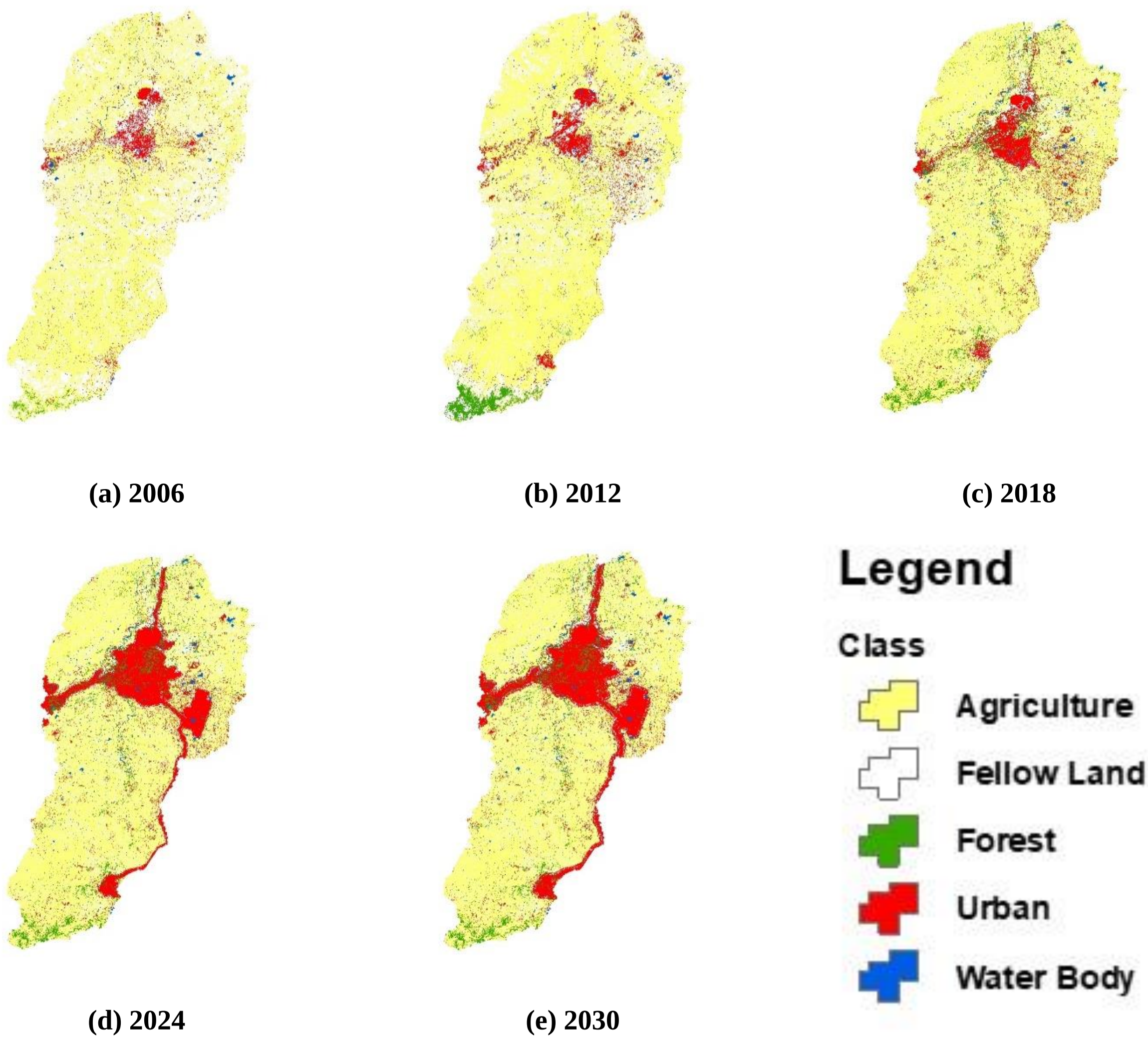


Figure 6: Classified and Forecasted LULC of years 2006, 2012, 2018, 2024 and 2030

Simulated and changed monthly flows indicate an increase of surface runoff for the entire season. The outcome from model in a daily time step reveals strong indications of increased flood magnitude in changed LULC scenario.

