DEVELOPMENT OF DATA-DRIVEN MODEL USING BAYESIAN STATISTICS, AND REMOTE SENSING TECHNIQUES FOR CONSTRUING NONLINEARITY IN LULC TRANSFORMATIONS

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KEYWORDS: Data driven model, Machine learning, Bayesian statistics, hotspots, fuzzy-Shannon's heterogeneity index

ABSTRACT: Machine learning techniques help in construing the complexities of combinatorial analyses. Application of these techniques helps in assessing the significance of causal factors on spatial events. This work attempts to identify the hotspots of possible randomness in terms of land use / cover changes using machine learning and remote sensing techniques. Transformations in an urban landscape pattern are a consequence of congregation of different spatial and aspatial factors. Furthermore, there is a huge possibility that the characteristics of these factors may vary in spatio-temporal domain. Hence, it is difficult to investigate an urban event using a unidimensional approach. Non-linearity of urban events can be tackled using techniques which are effective in considering and representing the possible transitions of causal factors from one state to another with probabilistic / possibilistic values. Hence, Bayesian model is employed in this study using historical and current data sets.

Firstly, the study area is segregated into different grids. Spatiotemporal assessment of land use / cover changes and transition of LULC class from one to another is performed for the years between 1992 and 2014 for each grid. Then, current landscape pattern is quantified using a proposed landscape indices termed as fuzzy-Shannon's heterogeneity index for different grids. It is developed by modifying conventional Shannon's heterogeneity index. The results obtained from the application of fuzzy-Shannon's heterogeneity index and spatiotemporal assessment of LULC changes and transition of LULC class from one to another are fed into the Bayesian model to determine the land use / cover changes hotspots. Results of the Bayesian model also help in identifying the factors which are the most significant actors in inducing randomness in LULC transformation. Hotspots obtained from the proposed model are witnessing unprecedented changes in LULC. Therefore, it can be inferred that results are in sync with the actual scenario.

1. INTRODUCTION

Studies on various dimensions on land use and land cover have been performed in past. In fact, different dimensions of land use and land cover studies were discussed, deliberated, and investigated to characterize the different facets of land use and land cover transformation phenomenon. Before attempting to understand the land use and land cover (LULC) transformation process, there is a need of proper monitoring of LULC change in a spatial-temporal domain as spatio-temporal complexities have significant role in triggering LULC transformations. Therefore, there has been a striking growth in the application of geospatial technology in investigations pertaining to land use and land cover domain. Reasons for such rise in the application of geospatial technology for LULC investigations are due to their capability in monitoring spatial-temporal variation of LULC changes effectively and accurately. There are other techniques and methods which have been in use for studying LULC monitoring or transformations phenomenon. However, there is a need to understand that the factors which attribute to increase the complexities of LULC change or transformations may change in nature or degree with time. Therefore, techniques which investigate LULC transformation events without considering this possibility may not be able to characterize the land use and land cover transformation phenomenon effectively and accurately. Hence, effective characterization of LULC transformation needs techniques or methods which can accommodate the conditions or rules which can possibly resemble the characteristics of field and may provide flexibilities which can accommodate the aspect of possible randomness and uncertainty from the perspective government policies.

