Land Use/Land Cover Prediction and Transformation for 2035 Utilizing MLP Neural Network and Markov Chain Model: A Case of Hisar City, Haryana, India

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Abstract

The integrated different geospatial approaches such as GIS and multi-spectrum remote sensing-based analysis are significant in comprehending land use changes and provide invaluable information for the management of land and sustainable development. This study aims to analyse the LULC change between 2011 and 2021 and the simulation of future land use for the year 2035 in Hisar City and its per-urban area. The LULC maps of 2011 and 2021 are prepared by using Landsat images after applying the supervised classification and classified into six different categories. The respective maps are used for the predation of LULC of the year 2035 by using the Multi-Layer Perceptron Neural Network and Markov Chain model built-in Land Change Modeler tool of TerrSet software. The model has been validated by applying Validate and Crosstab modules. The examination of LULC change revealed that the area under built-up approximately doubled between 2011 and 2021 at the cost of open spaces, agricultural land and vegetation cover. The LULC model for 2035 predicted that the built-up will increase by 47 percent between 2021 and 2035. The outcomes of the study can be utilised for the sustainable urban development and conservation of fertile agricultural land.

Keywords: Change Detection, Future Prediction, Hisar, Land Use and Land Cover, Markov Chain Model, MLP Neural Network

1. Introduction

Land use and land cover (LULC) are significant components of our surroundings. The changing LULC leads to a large number of ecological as well as environmental problems [1][2] and [3]. The confrontation between sustainable development and environmental changes is mainly linked to untoward human activities at the cost of rising demand for land with the growth in the population [4] and [5]. The whole world, particularly the developing countries, is suffering from extensive land use and land cover change, dominantly from the recent past [6]. LULC is consistently altered by natural and anthropogenic forces. A wide range of natural variables including physical and climatic variables altered the landscape throughout the earth's history [7]. But in the current situation, anthropogenic activities have become a major accelerating factor in LULC changes, for example, the natural landscape is transformed into agriculture use to support the rising population and agricultural land is converted into urban dwellings to meet the demand for housing and all [6] and [8].

The rate of urbanisation acts as an agent of environmental degradation and works as a significant modifier of land utilization, function and structure globally. The process of urbanisation not only changes the physical aspect of an area but also brings changes to the cultural, social and economic aspects. In addition, the intrusion of changing demography over the globe has become a challenge for sustainability [9]. The rising human population is a notable driver of land use changes. The mount of anthropogenic activities will stand against the capacity of the earth's ecosystem, mainly in the developing world. The land area of the earth was degraded by 20 percent during the period of years 2000 and 2015, as per the UN Sustainable Development Goal Report 2019 [10]. In addition, the world's population has increased from 4 billion in 1974 to 8 billion in 2023 and will be expected to reach 9 billion in 2037. The majority of growth occurs in the urban areas.

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As an outcome, the landscape encircling the urban centres has been disrupted around the world [11]. Consequently, monitoring these changes is critical for resource management, particularly in developing countries.

Land Use and Land Cover are two different standard terms and both concepts are closely interrelated. Land cover is a broader concept and consists of natural and man-made physical features, such as water bodies, vegetation, soil, barren land and urban areas etc. identifiable on the surface of the earth. On the other end, land use refers to characterization of how these features are utilized by the human to satisfy their needs. The land use elements are described as residential infrastructure, commercial infrastructure, transport infrastructure and agriculture etc [12]. The variability in the types of land covers promotes the different usage of a single type of land cover, that varies from person to person or region to region within a country [13]. Regardless of these differences, a large number of studies analyse and monitor LULC together with the set of defined classes. A large number of attempts have been made by scientists worldwide for the development of a universal LULC classification scheme with no success because of the complexity and multiplicity of LULC throughout the world. There are numerous classification schemes that provides meaningful solutions to this problem and the classification schemes are divided into local, regional and national scales [14].

The development of geospatial technologies including Geographic Information System (GIS) and Remote Sensing (RS) during the last few decades has accelerated the spatial analyses of LULC at different scales. These geospatial technologies, nowadays, are considered as the most accurate and cost-efficient source for data to analyse LULC and LULC change detection because of the availability of large spatiotemporal data [15] and [16]. Remote sensing allows us to use multi-temporal as well as multi-spectral data for the LULC mapping [17]. A thorough knowledge of the spatial distribution of land use and land cover and its change along with their effects can be done, easily and affordably by utilising aerial and satellite imageries [18]. The data acquired by mean of remote sensing is mainly used for land management and planning to produce information regarding the physical attributes of the land or how a single parcel of land is allocated for different utilization. The satellite data helps to overcome the dearth of reliable data and information. The large number of various open sources and free availability of satellite imageries provide continuous and synoptic data that is used in the LULC monitoring and change studies. Since 1972, when the Landsat programme launched and its data has been openly accessible to all, it has been a revolutionary step in the field of spatial analysis [19]. In the study of LULC, the imageries of Landsat are widely used. But now imageries of some other satellites are also openly accessible like imageries of Resourcesat, Sentinel etc. The advancement in technology for monitoring and analysing the changing features of the earth's surface provides a separate platform for researchers.

Sustainable development needs an extensive analysis and modeling of the settlement system. The urban growth induces intense transformation in the spatial distribution of land uses and it has an impact on natural resources [20]. As a consequence of accelerated urbanization, the urban centres lead to the massive alteration of LULC at the global level and it is a subject of major concern [21]. Over the last few decades, the scant resource of land has become threatened. The drastic changes in land use mainly around the urban centre added significant challenges to the global and local environment [22]. The issues mainly caused by the land use transformation include environmental degradation, deforestation, alteration of the hydrological cycle, loss of ecosystems and fertile land and so many [23]. In order to manage land resources effectively and achieve sustainable growth of urban centres, it is crucial to study LULC changes. While addressing this issue of urban growth explosion is necessary to analyse the current situation of LULC and the future perspective. It helps in the planning and development of the urban centres. Thus, the dynamics of various urban land uses must be analysed and understood by utilising the recent and precise spatiotemporal LULC data.

In the recent time period, a large number of static and dynamic models have been developed and integrated with the GIS and RS for the simulation of future LULC. These models include statistical model, evolutionary model, convolutional neural network, cellular automation, Markov Chain model and other. Models for land use change are important decision-making and supporting tools. They enable the analysis and identification of change quality, the trends of future prediction based on past trends. They also help in planning sustainable development strategies [7][24] and [25]. The Markov Chain Model is used in this study. It is a stochastic modeling tool that is potentially discrete in state and time. Markov chain is a multivariate spatial mode, it drives the prediction of LULC on the basis of past trends of LULC.

While predicting the future LULC, it utilises the historical transition probabilities that are generated from the past transformation in the LULC state or classes by applying a transition matrix. There are some individual models that have the capacity to function to predict the LULC, and most of them provide analytical tools as an aid in urban studies. There are some restrictions on their uses. Consequently, the Markov Chain model is more effective and it incorporates recently developed techniques like machine learning, artificial intelligence and all [26] and [27].

In the Indian context, limited studies have tried to model the future LULC and its trends. If the state of Haryana, in particular, is considered, there are very few studies related to the LULC change and monitoring and study about the modeling of future LULC are almost absent. After a thorough literature review, the city of Hisar and its peri-urban area have been selected as a study area. The major reason to select Hisar as a study area is that it is developed as a centre of major urban centre in southwest Haryana. It was selected as the first and only counter magnet city of the Delhi-National Capital Region in the Haryana state. As a counter-magnet city, Hisar is suffering from the population explosion, large-size in-migration and industrialisation etc. All this leads to significant land transformation in and around the city. The alteration of Land Use and Land Cover are indistinguishably shackled to the development policies and the geographic conditions of the city in particular. The present study examined the land transformation from 2011 to 2021 by utilizing spatiotemporal data and stimulated the LULC for 2035 by using MLPNN and Markov Chain Model. The geostrategic importance of the city of Hisar is known from the continuously rising population of the city in the last few decades. The population of the city increased from 1,72,677 persons in 1991 to 3,01,383 persons in 2011 as per the Census of India.

