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Land Use Land Cover Change Detection using Remote Sensing and GIS in Srinagar, India

Ritu Saini
Project Associate
Department of Civil Engineering
Geomatics Department, IIT-Roorkee, Roorkee

Pradeep Aswal
Project Assistant
Department of Civil Engineering
Geomatics Department, IIT-Roorkee, Roorkee

Mohd Tanzeem
B.Tech
Department of Civil Engineering
Quantum University
Roorkee, Roorkee

Sanyam S. Saini
M.Tech
Department of Electrical Engineering
NITTTR Chandigarh, Chandigarh

ABSTRACT
Ecosystems in urban areas are strongly influenced by anthropogenic activities. Spatial-temporal transformations that occur in different classes of land use/cover like Built-up, Vegetation and Water are the key drivers of global change that reflects the territorial and socio-economic progress of an area and have significant implications for many policy issues.

The current study uses a maximum likelihood classification method to map five different land use land cover classes in the openly available Landsat satellite images of 2008 and 2016 for selected urban boundaries of Srinagar, India. Pixel to pixel change detection strategy is implemented to find out the changes occurred in individual land use land cover class. The results are compared and illustrated in the form of graph and maps for providing an interactive visual representation for administrators and policymakers.

Keywords
Land use, Land Cover, Change Detection, Remote Sensing, GIS

1. INTRODUCTION
India is a developing country and in such countries, the rate of urban growth is very high due to huge rural to urban migration of people (Tiwari et al., 2014). Industrial revolution way back in the 1970s followed by globalization in 1990s gives momentum to urbanization in India. The rapid growth in Indian urbanization, particularly in 'megacities', has improved the living of normal human being (Aswal et al., 2018). However, it has its own associated problems like loss of agricultural land, ecological unbalance, temperature rise, pollution, etc. To address such issues information needed at various levels, like spatial distribution of area among various urban land uses, local housing pattern and population growth pattern, etc. (Clark, 1982). However, remedies cannot be analyzed and addressed without a proper channel between new technologies and in-situ observations. Traditional methods are available for gathering demographic data, censuses data and other relevant information for mapping urban growth (Tiwari and Dixit, 2015). However, these techniques are unfeasible and insufficient for modem urban management purposes (Maktav et al., 2005).

The earth surface undergoes rapid changes due to human activities. To detect such changes over time is called change detection. Hence, change detection can be defined as "the process of identifying the difference in the state of a phenomenon or object by observing it at different times" (Singh, 1989). To assess urban growth, timely and accurate change detection of Land use and land cover (LULC) features is extremely important (Tiwari et al., 2018). LULC change (LUCC) is one of the most appropriate indications to monitor the impact of human being on the environment. Moreover, LUCC may largely reflect how intensively human being modifies the earth environment. Change detection using remote sensing images is becoming a hotspot, with the recent advances in remote sensing technology. Accordingly, better relationships and interactions between human and natural phenomena may be developed to promote better decision making.

Remote Sensing (RS) and Geographic Information Systems (GIS) framework help in collecting a substantial amount of data about LULC (Tiwari and Jain, 2014). Remotely sensed satellite imagery delivers wide rouge of information about LULC (Bauer et al., 2005). Hence, LULC classification and change detection using satellite dataset has long been a core area of research for the remote sensing community (Civco et al., 2002). Moreover, GIS interface offers an exceptional source of data handling, through which updated land use/land cover (LULC) information and change maps can be prepared, evaluated and interpret efficiently in very less time.

Remote sensing and GIS are extensively used for detecting LULC changes (Tiwari et al., 2018). There has been a growing trend in the development of change detection techniques using remote sensing data. The change detection techniques, thus developed, could be grouped into two general categories; (i) those based on spectral classification of input data, such as post-classification comparison (Mas, 1999) and direct two-date classification (Yeh and Li, 1997), and (ii) those based on radiometric change between acquisition dates, including (a) image algebra method, such as band differencing (Weismiller et al., 1977), rationing (Howarth and Wickware, 1981) and vegetation indices (Nelson, 1983), (b) regression analysis (Singh, 1986), (c) principal component analysis (Byrne et al., 1980; Gong, 1993), and (d) change-vector analysis (CVA) (Malila, 1980). In addition, hybrid approaches involving a mixture of categorical and radiometric change information have also been proposed and evaluated (Colwell and Weber, 1981).

This study assessed the changes in land use land cover in Srinagar, the summer capital and the largest city of the Indian state of Jammu and Kashmir. Change analysis for the study area was also performed to evaluate the change in land use land cover within the time period of 10 years using Remote Sensing and GIS techniques.