Unprecedented urbanization gripped the world in the first decade of 21^{st} century. It needs to be noticed that urban areas of world already inhabits half of the population of world which would become two-third by 2050 (Wang et al., 2017). Consequently, urban areas are expanding to fulfill the demand of urban residents and accommodate the swarming of people from other regions into the urban areas. Therefore, Newman (2006) highlights the possibility of worsening the environmental state of a city due to whirlwind growth of cities. The authors further raise questions about the significance of opportunities which may be at the cost of damaging environmental sustainability. The observations of authors compel the researchers of urban fraternity to perform investigations in different dimensions of urban landscape science to construe the complexities involved in shaping various facets of urban landscape. Hence, the investigations performed by Prestele et al. (2016) needs attention. It is highlighted in the study that spatially explicit assessment of uncertainties needs to be included in studies pertaining to urban science. It would help in assessing the amount and location of uncertainties (Prestele et al., 2016). Based on the review study, it is highlighted that the proximate drivers of changes in landscape were quantified using satellite and aerial imageries. However, the factors which are actually responsible for triggering changes in landscape was performed based on personal interpretation. Consequently, the relationship between actors and driving factors did not get consideration (Plieninger et al., 2016). While performing investigations on urban landscape, there is a need of clear understanding about the meaning of land use and land cover, and how these aspects are related to each other and possible affect the processes of earth systems. This understanding would help to understand the urban processes more clearly. Riebsame (1994) states that the meaning of land use and land cover is distinct in principle, but has significant impact in characterizing earth's surface. It is also highlighted by the authors that changes occurring on land use or land cover affect each other.

Hassan & Nazem (2016) assessed spatio-temporal changes in land use and land cover using remote sensing and GIS technology, and further assessed the urban growth dynamics. In addition, the study also aimed to assess the environmental sustainability of the study area. The results obtained from the study suggest that there has been significant change in the land cover due to considerable growth of builtup areas. Specifically, result of the study suggests that 56% of the land cover changed. Byrne et al. (1980) used the principal component analysis technique for assessing changes in the urban landscape. It specifically used principal component analysis of multitemporal data for achieving the objective. Cihlar (2010) focused on understanding the mapping strategies from the perspective of resolution i.e. coarse and fine resolution. It further attempted to assess the land cover status in the context of requirement, data sources, and analysis methodologies. This study helps in deciding about the research priorities in data pre-processing and classification. Nong et al. (2014) performed investigation to assess urban growth of the capital city of Vietnam, i.e. Hanoi using remote sensing technology and landscape indices. The composition and distribution of different possible growth types were also assessed in the study. In addition, the significance of distance on the pattern of urban growth was also assessed. The results which were obtained from the study hints at the possibility that the urbanization of the study area is mainly driven by the infrastructures. That actually becomes the primary reason for uneven distribution of urban growth of the study area. Rawat & Kumar (2015) performed investigation in the same direction. The authors assessed the spatial-temporal dynamics of land use cover. It was found that land use classes such as builtup and vegetation increased in last two decades, while land use classes such as barren land, and water body decreased. Investigations such as Odunuga & Badru (2015) and Fung (1990) were in different directions of land use and land cover studies. Former, attempted to assess the changes in environmental parameters based on the relationship between land cover change, land surface temperature, surface albedo, and topography, while the later, attempted to appraise the information content and accuracy of the Landsat digital TM image used for detecting changes in land use and land cover of the study area.

This study is primarily an attempt to assess the possible hotspots of land use and land cover changes of the study area i.e. the capital city of the Jharkhand state which has been witnessing unprecedented growth in urbanization in the city for last few years. This may be happening due to formation of Ranchi city as the capital of Jharkhand state. After becoming the capital city, it attracted various kinds of activities due to increase in opportunities. That attracted huge influx of people which increased pressure on the land system of the city. Consequently, the city expanded to accommodate the demand of the city. However, the expansion of the city is not planned and encouraged randomness in the city. Therefore, there is an absolute necessity of studies which assesses the possible randomness and non-linearity in the land use and land cover transformation process of the city. Therefore, this study also assesses the possible states of different land use and land cover classes in different grids of the study area in near future. The aim of the proposed study does not confine to identification of land use and land cover change hotspots, and quantification of possible states of different land use and land cover classes, it also demonstrates the utility of bayesian statistics in assessing the non linearity of land use and land cover change process.

This article is organized in five different sections, namely, introduction, study area, methodology, results and discussion, and conclusion. The first section i.e., introduction briefly explains the significance of this study and provides background of the study with the help of available literature, and states the objectives of the study. Next, comes the study area section which provides a brief description about the city. Then, the section, methodology, explains about the research framework which is used to achieve the objectives of the proposed study. The result and discussion section provides the results which are obtained from the study, and elaborates on it. Finally, the conclusion section provides concluding remarks about the study.