In the Census 2011, there were five new census towns emerged along the city boundary viz. Satrod Khas, Satrod Kalan, Satrod Khurd, Mayyer and Gangwa. The city of Hisar is just 160 km from the Country's capital New Delhi. The city is well connected through the road, rail, and air network. The city is also recognised as the counter magnet town of the Delhi NCR, to shift the burden of the Delhi NCR. The counter-magnet area was created to intercept the migratory flows into NCR and develop as regional growth centres in the region of their setting. The central government and planning board of NCR provide economic assistance for the regional strengthening of linkages like communication and transport. It helps in the economic strengthening and upgradation of social and physical infrastructure. Hisar, after becoming the counter magnet town getting more in-migration than the out-migration. the government policies primarily aimed at developing the city periphery to retain out-migration. For this, its regional connectivity was improved and basic amenities and facilities were also ensured. The in-migrants settle on the city outskirts for low-cost housing which has caused massive land alteration on the periphery. Its regional connectivity has improved and work participation has increased. the sewage system and water supply increased. All these factors lead to the rapid growth of the city. The city also serves as a base for the army and Border Security Force. Also, many industries, educational and research institutions and an international airport were constructed on its periphery. Thus, government policies for developing industrial estates and affordable housing for all and also provision of public utilities in the city outskirts have led to the peri-urban land transformation of Hisar City. Furthermore, the rapid built-up growth set the city to sprawl in all directions from the city centre. To overcome the haphazard and unplanned urban expansion, factors of urban growth under the changing land use scenarios are considered.

Additionally, research is still required on the Decadal LULC change and its future projection in the Hisar city and its peri-urban area. This research examines the patterns of LULC change and the variables affecting these changes. How these variables become the driver of future land use changes? Therefore, the objectives of the study are the spatio-temporal analysis of land use and land cover over the period of 2011 to 2021 and the simulation of future LULC by applying MLP-NN and MC model for the year 2035 in Hisar city and its peri-urban area. This study also draws attention towards the significance of open-source satellite data and its use in the research. The result of the study offers valuable information for urban planners and decision-makers.

2. Study Area

The Hisar city is located in the Haryana, a state of India. The geographical location of the city is 29.17 North and 75.72 East as shown in Figure 1. The city is located at an elevation of 215 m above mean sea level. The city is located in the alluvial plains of the Yamuna and Ghaggar rivers. The western and southern parts of the city now transited into the deserts. The continental type of climate makes the city as the hottest and coldest place in Haryana during summer and winter respectively.

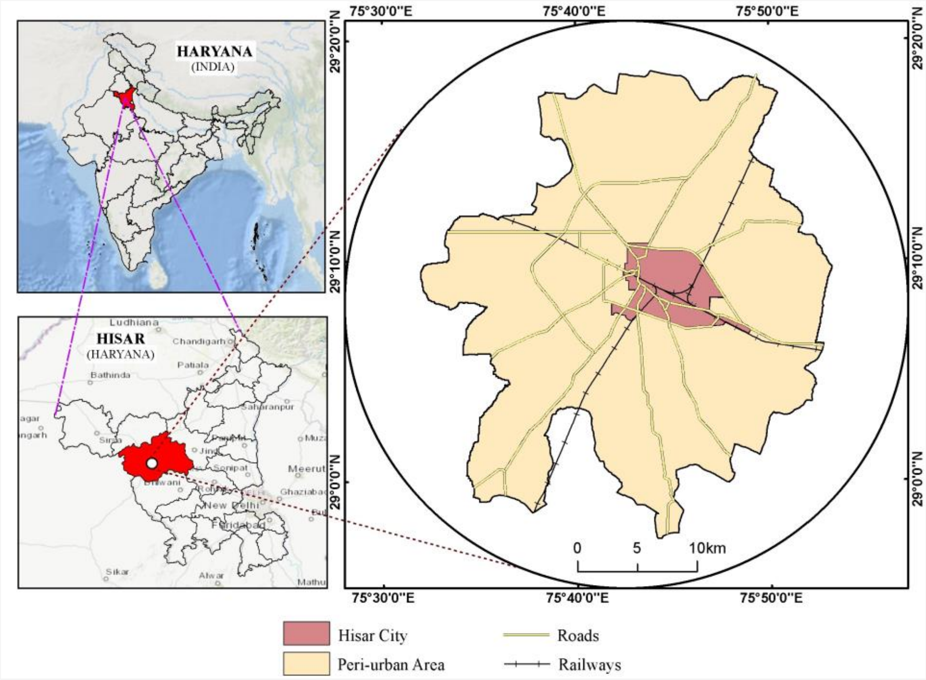

Figure 1: Haryana, India

The study region witnesses the unique characteristics of climate with temperature extremes, dryness, scanty rainfall and loo (local hot wind). There is evidence of pre-Harrapan settlement in and around the Hisar. But in a true sense, the Hisar was founded in 1354 A.D. by 'Firozshah Tughlaq' a Muslim ruler. The word Hisar was derived from the Arabic language which means a 'Fort'. The city is located merely 160 km from the National Capital New Delhi. The city is well connected by road, railways and air transport. By virtue of its location, it acts as a counter-magnet town of the Nation Capital Region and the city grows as an alternate centre of growth for or nearby Delhi. The city is included in the fast-growing urban centers of the country, in demographic and economic terms. The total population of the city was 1.7 lakhs in 1991 and it rose to 3.6 lakhs in 2021. The city has robust basic facilities and amenities, that act as a pull factor and attract the people. The city is the home of a large number of migrants from the neighbouring state. The growth of urban population and urban sprawl of the city beyond its administrative boundary to meet the demand of land for the residential as well as for the industrial setting considerably altered the land use and land cover in and around the city over the last 30 years.

3. Data Collection

The future prediction of LULC with the MLP-MC model requires the historical data of LULC (as a dependent variable). To prepare the LULC of 2011 and 2021, the Landsat images have been downloaded from the USGS, available at http://glovis.usgs.gov. The collected imageries are of the March month (within the close date) and cloud-free, to minimise the effect of seasonal variation on LULC. The MLP-MC model is assisted with several driver variables. So, the following six variables namely slope, elevation, distance from the road, distance from railways, distance from the built-up area and distance from the city centre are considered while simulation of the future LULC. The Cartosat DEM-V3 was downloaded from the Indian Geo Platform of ISRO-Bhuvan. The elevation and slope were derived from the Cartosat DEM-V3. The vector data of road and railways have been digitized from the Google Earth Pro and the built-up area was extracted from the LULC. The administrative boundaries of Hisar city and nearby villages are collected from the site of Town and Country Planning, Haryana and Survey of India. The boundary of the peri-urban area was delineated by using different variables from administrative, demographic and economic criteria [28]. All the data has been processed with the help of the following software: ArcMap, Erdas Imagine, Google Earth Pro and TerrSet. The detailed methodology that has been followed in the present study is shown in Figure 2.