The developed model was calibrated and simulated. The observed discharge data at the outlet of the Kharun basin used to identify the calibration efficiency. The water balancing components of hydrologic cycle are evaluated and was used to understand the impacts of LULC change over the long period of time. The suitability of different types of water management measures depends on the exactness of the results obtained by simulation. The output from simulation model depends on the capability of the models and the quality of model inputs.

The SWAT model calibration parameters were identified by developing three different models corresponding to LULC of years 2006, 2012 and 2018. Figure 7 reveals the statistical graph of simulated and observed discharge at the Patharidih gauging site. Surface runoff was then simulated for the same rainfall of year 2018 to quantify the changes that have taken place due to change in LULC corresponding to the LULC of 2006, 2012 and 2018. The results are graphically depicted in figure 8 (a).

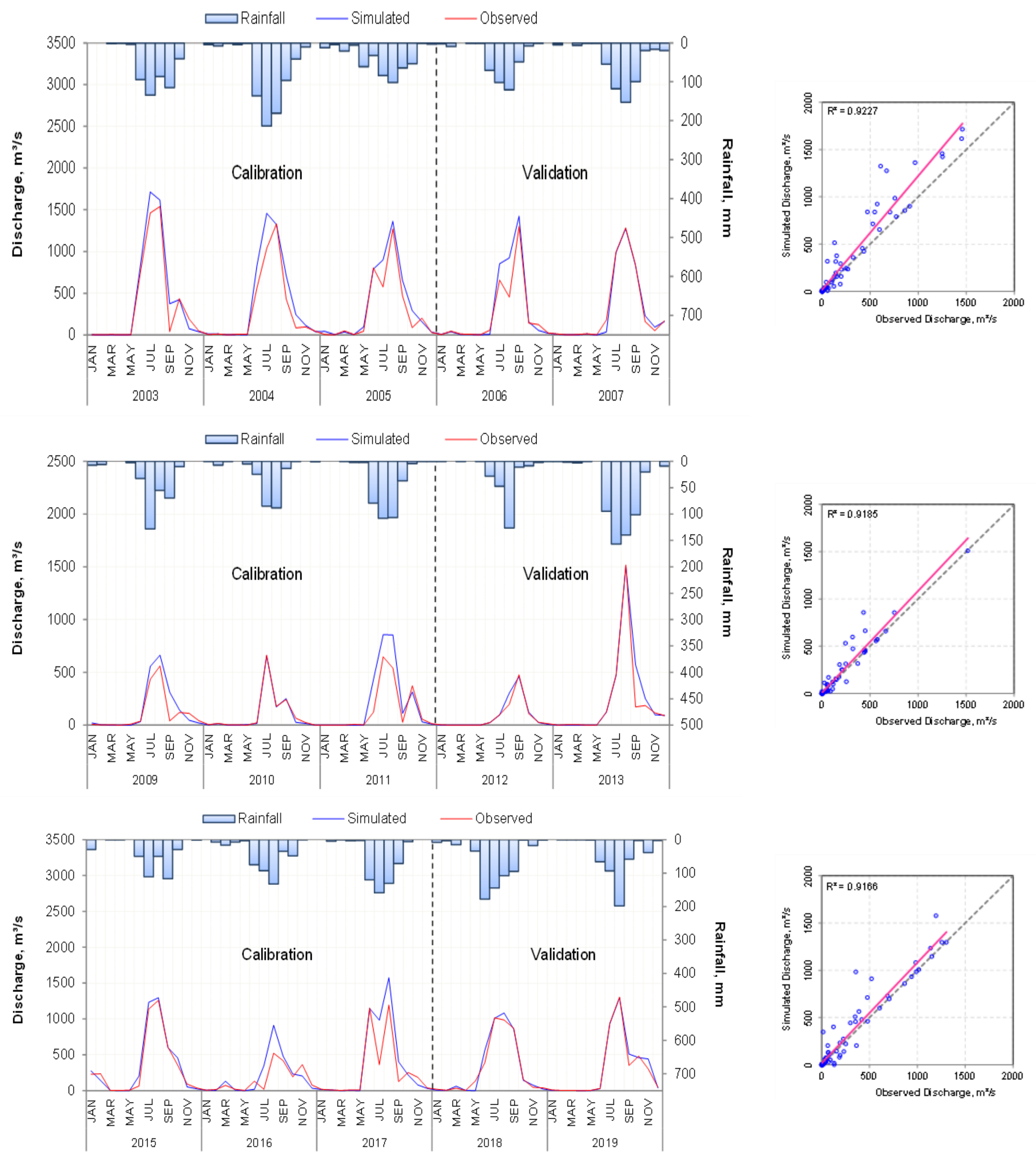
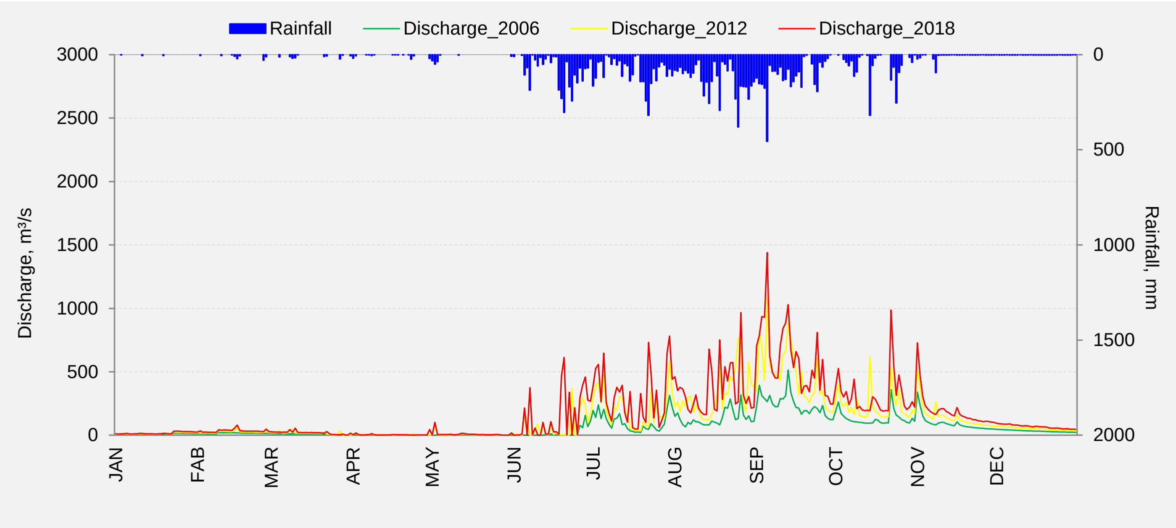
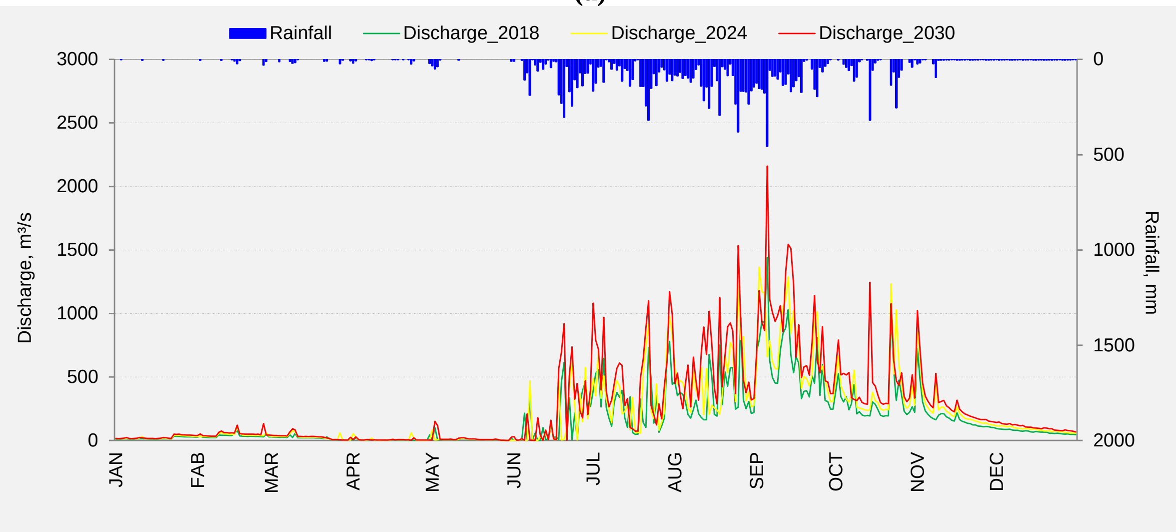