2. STUDY AREA

The study area chosen for performing the proposed study is Ranchi which is the capital of Jharkhand state. The study area is located from 23° 24' 06'' N to 23° 25' 47" N to 85° 26' 57'' E to 85° 27' 26'' E. After becoming capital city in the year 2000, there has been an unprecedented growth in social, economical, and administrative activities. The increase in the aforementioned activities became the primary reason for swarming of people from other areas into the city. That increased demand in terms of space for accommodation, economical activities to sustain the livelihood of people. Therefore, the city expanded to meet the aforementioned demands. However, the city has not been expanding according to any scientific basis. It instead expanded randomly. Consequently, the city now faces various kinds of problems which may threaten the sustainability of city in near future if proper measures are not taken soon to address the issues.

Most part of the city’s landscape is characterized by mixed land use types which is the resultant of random settlements. Absence of framework which can monitor the urban landscape accurately and effectively encouraged random conversions of land use and land cover classes. It can easily be observed in the peripheral areas of the city that there has been an unprecedented growth in conversions of agricultural land into built-ups. Furthermore, the city is surrounded by three national highways, the NH-33 (national highway-33) has been the most affecting highway in inducing land use and land cover changes in the city. The evidence of this claim can easily be observed as most of the land along the highway which is in the periphery of the city is converted into built-ups. Furthermore, recent infrastructural establishments such as JSCA International Stadium Complex, Birsa Munda Hockey Stadium, Indian Institute of Management may become nodal factors in inducing land use and land cover transformations in the city. The map of the study area is shown in the figure 1.