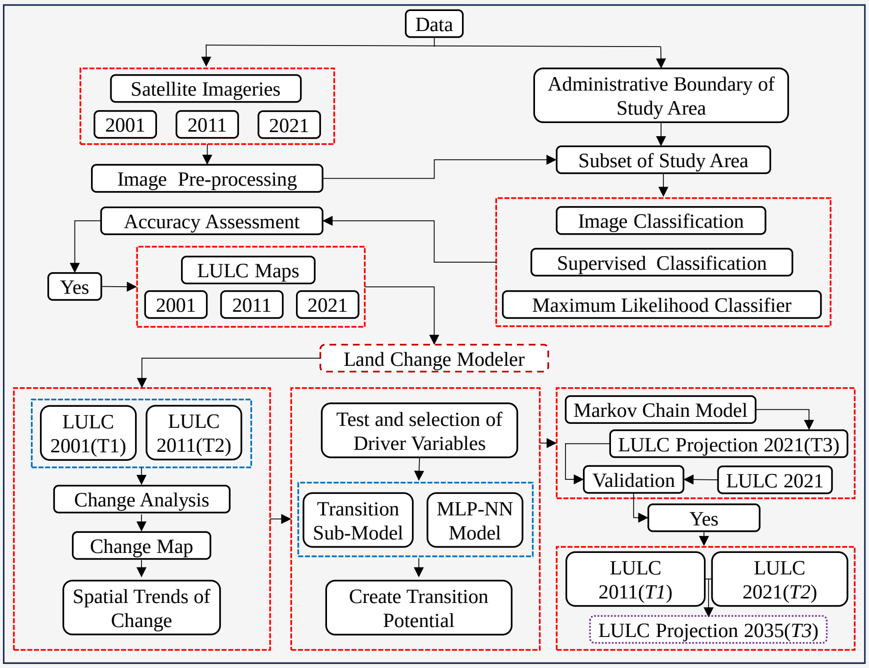

Figure 2: Land use land cover transformation and prediction study workflow

4. Methodology

4.1 Image Pre-Processing and Land Use and Land Cover Classification

The image pre-processing of satellite data was vital before performing the task [29]. In the present study, the task of pre-processing mainly includes the band composition and image enhancement by the adjustment of brightness, contrast and sharpness. After that, the area of interest was clipped to perform the further steps including image classification and accuracy assessment.

The land use and land cover classification were performed for the study area to extract land use categories. In the image classification, the supervised image classification technique was implemented with the maximum likelihood classifier this technique is widely used [30][31] and [32]. The imageries for the years 2011 and 2021 were classified into six classes namely water bodies, built-up, agricultural land, vegetation cover, open/barren land and mining areas. Image classification was followed by the accuracy assessment; to measure it 250 random points were taken for ground truthing. The image of 2011 and 2021 have overall accuracy of 92.4 and 94 percent respectively and the kappa coefficient were 0.90 and 0.92 for the respective year.

4.2 Prediction of future Land Use and Land Cover

The prediction of future LULC simulation was carried out with the Land Change Modeler (LCM) a tool of TerrSet Software. It is an empirical process that was performed by performing different steps including change analysis, modeling of transition potential, driver variable and their testing, transition sub-model, change prediction and validation [4] and [29]. All this is based on the change in the historical LULC from

T1(Time 1= 2011) to *T2*(Time 2= 2021). The simulation process integrates the MLPNN and MC models. Furthermore, the detailed methodology for the prediction of 2035 LULC is discussed below.

4.2.1 Change detection analysis

LULC change detection is a significant task in analysing changing patterns of different land uses over time [33][34] and [35]. The change detection analysis provides the gains and losses among the LULC types with their net change [36]. This also provides the LULC change matrix that shows how one class is converted into another class [37]. In the present study, the LULC change detection was performed within the LCM tool of TerrSet software. The change analysis tool of LCM also provides the spatial trends of change. In the present study, the spatial trend of the top four transformations was also performed.

4.2.2 Driver variables

The nature of land use and land cover is directly or indirectly affected by several variables. The simulation of LULC change needs to consider the potential power of driving variables [26].

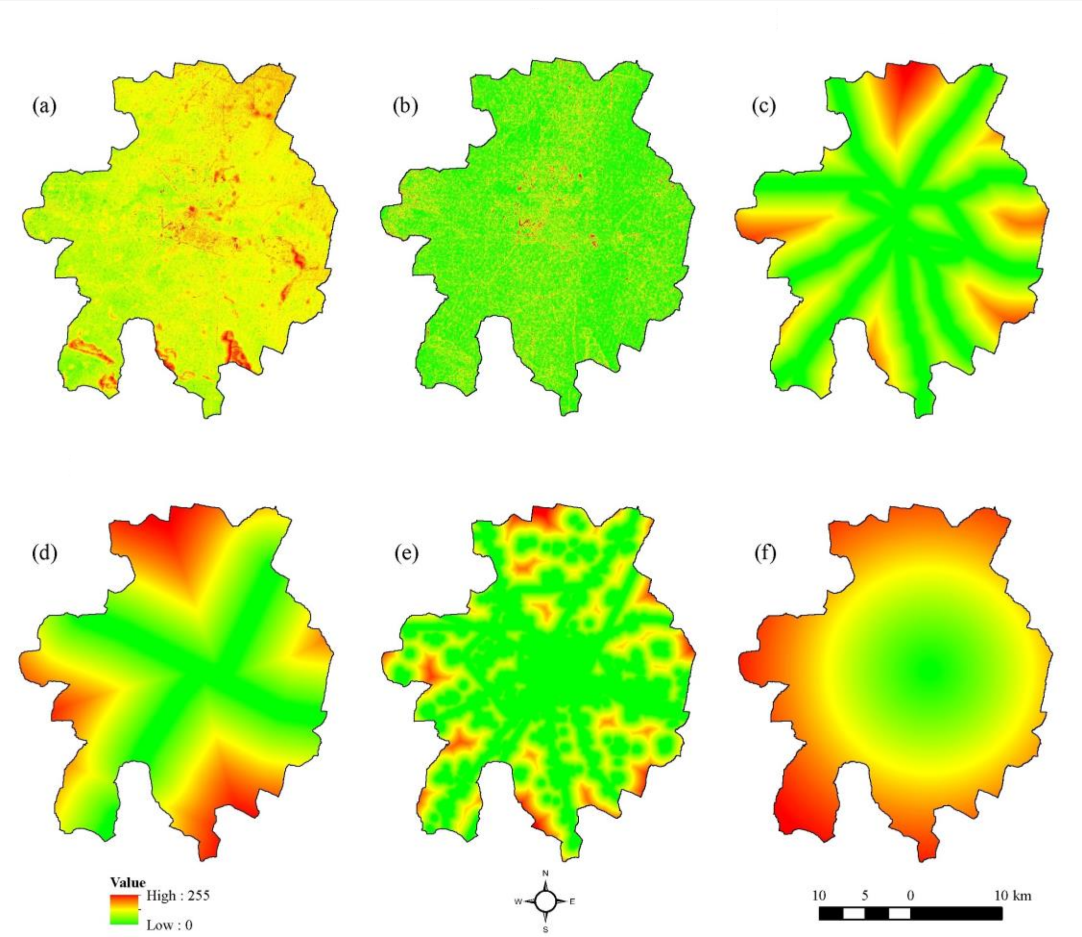

Figure 3: Driver variables: (a) Elevation (b) Slope (c) Distance from major roads (d) Distance from railways (e) Distance from built-up area (f) Distance from city centre

The significant drivers were elevation, slope, distance from roads, distance from railways, distance from existing built-up and distance from the city centre considered in the present study as shown in Figure 3. The elevation and slope of any region affect the land use and land cover trend, low elevation and gentle slopes are easier to use and economically viable for development. On the other hand, the distance from the roads, railways, existing built-up and city centre are the major decisive factors of accessibility and accelerated urban expansion. After considering the driver variables, a test was performed to check the explanatory power of the variables. This test provides the Cramer's V and P-Values to assess the relevance and potential explanation of driver variables. A high Cramer's V value and zero P-value suggest that the variable may have good and higher-quality explanatory power [38].

4.2.3 Transition potential creation and projection of LULC

The driver variables after the skill test were imported into the transition sub-model structure. After that transition sub-model was run by employing the MLP Neural Network Model to create transition potential as it performs multiple regression [39]. It provides the maps of the potential for transition from one class to another. Next, the process of prediction was carried out based on the transition potential maps and the prediction date. In the prediction of 2021 and 2035 LULC, the Markov- Chain model was used as illustrated in Figure 2. The LULC of 2021 was predicated only to check the validation of the MLPNN and MC model.

4.2.4 Validation of predicted LULC

The validation process was performed to quantify the agreement and disagreement between the projected LULC of 2021(T3) and the actual LULC of 2021 that was classified from the satellite image.