Figure 7: Calibration and validation graphs of observed and simulated discharge for LULC of years 2006, 2012 and 2018



(a)



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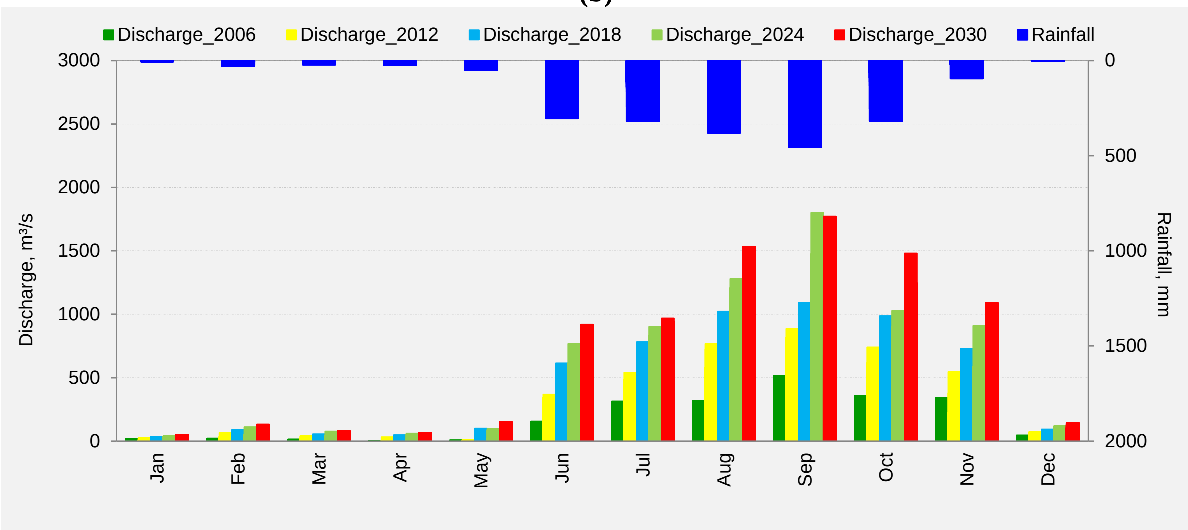

(c)

Figure 8: Graphical variation of simulated discharge for LULC of years 2006, 2012, 2018, 2024 and 2030

It can be observed that the same model with the same rainfall value under different LULC maps produces surface runoff with significant change. The simulated runoff discharge is progressively increasing as the built-up/urban and agriculture area increase. The same procedure is applied to the LULC of predicted year 2024 and 2030. From the figure 7 (b), it is clear that the runoff value is getting more intense with time due to LULC change. The overall change in runoff discharge for five years under the same model is shown in figure 8 (c). The statistical observation is listed in table 5 for the models developed corresponding to LULC of years 2006, 2012 and 2018.