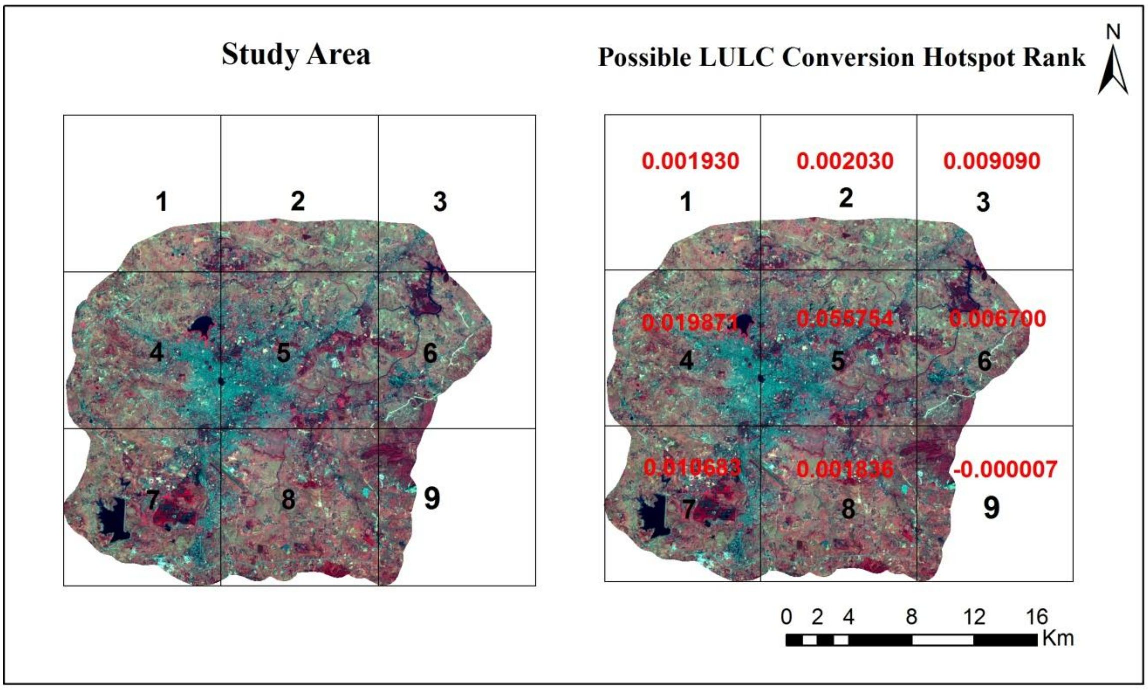

Figure 1. Study Area and Possible LULC Conversion Hotspot rank

3. METHODOLOGY

The research methodology for this work is segmented into different sections to elucidate the flow of work. There are three different segments of the research methodology framework i.e. collection and classification of the data, spatiotemporal assessment of the change in land use and land cover of the data, and application of bayesian statistics to identify the land use and possible land cover conversions hotspots and quantify the possible states of different land use and land cover classes in future. The research methodology flowchart is shown in figure 2.