The LULC of 2021 was projected on the basis of the LULC of 2001(T1) and 2011(T2) (Figure 2). It is significant to ensure the acceptance and reliability of the model for the prediction of 2035 LULC. Different validations were performed by utilising hard prediction to assess the accuracy of the results, for this VALIDATE and CROSSTAB modules are used [1][40] and [41]. The statistical report shows that Kstandard is 0.8827, Kno is 0.9166, Klocation is 0.9109, and KlocationStrata is 0.9109. Similarly, the CROSSTAB modules report shows an overall Kappa index of 0.8827. This also provides the class-wise kappa index of agreement (KIA). The result of class-wise KIA shows that the built-up recorded the highest KIA which was 0.8876 followed by the agriculture, vegetation, water bodies and open area with KIA 0.8655, 0.8593, 0.8416 and 0.5795, respectively.

On the other hand, the lowest Kappa index of agreement recorded for mining areas was 0.4778. In the prediction of 2035, the LULC of 2011 and 2021 were considered as a dependent variable based on the usual scenario. In the following part the prediction of 2035 LULC has been discussed.

5. Result

5.1 Land Use and Land Cover Analysis between 2011 and 2021

The satellite images of 2011 and 2021 have been classified into six categories namely water bodies, built-up, agricultural land, vegetation cover, open space and mining. Their spatial distribution is shown in Figure 4. As per the result, the proportion of each classified class is shown in Table 1.

Table 1: Area statistics for the LULC of 2011 and 2021

Classes	2011 Area		2021 Area		Area change	Percentage change
	Hectare	%	Hectare	%		
Water	720.45	0.88	775.44	0.94	54.99	7.63
Built-up	6373.17	7.75	9889.2	12.03	3516.03	55.17
Agriculture	66355.83	80.71	63685.8	77.47	-2670.03	-4.02
Vegetation	1229.04	1.49	1171.98	1.43	-57.06	-4.64
Open	7127.46	8.67	6317.28	7.68	-810.18	-11.37
Mining	405	0.49	371.25	0.45	-33.75	-8.33

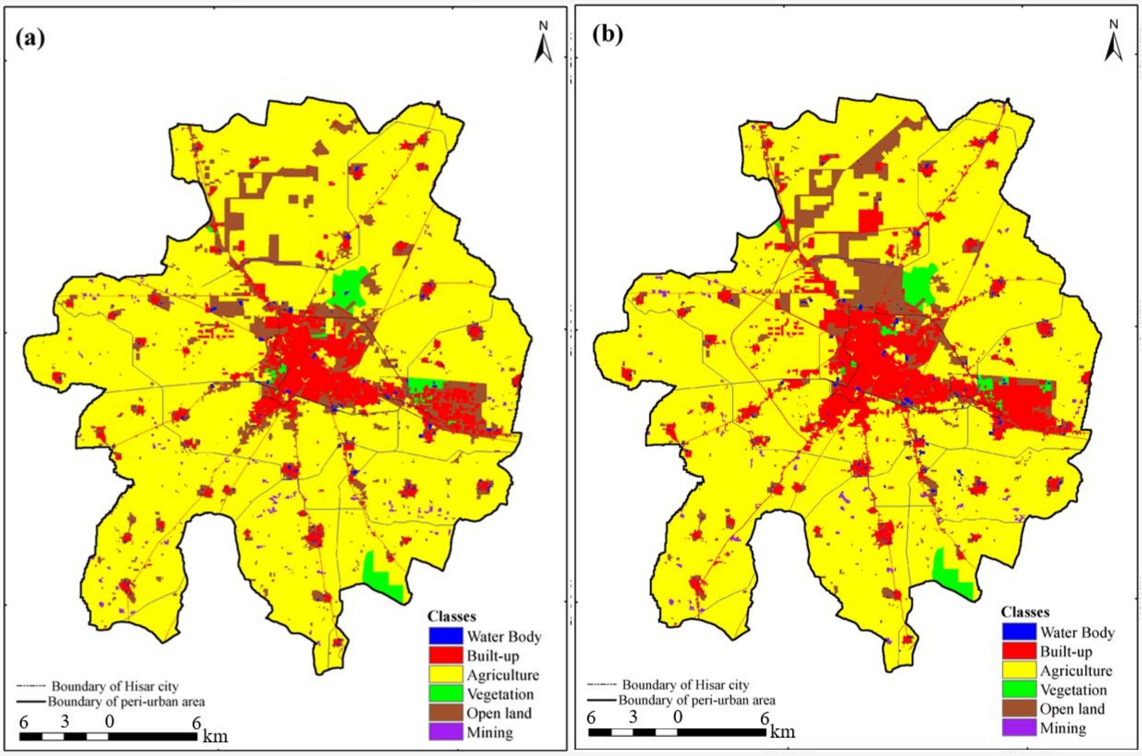

Figure 4: LULC classification of Hisar and its periphery: (a) 2011, (b) 2021

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The result of classification shows that the most dominant category of the study area was agricultural class but it declined by 4.02 percent between 2011 and 2021. It was followed by the open land in 2011 but in 2011 the agricultural class was followed by the built-up area. The expansion of the built-up area was significant, it increased from 6,373.17 ha in 2011 to 9,889.2 ha in 2021. It has also been noted that the area under the water bodies and built-up increased between 2011 and 2021, while all the other classes recorded a decline in their area. The area under the water bodies increased by 7.63 percent because of an increase in the number of waterworks and ponds in the study area. The deforestation caused the decline in vegetation cover from 1,229.04 ha to 1171.98 ha. The vegetation cover was reduced by 4.64 percent. The mining area includes the brick kiln and their associated area also decreased by 8.33 percent. On the basis of classification results, it is noted that the study area has been continuously impacted by rapid urbanization. The high rate of urbanisation altered the land use pattern, it causes a quick decline in the fertile agricultural land and vegetation cover. The gains and losses of all the categories along the net change between 2011 and 2021 are shown in Figure 5.

The maximum gain was recorded by the built-up class followed by the open spaces and agricultural land. Contrary to this the maximum loss was observed in the agricultural land followed by the open spaces. The contribution of the individual class in the net change in different classes is shown in Figure 6. As the built-up class get maximum gain, the largest contributor to this gain was open space with 2041 ha followed by agricultural land with 1,369 ha of land. On the other hand, the maximum loss was recorded in the agricultural land of 3,726.9 ha. Built-up and open spaces were the primary contributors to agricultural land loss, with 1,369 and 1,281 ha of agricultural land transformed into built-up areas and open spaces, respectively. It is also visible in Figure 6, that the increased built-up area was a major and only contributor to the loss of vegetation cover. The land use change and persistence between 2011 and 2021 are shown in Figure 7 and the land transformation matrix is exhibited in Table 2.

The LULC change map shows the top 4 land transformations that occurred between 2011 and 2021. The major transformation recorded in terms of area occurred in the form of agricultural land to built-up and open land to built-up. The map of persistence shows the LULU of 2011 remains the same in 2021. The most persistent class was built-up (100 percent) followed by agricultural land (94.38 percent).