Land use/cover change impact assessment in sub catchment scale: In this modeling, the Kharun was divided into 5 sub basins as depicted in figure 9. The effect of LULC change on hydrological parameters in the sub basin scale was examined. The study area was chosen as the urban area, with two of the sub-basins being specifically considered. The basin was selected by estimation according to the characteristics. For this estimation of the growth of the change in the built-up by means of the equation, LULC was done between 2006 and 2018 LULC.

First two sub-basins (1 and 2) selected showed already a greater ratio of built-up cover at beginning of the considered time period in the study to assess impact. Selected sub-basin is shown in figure 9 with different colors.

Therefore, it is appropriate to analyze and to quantify the various components of hydrological process taking place in the region as per the study of figure 9, which is the most essential component of the water balance of the sub basins. Eight rainfall measurement stations were distributed throughout the catchment area, based on the principle of the Thiessen polygon method. Raipur and Bhilai measurement station values have been included in this sub-basin. The rainfall values in the station are around 1005.05 mm and 1178.70 mm. The analysis results are shown in table 6.

Conclusion

This study simulates hydrological model with remote sensing data in GIS platform for the assessment of the impacts of LULC change on hydrology of the Kharun basin. This study proves very effective to understand the disturbance caused due to anthropogenic activity in water balancing components. A strong connection is developed between LULC and surface runoff with the help of this study.

Table 5
Statistical compression of observed and simulated daily stream flow

Statistics	Observed Flow (mm/day)	Simulated Flow (mm/day)	Observed Flow (mm/day)	Simulated Flow (mm/day)	Observed Flow (mm/day)	Simulated Flow (mm/day)
	2003-2007		2009-2013		2015-2019	
Mean	201.74	167.56	141.92	109.95	192.33	160.37
Median	5.48	11.25	11.62	9.77	2.50	13.36
Variance	828.43	710.70	576.36	447.71	622.64	491.30
Standard Deviation	414.22	355.35	288.18	223.86	311.32	245.65
Kurtosis	4.18	5.87	5.75	6.45	0.76	1.06
Skewness	2.26	2.53	2.50	2.62	1.46	1.53
Minimum	0.00	0.26	0.00	0.12	0.00	0.78
Maximum	1618.00	1485.25	1254.57	1001.03	1023.00	865.61

Table 6
Statics representation of Water balance components

W1						
Year	Rainfall (mm)	Runoff (mm)	Lateral flow (mm)	Ground water contribution to stream-flow (mm)	Actual evapotranspiration (mm)	Water yield (mm)
2006	1005.05	577.46	0.29	188.39	483.89	482.08
2012		609.33	0.21	94.15	469.39	510.83
2018		643.56	0.18	43.34	465.49	520.60
2024		661.21	0.14	6.31	446.77	550.76
2030		696.07	0.13	5.92	446.46	551.24
W2						
Year	Rainfall (mm)	Runoff (mm)	Lateral flow (mm)	Ground water contribution to streamflow (mm)	Actual evapotranspiration (mm)	Water yield (mm)
2006	1178.70	797.86	0.29	0.80	393.37	798.11
2012		831.52	0.26	0.50	363.12	831.75
2018		873.90	0.20	0.30	323.41	874.07
2024		802.91	0.21	0.10	321.41	876.05
2030		879.41	0.21	0.08	318.60	879.58