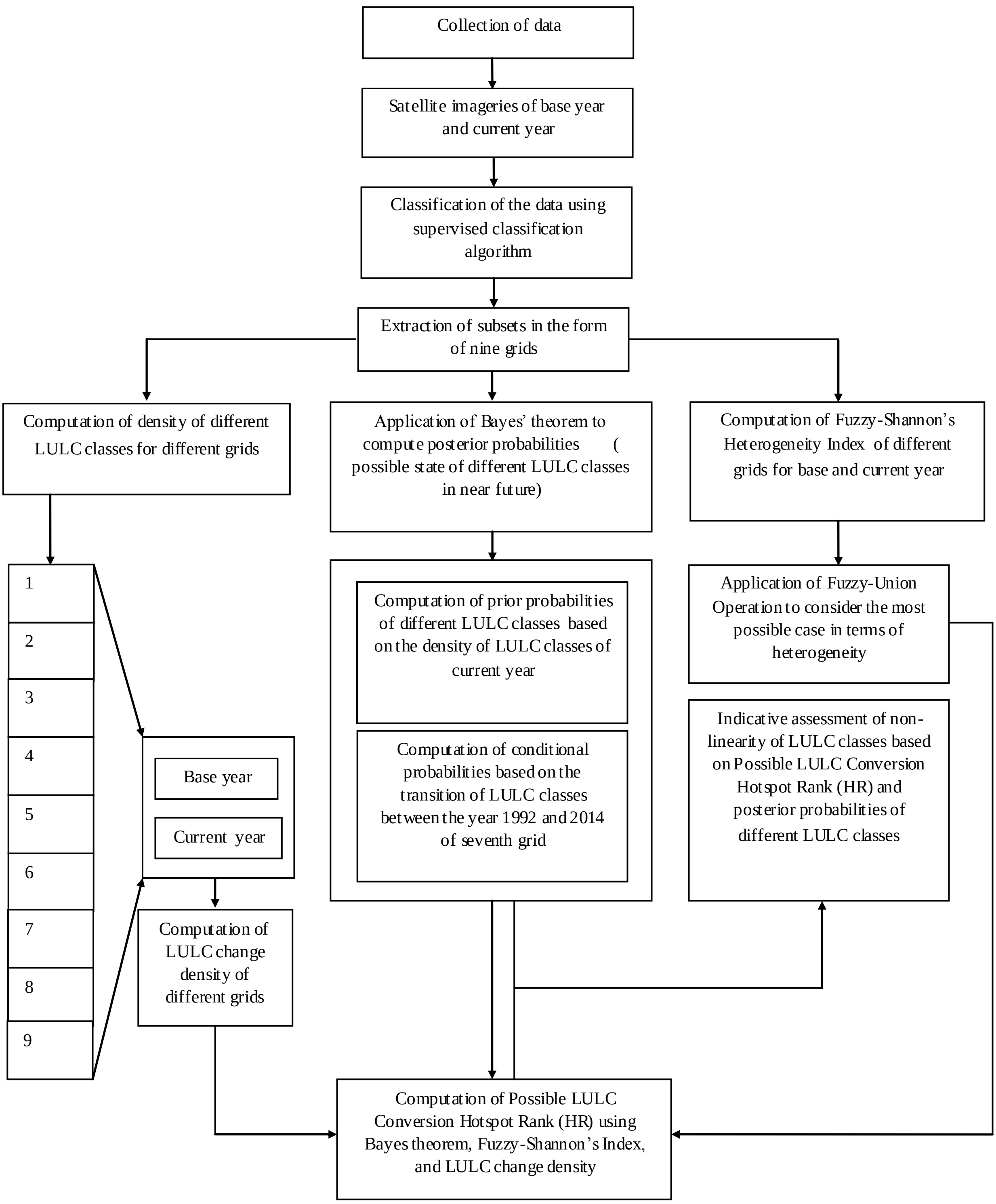

Figure 2. Research methodology flowchart

3.1 Collection and classification of data

The proposed study was performed over a period of twenty two years and intends to assess the changes in land use and land cover over the aforementioned duration. Therefore, satellite imageries of Landsat series data were collected for the years 1992 and 2014 as satellite imageries are effective sources for characterization of spatial-temporal variation. The imageries need to be classified for assessing the spatial-temporal variations. Before classifying the images, there are two issues which need to be considered. First, preferably, the spatial resolution of temporal satellite imageries needs to be equal and the second issue is regarding the criteria of selection for classification algorithm; the classification algorithm which is chosen for classifying the satellite imageries should be in the context of study area. This work employed supervised classification algorithm as the study area is known and can be accessed for field observations to validate the findings. If the study area is unknown and cannot be accessed then the supervised classification learning algorithm should be avoided. The satellite imageries of 1992 and 2014 were classified into four land use and land cover classes i.e. fallow land, built-up land, water bodies, and low land. More number of classes could be selected for characterizing the study area, but primarily, transformations into built-up land from lowland is ubiquitous in the study area. Therefore, based on the field observations, it is decided that the aforementioned land use and land cover classes is adequate for serving the purpose of this work.

3.2 Spatial-temporal assessment of land use and land cover change

As discussed in the 3.1 section, the satellite imageries of 1992 and 2014 were classified using supervised classification algorithm into land use and land cover classes, namely fallow land, built-up land, water bodies, and low land. The whole study area was categorized into nine different grids. Then details of land use and land cover changes extracted for each grid to identify the grids which have been the most affected by land use and land cover changes over the period of twenty two years (1992-2014). In addition, the details of inter class land use and land cover conversions was obtained for one grid. The information about the inter class conversion was used to quantify the conditional probabilities for different land use and land cover classes. The details of land use and land cover changes extracted for each grid was also used to obtain prior probabilities for different land use and land cover classes.

3.3 Identification of possible LULC conversion hotspots using Bayesian statistics and fuzzy-Shannon's heterogeneity index

This section of the research framework focused on applying the concept of Bayes theorem for identification of the hotspots of land use and land conversion (LULC) change. In addition, application of Bayes theorem helps in quantifying the possible state of different land use and land cover classes in near future. That would help in containing non-linearity in the land use and land cover conversions. The Bayes' theorem (Stattrek, 2017) was first given by Thomas Bayes (Wikipedia, 2017). Steps which are required to apply Bayes theorem to construe the non-linearity in LULC conversion is appended below:

<u>Computation of prior probabilities</u>: Prior probabilities of different land use and land cover classes for different grids of the study area were computed using the details derived from the current dataset i.e. classified satellite imagery of the 2014. The density of different LULC class was used as the prior probabilities. The formula for determining prior probability is as following:

$$P(FL) = \frac{Area\ \ of\ \ fallow\ \ land}{Total\ \ area\ \ of\ the\ grid} \quad (1)$$

$$P(BL) = \frac{Area\ \ of\ \ builtup\ \ land}{Total\ \ area\ \ of\ \ the\ grid} \quad (2)$$

$$P(WB) = \frac{Area\ \ of\ \ water\ \ bodies}{Total\ \ area\ \ of\ the\ grid} \quad (3)$$

$$P(LL) = \frac{Ares\ of\ lowland}{Total\ area\ of\ the\ grid} \quad 4$$

where P(FL) corresponds to prior probability for fallow land, P(BL) is prior probability for builtup land, P(WB) is prior probability for water bodies, and P(LL) is prior probability for low land.