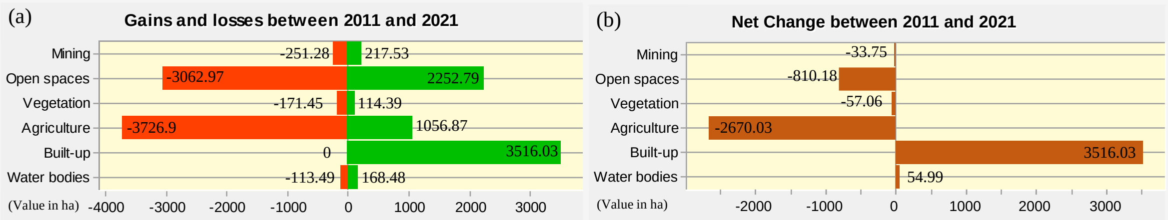

Figure 5: LULC change between 2011 and 2021: (a) Gains and losses (b) Net change

Table 2: Land Use and Land Cover conversion matrix between 2011 and 2021

	LULC	LULC Type 2021(Area in Hectares)						
		Water	**Built-up**	**Agriculture**	**Vegetation**	**Open**	**Mining**	**Total (2011)**
LULC Type 2011	**Water**	**606.96 (84.25)**	21.33 (2.96)	11.43 (1.59)	5.40 (0.75)	75.33 (10.46)	0.00	720.45
	Built-up	0.00	**6,373.17 (100)**	0.00	0.00	0.00	0.00	6,373.17
	Agriculture	51.12 (0.08)	1,368.63 (2.06)	**62,628.93 (94.38)**	8.64 (0.01)	2,084.04 (3.14)	214.47 (0.32)	66,355.83
	Vegetation	2.16 (0.18)	83.79 (6.82)	4.50 (0.37)	**1,057.59 (86.05)**	81.00 (6.59)	0.00	1,229.04
	Open	115.20 (1.62)	2,041.38 (28.64)	802.98 (11.27)	100.35 (1.41)	**4,064.49 (57.03)**	3.06 (0.04)	7127.46
	Mining	0.00	0.90 (0.22)	237.96 (58.76)	0.00	12.42 (3.07)	**153.72 (37.96)**	405.00
	Total (2021)	775.44	9,889.20	63,685.80	1171.98	6317.28	371.25	**82,210.95**

**Values in Brackets and Italics are in Percent*

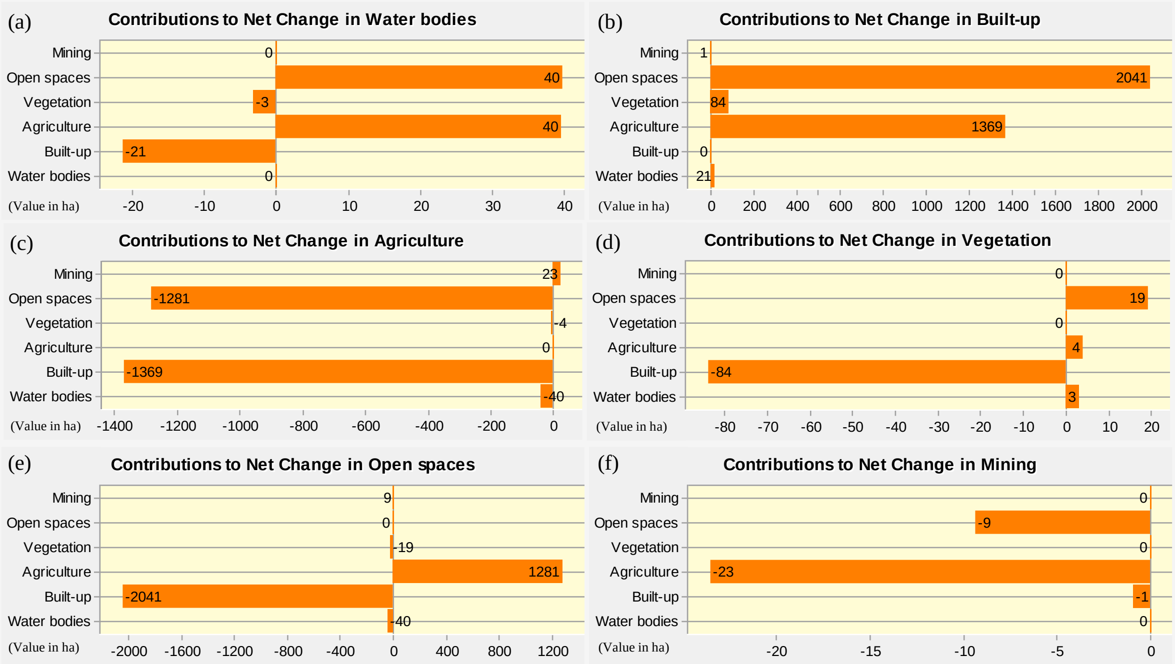

Figure 6: Contributions to net change in each class between 2011 and 2021: (a) Water bodies (b) Built-up (c) Agriculture (d) Vegetation (e) Open spaces (f) Mining

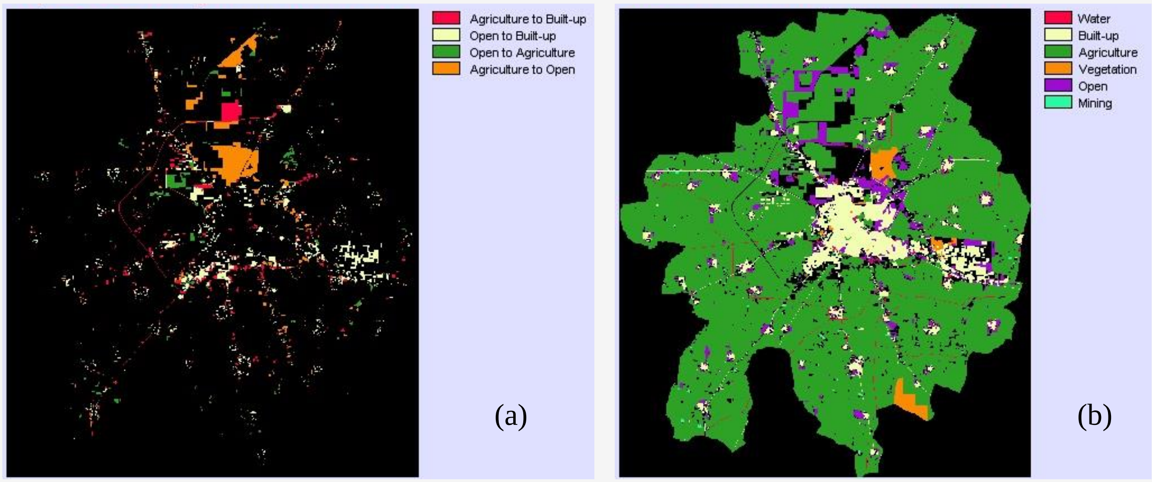

Figure 7: LULC between 2011 and 2021 (a) Top 4 LULC change (b) LULC persistence

The land use and land cover matrix of 2011 and 2021 reveals that 84.25 percent of the area that was under the water in 2011 had remained unchanged in 2021, while the remaining 15.75 percent underwent different land use transformations majorly in with open space. The built-up area from 2011 remained intact in 2021 because the built-up area is irreversible in nature. In 2021, 94.38 percent of the area that was covered by agriculture in 2011 stayed the same, while the remaining transformed into open space (3.14 percent), built-up land (2.06 percent), mining (0.32 percent), and water and vegetation. In a similar vein, 86 percent of the area that was covered by vegetation in 2011 remained covered by vegetation in 2021, a major area of vegetation was converted to built-up. Open terrain witnessed a considerable shift. The area deemed as open land (57.03 percent) remained unaltered; the majority of the open land was turned into built-up (28.64 percent); the remaining open land was converted into agricultural land (11.27 percent), water (1.62 percent), vegetation cover and mining.