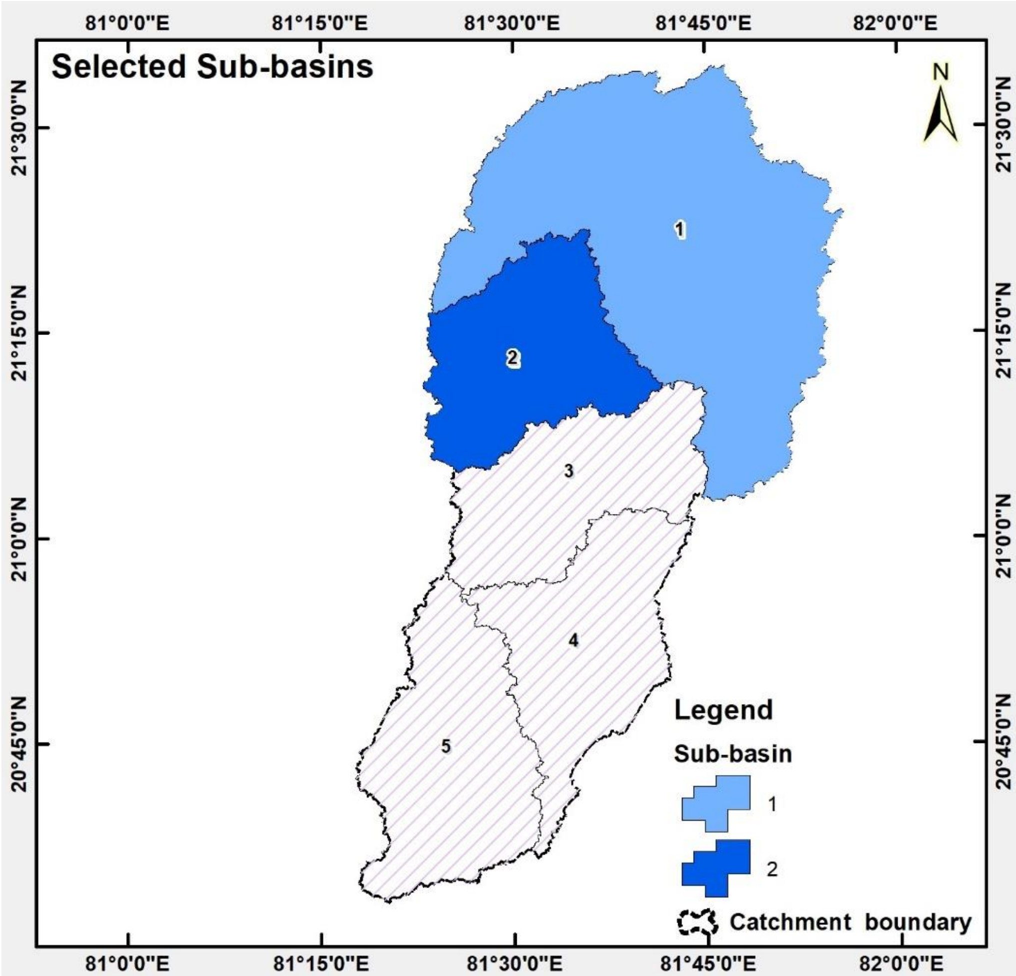

Figure 9: Sub-basins for assessment of LULC change impact on hydrological parameters

On the assessment of the result with certainty, it was disclosed that disturbance caused was due to surface imperviousness as the altered surface caused significant spatial and temporal impact on movement of water in the system. The outcome of the SWAT modelling reveals that the surface runoff continuously increases over the period under consideration. Consequently, percolation, lateral flow and evapotranspiration component get decreased and water yield increased. The results obtained from the analysis reveal the increase in surface runoff over the interval of 6-year period continuously which gives indication of the alarming situation for the Kharun river basin.

The quantity of water in different compartments is getting disturbed due to change in LULC, causing changes in the flow path of runoff water. This may consequently reduce the surface recharge. The higher quantity of surface runoff may spill out from the storm water drains. This may cause flood like situation event at low rainfall which may severally affect the users. This study may also help to suggest the early warning system for the uncontrolled situation due to developmental activity.

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