Computation of conditional probabilities: The study area was divided into nine grids. The conditional probabilities for different grids can be computed and used for application of Bayes theorem. But, this work considered only the values of conditional probabilities of only one grid and these values are used for all the grids. The formula for computation of conditional probabilities of different LULC classes under different class is :

For fallow land:

$$P(C/FL) = \frac{Area\ remained\ as\ fallow\ land\ in\ current\ year}{Total\ area\ of\ fallow\ land\ in\ the\ base\ year} \quad 5$$

$$P(C/BL) = \frac{Area\ converted\ into\ builtup\ land}{Total\ area\ of\ fallow\ land\ in\ the\ base\ year} \quad 6$$

$$P(C/WB) = \frac{Area\ converted\ into\ water\ bodies}{Total\ area\ of\ fallow\ land\ in\ the\ base\ year} \quad 7$$

$$P(C/LL) = \frac{Area\ converted\ into\ low\ land}{Total\ area\ of\ fallow\ land\ in\ the\ base\ year} \quad 8$$

For lowland:

$$P(C/FL) = \frac{Area\ converted\ into\ fallow\ land}{Total\ area\ of\ low\ land\ in\ the\ base\ year} \quad 9$$

$$P(C/BL) = \frac{Area\ converted\ into\ builtup\ land}{Total\ area\ of\ low\ land\ in\ the\ base\ year} \quad 10$$

$$P(C/WB) = \frac{Area\ converted\ into\ water\ bodies}{Total\ area\ of\ low\ land\ in\ the\ base\ year} \quad 11$$

$$P(C/LL) = \frac{Area\ remained\ as\ low\ land\ in\ current\ year}{Total\ area\ of\ fallow\ land\ in\ the\ base\ year} \quad 12$$

Similarly, the conditional probabilities for different LULC classes under builtup land and water bodies LULC class were computed.

Computation of posterior probability: The posterior probability of different LULC class was computed using the Bayes formula and the results obtained from this would correspond to the possible state of different LULC classes in different grids of the study area. These computed values would help in identifying the possible hotspots for LULC conversions. The formula for computation is:

P(FL/C) = { P(FL) * P(C/FL) } / { P(FL) * P(C/FL) + P(BL) * P(C/BL) + P(WB) * P(C/WB) + P(LL) * P(C/LL) } 13

P(BL/C) = { P(BL) *P(C/BL) } / { P(FL) * P(C/FL) + P(BL) * P(C/BL) + P(WB) * P(C/WB) + P(LL) * P(C/LL) } 14

P(WB/C)={ P(WB) * P(C/WB) } /{ P(FL) * P(C/FL) + P(BL) * P(C/BL) + P(WB) * P(C/WB) + P(LL)* P(C/LL)} 15

P(LL/C) = { P(LL) * P(C/LL) } / { P(FL) * P(C/FL) + P(BL) * P(C/BL) + P(WB) * P(C/WB) + P(LL) * P(C/LL) } 16

Computation of fuzzy-Shannon's heterogeneity index: The Shannon's heterogeneity index (Fragstatsmetrics., 2017) is computed for different grids of the study area for both years (1992 and 2014). This index was first proposed by Claude Shannon (Wikipedia, 2017). These values of Shannon's heterogeneity index were converted into fuzzy weights using a continuous membership function which is in the range between 0 and 1. Then fuzzy-Union operation (Klir & Yuan, 1995) was performed on the two fuzzy sets. First fuzzy set contains fuzzy weights for the Shannon's heterogeneity index of the year 1992, and the second fuzzy set contains fuzzy weights for the Shannon's heterogeneity index of the year 2014. The concept of fuzzy set was first given by Lotfi A. Zadeh and Dieter Klaua in 1965 (Wikipedia, 2017). The formula for the Shannon's heterogeneity index, continuous membership function and fuzzy-Union operation are:

$$\text{Shannon's heterogeneity index} = -\sum p_i \, log_{p_i} \tag{17}$$

$$\text{Continuous membership function} = \frac{Value \quad in\ the\ current \quad cell}{maximum \quad value \quad in\ the\ array} \tag{18}$$

$$\text{Fuzzy Union Operation} = CW_{\text{CSHDI1992 U CSHDI2014(I)}} = \max \{ CW_{\text{CSHDI1992(I)}}, CW_{\text{CSHDI1992(I)}} \} \tag{19}$$

Computation of possible LULC conversion hotspot rank: Finally, with the help of change in lowland density (CLLD) i.e. difference between lowland density of the current year(2014) and lowland density of the base year(1992), posterior probability for builtup-land (P(BL/C)), and the results obtained from the fuzzy-union operation (RFU) were used to compute the 'possible LULC conversion hotspot rank' (HR) for different grids of the study area. The formula used for computation of HR is:

$$\text{Possible LULC conversion hotspot rank (HR)} = -(\text{CLLD} \times \text{P(BL/C)} \times \text{RFU}) \tag{20}$$

4.RESULTS AND DISCUSSION

Results of Possible LULC conversion hotspot rank (HR) and posterior probabilities of different land use and land cover classes of different grids is presented in the Table 3. Table 1 contains the details of density of different land use and land cover classes of both years i.e. 1992 and 2014. The conditional probabilities which were used to compute the posterior probabilities is presented in the Table 2. Figure 3 shows the map for the results of Possible LULC conversion hotspot rank (HR). It is clearly evident from the Table 3 that grid no.5 with 'HR value' 0.055754 has the highest possibility of land use and land cover conversions. This grid is followed by grids 4 and 7 with 'HR' value 0.019871 and 0.010683 respectively. The grid which has the lowest 'HR' value is grid no. 9. The results seem to be in completely sync with the field scenario as the grid no. 5 contains the central region and peripheral region of the study area. There has been unprecedented growth of economic activities for last a few years in the central region of the study area and the peripheral region of this grid has the one of the most important highway crossing across and therefore it becomes a primary reason for attracting LULC conversions. As far as grid no. 4 and 7 is concerned, most of the administrative infrastructures are now being established in these regions, and one of the most important industrial infrastructures is in this region, these factors attribute to encouraging newer infrastructural establishments in these areas. Hence, there is a huge possibility of LULC conversions in these regions. As far as non-linearity in LULC conversion is concerned, the results of posterior probabilities of builtup-land and lowland should be observed. For example, grid no. 5 has the highest posterior probability value for builtup-land which is 0.229031 and high value for lowland with 0.762878 respectively. At first glance, it may seem that the possibility of having lowland in near future is highest in this region which could be true as this grid contain peripheral areas of the study area where infrastructural establishments is comparatively lower than the interior regions of the city. However, it has to be noticed that the posterior probability value for builtup-land of this grid is determined when conditional probability of another grid is considered where relatively lowland is more retained in the current year than a few of the other grids. That means it is one of the best case which is considered for computation of posterior probability value for grid no.5. Even in this scenario, if this grid has the highest posterior probability value for builtup-land then it suggests that there is a high possibility of randomness in LULC conversion in this grid if LULC conversion is not monitored.