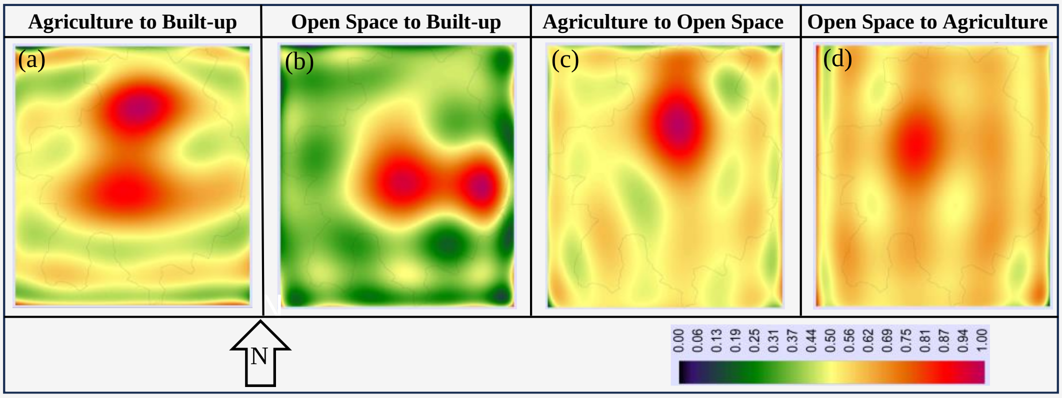

Figure 8: Spatial trends of change from 2011 to 2021 in the top four transformations: (a) Agriculture to built-up (b) Open space to built-up (c) Agriculture to open space (d) Open space to agriculture

Table 3: Cramer's V of driver variables

S.no	Driver variable	Cramer's V	P value
1	Slope	0.034	0.000
2	Digital Elevation Model	0.139	0.000
3	Distance from the existing built-up	0.292	0.000
4	Distance from the city centre	0.217	0.000
5	Distance from major roads	0.149	0.000
6	Distance from the railway line	0.162	0.000

On the other hand, only 38 percent of the mined area, which was under brick kilns and related areas in 2011, remained unchanged in 2021, indicating a significant transition. About 59 percent was transformed into agricultural land, remaining 3.3 percent was converted into built-up and open spaces. On the basis of the land transformation between 2011 and 2021, the spatial trends of changes were also analysed. In the present study, the spatial trends of change were analysed for only the top four land class categories. That includes transformation from agriculture to built-up, open spaces to build-up, open to agriculture and agriculture to open spaces. The trends are calculated and presented in Figure 8. These spatial trends show the patterns of changes from one class to another between 2011 and 2021.

5.2 Transition Potential Modeling

In the analysis of the transition potential, only those transformation classes included those areas that were more than 500 ha. On this basis, only four transition potential maps were created and utilized for the transition sub-model. These transitions were agriculture to built-up, open spaces to built-up, agriculture to open spaces and open spaces to agriculture. These four transitions are also utilized as the transition sub-model. These help in producing results with better accuracy while the training of MLP Neural Network. In addition, six explanatory variables were also considered in the modeling. The variables were Slope, Digital elevation model, Distance from the existing built-up area, Distance from the city centre, Distance from the major roads, and Distance from the railway line. These variables are only considered after testing their explanatory power as shown in Table 3. After testing the potential explanatory power of the variables (that demonstrates how strongly the variable is interconnected with the distribution of the distinct land cover classes), all the variables except 'Slope' are considered for the model as its value of Cramer's V is very low.

Following the selection of the driver variable, MLP-NN was run to create the potential transition maps. In the present Transition potential modeling, four main transitions that occurred in the study area are selected for the creation of transition potential maps. Four different sub-models were run to create the transition potential maps and their accuracy and skill measures are shown in Table 4. The Sub-model 'Agriculture to Built-up' have the highest accuracy and skill measure while the Sub-model 'Open to Built-up' have the lowest accuracy and skill measure. Model Skill Breakdown by Transition and Persistence result is shown in Table 5. The results show that the transition skill measures for agriculture to built-up is highest and followed by the open to agriculture. On the other hand, the persistence skill measure for agriculture is highest in the 'Agriculture – Builtup' and 'Agriculture – Open' Sub Model.

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Table 4: General model and performance

S.no	Model	Accuracy rate (%)	Skill measure
1	Agriculture to Built-up	92.05	0.841
2	Open to Built-up	78.70	0.574
3	Agriculture to Open	83.31	0.666
4	Open to Agriculture	68.80	0.376

Table 5: Model skill breakdown by transition and persistence

S.no	Class	Skill measure
1	Transition: Agriculture to Built-up	0.990
2	Transition: Open to Built-up	0.971
3	Transition: Agriculture to Open	0.656
4	Transition: Open to Agriculture	0.248
5	Persistence: Agriculture (Built-up)	0.694
6	Persistence: Agriculture (Open)	0.677
7	Persistence: Open (Open)	0.179

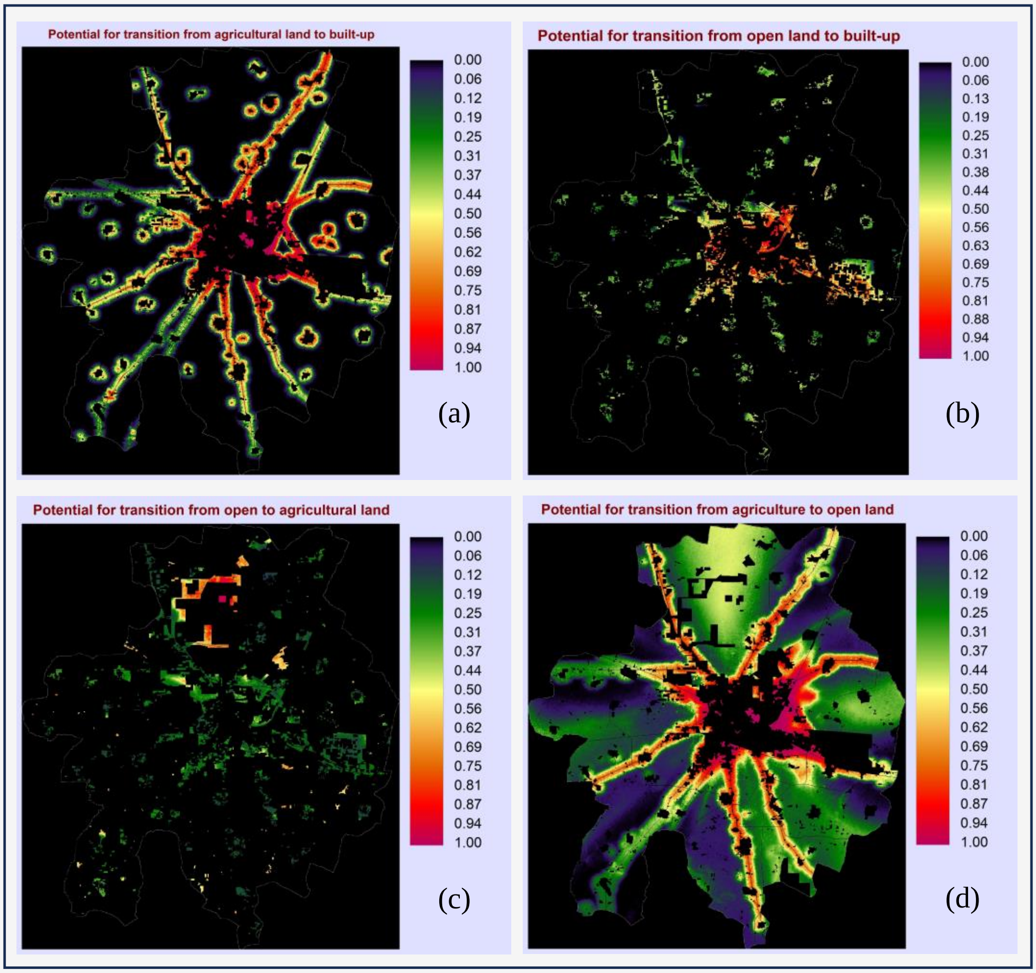

Figure 9: LULC transition potential: (a) Agriculture to built-up, (b) Open land to built-up (c) Open land to agriculture, (d) Agriculture to open land

After getting the required and acceptable accuracy of the Transition sub-models. The Four transitional potential maps were created as shown in the Figure 9. As depicted in maps, the pixel values range between 0 and 1, which implies values closer to 1 shows a higher probability of conversion.

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5.3 LULC Prediction for 2035

The projection of LULC change for 2035 was made based on 2011 and 2021 LULC maps as input using the default Markov Chain model within LCM. Therefore, the LULC of 2035 is predominantly dependent on the trends of land cover transition between 2011 and 2021.