Table 1. Density of different LULC class in different grids

Grids	1992				2014			
	FLD	BD	WD	LLD	FLD	BD	WD	LLD
1.00	0.0619	0.0206	0.0044	0.9131	0.0781	0.0781	0.0016	0.8422
2.00	0.0606	0.0103	0.0027	0.9264	0.0759	0.0780	0.0071	0.8390
3.00	0.0735	0.0231	0.0219	0.8815	0.0621	0.1735	0.0167	0.7477
4.00	0.0693	0.0612	0.0102	0.8593	0.0527	0.2568	0.0106	0.6799
5.00	0.0539	0.0818	0.0053	0.8590	0.0303	0.4144	0.0027	0.5526
6.00	0.0641	0.0156	0.0090	0.9113	0.0733	0.1258	0.0101	0.7908
7.00	0.1030	0.0478	0.0358	0.8134	0.0572	0.2137	0.0167	0.7124
8.00	0.0817	0.0146	0.0022	0.9015	0.0372	0.1131	0.0013	0.8484
9.00	0.0797	0.0116	0.0028	0.9059	0.0681	0.0229	0.0019	0.9071

Note: FLD: Fallow land density, BD: Builtup land density, WD: Water bodies density, LLD: Lowland density

Table 2. Conditional probabilities of different LULC class under different LULC class

LULC-1992/LULC-2014	P(C/FL)	P(C/WB)	P(C/BL)	P(C/LL)
LL	0.045	0.001	0.187	0.067
WB	0.116	0.588	0.029	0.267
BL	0.020	0.011	0.762	0.207
FL	0.121	0.001	0.251	0.627

Table 3. Posterior probabilities and LULC conversion hotspot rank

Grids	Posterior probabilities				Computation of LULC conversion hotspot rank				
	P(FL/C)	P(BL/C)	P(WB/C)	P(LL/C)	CLLD	S92	S14	max(S92, S14)	HR
1	0.016967	0.035166	0.000003	0.947864	-0.0709	0.774	0.727	0.774	0.001930
2	0.016546	0.035285	0.000013	0.948154	-0.0874	0.477	0.658	0.658	0.002030
3	0.014460	0.083782	0.000032	0.901726	-0.1338	0.763	0.811	0.811	0.009090
4	0.012823	0.129635	0.000021	0.857521	-0.1794	0.751	0.854	0.854	0.019871
5	0.008085	0.229031	0.000006	0.762878	-0.3064	0.580	0.794	0.794	0.055754
6	0.016548	0.058897	0.000019	0.924536	-0.1205	0.850	0.944	0.944	0.006700
7	0.013649	0.105753	0.000033	0.880565	-0.1010	1.000	1.000	1.000	0.010683
8	0.007976	0.050245	0.000002	0.941777	-0.0531	0.582	0.688	0.688	0.001836
9	0.014131	0.009863	0.000003	0.976003	0.0012	0.689	0.604	0.604	-0.000007

Note: CLLD: change in lowland density, S92: Shannon's heterogeneity index(1992), Shannon's heterogeneity index(2014), HS: Hotspot rank

5. CONCLUSION

This work aims to identify the possible land use and land cover conversion hotspots and assess the possibility in nonlinearity in LULC conversions in the study area. Here, the term nonlinearity corresponds to the possibility of randomness in LULC conversions. The effectiveness of Bayesian statistics was also demonstrated in this work to identify the possible land use and land cover conversion hotspots. With the help of variables such as lowland density, posterior probability of builtup-land and the result of fuzzy-union operation between two fuzzy sets containing the continuous weights for Shannon's heterogeneity index for the years 1992 and 2014, the hotspot rank (HR) is computed for different grids to represent the possibility of LULC conversions in different grids. In addition, the non linearity in LULC conversions can be understood through careful observation of posterior probabilities of different LULC classes and comparing it with the 'HR rank value'. The results obtained from this study seem to be in sync with the actual field scenario and therefore, it can be considered that this work succeeds in representing the various possibility LULC conversions.

ACKNOWLEDGEMENT

Authors thank the Vice-chancellor of Birla Institute of Technology, Mesra, Ranchi-835215 for providing all necessary facilities which are required to perform this investigation in the GIS and DIP lab.

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