5.4 Distribution of Land Use and Land Cover of 2035

The map LULC for 2035 is shown in Figure 10 and its statistics in the Table 6 depict that most of the land will be under agriculture. Its shares among the total area were 73.66 percent and in absolute terms, it occupied 60,555.4 ha of land. The area under agriculture will shrink as compared to the year 2021. The built area will stand on the second position in terms of share among all the classes. The built-up area will get a sudden expansion and spread over the peri-urban area. The built-up area will occupy 17.67 percent of the total area. The built-up area will be followed by the open land with 6.01 percent and occupied 4,944.78 ha of land. The other three classes namely vegetation cover, water bodies and mining area together shared less than 3 percent of the total area.

5.5 Land Use/Land Cover Changes from 2021 to 2035

The analysis of Land Use/Land Cover Changes from 2021 to 2035 is shown in Table 6. The result revealed that only two classes that are built-up and mining will gain and the remaining four classes will face losses in terms of total area. The area under built-up will increase by 4,637.9 ha (46.89 percent) from 9,889.2 ha in 2021 to 14527.1 ha in 2035. The mining area will get a significant increase of 61.02 ha (16.44 percent). On the other hand, agricultural land will decrease by 4.92 percent in absolute terms it will decrease by 3,130.4 ha. The area under the open spaces, vegetation and water bodies will also decrease by 21.73, 8.54 and 12.37 percent respectively. The results of gains and losses and net change from 2021 and 2035 are shown in Figure 11.

The analysis of gains and losses and net change from 2021 and 2035 depicts that the maximum gain will be recorded by the built-up class followed by the open spaces and agricultural land. Contrary to this the maximum loss will be observed in the agricultural land followed by the open spaces.

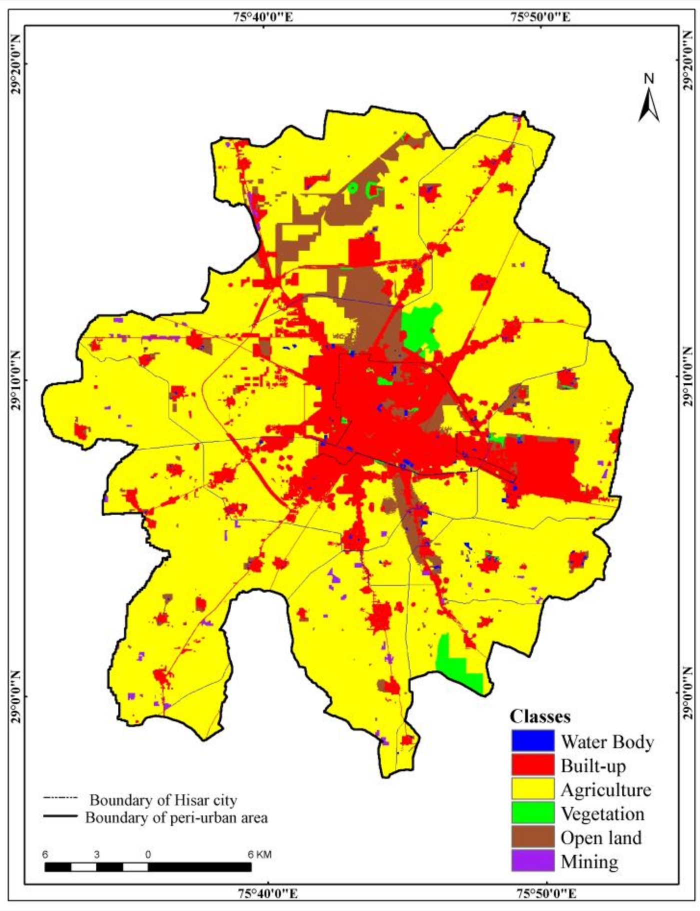

Figure 10: LULC prediction map of 2035

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Table 6: Land Use/Land Cover changes statistics from 2021 to 2035

Class	2021 Area		2035 Area		Area Change	
	Hectare	%	Hectare	%	Hectare	%
Water bodies	775.44	0.94	679.5	0.83	-95.94	-12.372
Built-up	9,889.2	12.03	14,527.1	17.67	4,637.9	46.899
Agriculture	63,685.8	77.47	60,555.4	73.66	-3130.4	-4.915
Vegetation	1,171.98	1.43	1,071.9	1.30	-100.08	-8.539
Open	6,317.28	7.68	4,944.78	6.01	-1,372.5	-21.726
Mining	371.25	0.45	432.27	0.53	61.02	16.436
Total	82,210.95	100	82,210.95	100.00		

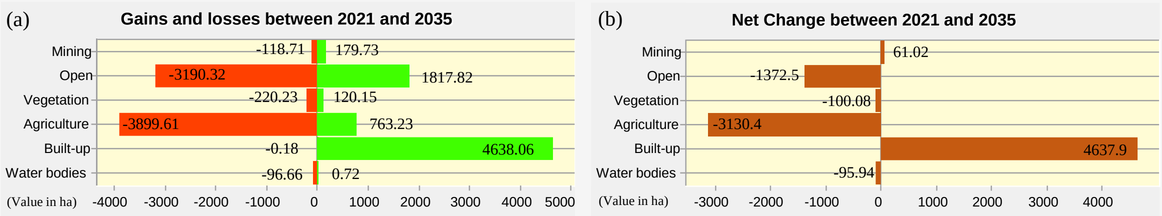

Figure 11: LULC change between 2021 and 2035 (a) Gains and losses (b) Net change

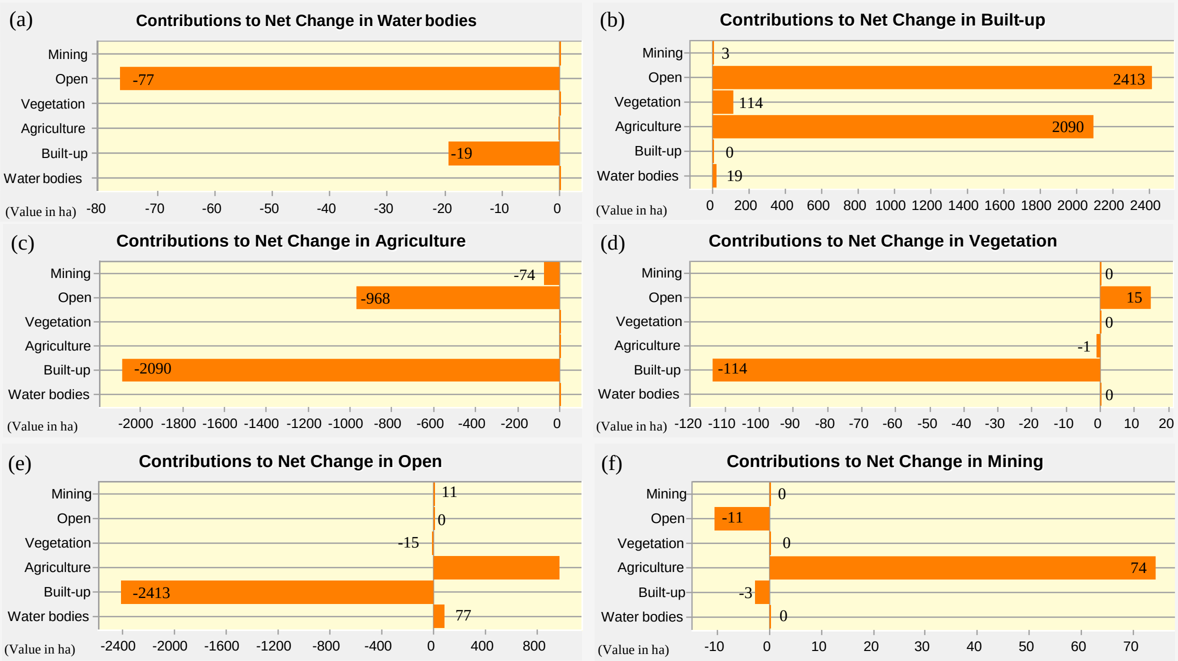

Figure 12: Contributions to net change in each class between 2021 and 2035: (a) Water bodies (b) Built-up (c) Agriculture (d) Vegetation (e) Open spaces (f) Mining

The contribution of the individual class in the net change in different classes is shown in Figure 12. Again, the built-up class will get maximum gain, the largest contributor to this gain will open space with 2,413 ha followed by agricultural land with 2,090 ha of land. On the other hand, the maximum loss will be recorded by the agricultural land of 3,899.61ha. Built-up and open spaces will be primary contributors to agricultural land loss. It is also visible in Figure 12, that the loss of vegetation cover will be directly linked to the rising built-up. The land use change and persistence between 2021 and 2035 are shown in Figure 13 and the land transformation matrix is presented in Table 7.

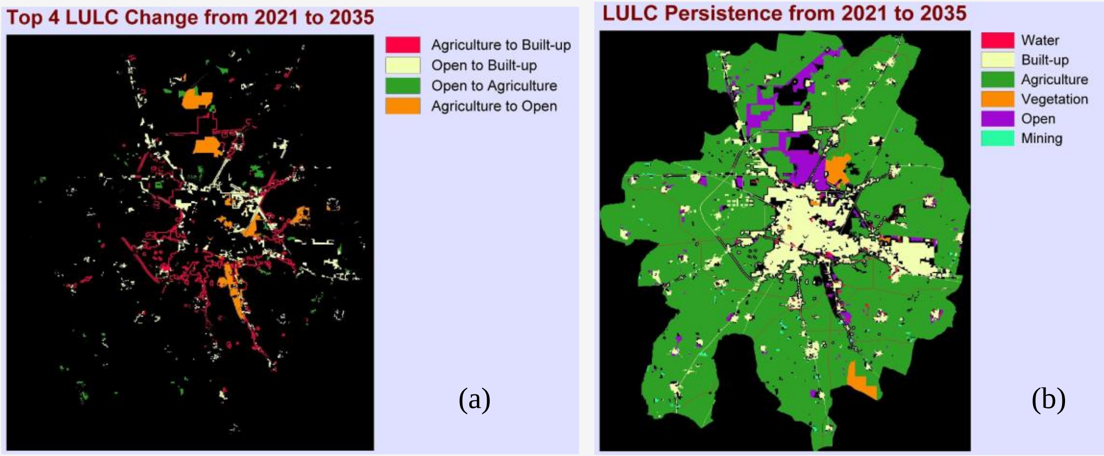

Figure 13: LULC between 2021 and 2035: (a) Top 4 LULC change, (b) LULC persistence

Table 7: Land Use and Land Cover conversion matrix between 2021 and 2035

	LULC	LULC Type 2035(Area in Hectares)						
		Water	**Built-up**	**Agriculture**	**Vegetation**	**Open**	**Mining**	**Total (2021)**
LULC Type 2021	**Water**	**678.78 (87.53)**	19.35 (2.50)	0.27 (0.03)	0.00	77.04 (9.94)	0.00	775.44
	Built-up	0.18 0.00	**9,889.02 (100)**	0.00	0.00	0.00	0.00	9,889.20
	Agri	0.00	2,089.53 (3.28)	**59,786.19 (93.88)**	6.48 (0.01)	1,627.65 (2.56)	175.95 (0.28)	63,685.80
	Vegetation	0.00	113.76 (9.71)	7.65 (0.65)	**951.75 (81.21)**	98.82 (8.43)	0.00	1171.98
	Open	0.54 (0.01)	2,412.63 (38.19)	659.70 (10.44)	113.67 (1.80)	**3,126.96 (49.50)**	3.78 (0.06)	6,317.28
	Mining	0.00	2.79 (0.75)	101.61 (27.37)	0.00	14.31 (3.85)	**252.54 (68.02)**	371.25
	Total (2035)	679.50	14,527.08	60,555.42	1,071.90	4,944.78	432.27	**82,210.95**

The land use and land cover matrix of 2021 and 2035 reveal that 87.53 percent of the area that was under the water in 2021 will remain unchanged in 2035, while the remaining 12.47 percent underwent different land use transformations, with open land accounting for the majority of changes i.e. (9.94 percent), followed by built-up and agricultural land which all accounts for 2.53 percent. The built-up area from 2021 will remain intact in 2035 because the built-up area is irreversible. In terms of area, the built-up will get major gain from the open land (2,412 ha) and agricultural land (2,089 ha) in 2035. In 2035, 93.88 percent of the area that was covered by agriculture in 2021 will stay the same, while the remaining 6.12 percent will transform into built-up land (3.28 percent), open space (2.56 percent), mining (0.28 percent) and vegetation. In a similar vein, 81.21 percent of the area that was covered by vegetation in 2021 will remain covered by vegetation in 2035, only 18.79 percent of the land will convert to other classes out of this 9.71 percent will convert to built-up land and 8.43 percent in open land. Between 2021 and 2035, the open terrain will witness a considerable shift. The area deemed as open land (49.5 percent) will remain unaltered; the majority of the open land will turn into built-up (38.19 percent); the remaining open land will convert into agricultural land (10.44 percent), vegetation cover (1.8 percent), water bodies and mining. On the other hand, 68.02 percent of the mining area, which was under brick kilns and related areas in 2021, will remain unchanged in 2035. About 27 percent will transform into agricultural land, remaining 4.6 percent converted into built-up and open spaces.

6. Discussion

The findings of the study revealed that socioeconomic and physical factors have a significant impact on the land use change in and around the city.

In general, the city is located in the plain area so there is no physical hindrance in the sprawl of the city. The favourable geographical and climatic conditions are more conducive to human activities that promote rapid LULC changes. The transport networks are the major drivers of the land use transformation. It is noted that all the major transformations occurred along the major highways but in recent time the transformation of land use also occurred along all the roads that originate from the city. Most of the built-up raised along the transport networks in the form of residential colonies, industries, educational and research institutes etc. The private and government agencies also played an important role in the land use transformation mainly in the peri-urban area of the Hisar. All the recent projects by the private and government agencies took place on the city outskirts. The study also found that the rising population of the city as well as its periphery has a direct impact on land use alteration. With the increase in the population, the demand of land for urban land use increased which was completed from the agricultural land. The demand for agricultural land also increases to cater for the rising population which is fulfilled by the open and vegetation cover. But the conversion of land for built-up is much higher than agricultural land. This rising demand for land for urban growth has a detrimental influence on the limited resource land. The land is limited but has alternate uses, these alternate uses of land create scarcity of land. For sustainable urban development, we need to use the available and limited resources in a well-planned manner. According to the present study, the land use of the Hisar and its per-urban area has suffered from the massive land transformation as a consequence of rapid urbanisation. From 2011 to 2021 the built-up area increased by 3,516 ha, this was mainly contributed by the land from open spaces and agriculture. The agricultural and open land decreased by 2,670 and 810 ha respectively.

Additionally, the simulation of the future LULC of 2035 proclaims that the area under built-up will increase by 4637.9 hectares between 2021 and 2035. On the other hand, the area under the water bodies, vegetation, agriculture and open will decrease. The result of the study indicates the direct role of urbanisation on land transformation.

7. Conclusion

The study analysed the spatio-temporal change in the LULC and projected the future scenario of LULC for the year 2035 by utilizing different driving factor in Hisar and its peri-urban area, India. The dynamics of LULC leads to many challenges, the drastic transformation in LULC, mainly urban growth, fragmentation of agricultural land and decreasing vegetation cover could endanger the natural resources and environment. The expansion of built-up and decreasing fertile agricultural land is a major issue. Consequently, the simulation of LULC for 2035 will aid policymakers in understanding the future land use and its change, intensity and drivers of the transformation. This will surely facilitate in promoting sustainable development.

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