1.1 Study Area
The present study has been conducted for the 10km buffer starting from the city center of the Srinagar, Jammu & Kashmir in India. Srinagar is spread in the heart of the oval-shaped valley of Kashmir, located between 34° 5' 1.1616" N and 74° 47'50.5356" E. Being one of the several places that have been called the "Venice of the East", the city as well as its hinterland

is bounded by natural wall of mountains (sub-mountain branches of Pir Panjal Ranges and Zanskar mountains). In the east, the city is bounded by Zabarwan Mountains with lush green vegetation, locating famous Dachigam Sanctuary and Mughal Gardens and is environed by the shallow and swampy lakes of Dul and Nagin with the eminence of hillocks of Takht-e-Sulaiman in the east and Koh-e-Maran (Hariparbat) in the centre adding to its beauty and making surroundings of the city invigorating.

Srinagar has a humid subtropical climate. Winters are cool, with daytime temperature averaging to 2.5 °C (36.5 °F), and drops below freezing point at night. The location map of the study area is shown in Figure 1.

Srinagar has shown fast growth with time and gained primacy in terms of functions associated with politics, administration, commerce, economic development, and tourism, etc. As per Census record, Srinagar had a population of 1,236,829 in 2011 having Literacy rate 69.41 percent and out of the total Srinagar population, 98.60 percent lives in urban regions of district. In 2011, there was a change of 20.35 percent in the population compared to 2001. In November 2011, City Mayors Foundation announced Srinagar as the 92nd fastest growing urban areas in the world in terms of economic growth.

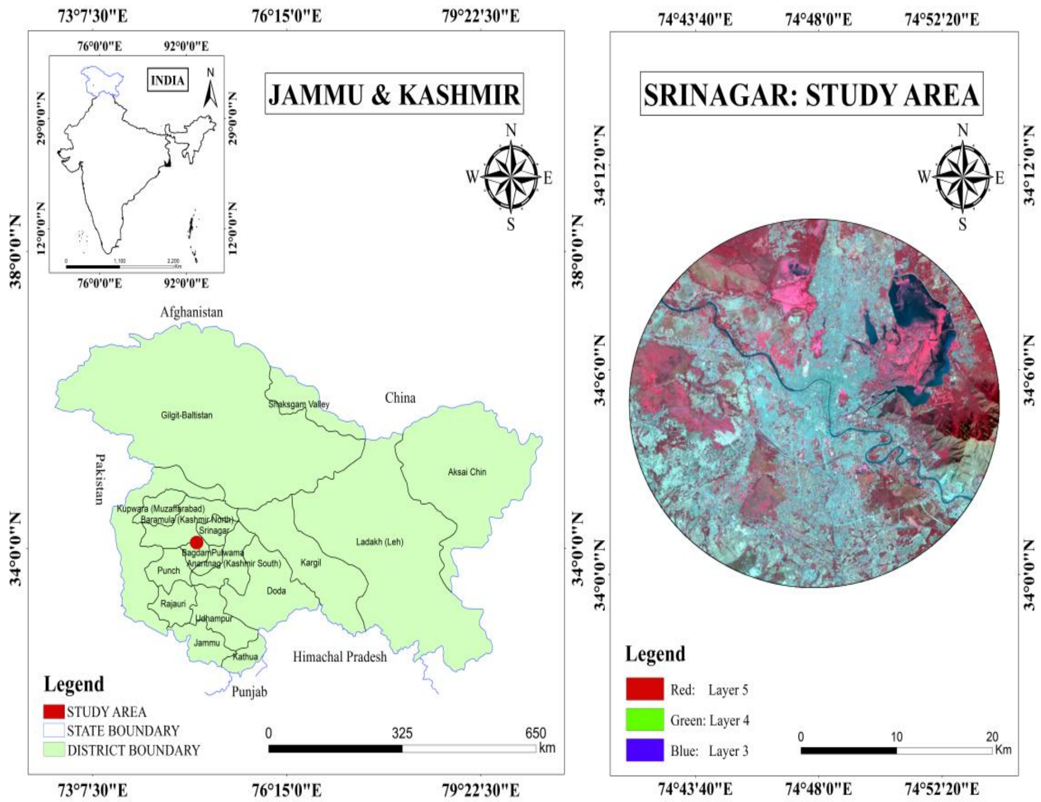

Figure1. Location map of the study area

1.2 Data Used

Multi-Spectral satellite imagery of Landsat-5 (ETM+) and Landsat-8 (OLI/TIRS) satellite has been used as the primary dataset. The detail specifications of both images are presented in Table 1. Both the images are downloaded from the United States Geological Survey (USGS) Earth Explorer web portal (http://earthexplorer.usgs.gov). The satellite image map has shown in figure 2 and 3.

Table1. Data used table for selected satellite data products

Satellite	**Sensor**	**Path**	**Row**	**Acquisition Date**	**Resolution (m)**
Landsat 5	MSS/TM	149	36	25-09-2008	30/100
Landsat 8	OLI/TIRS	149	36	01-10-2016	30/100

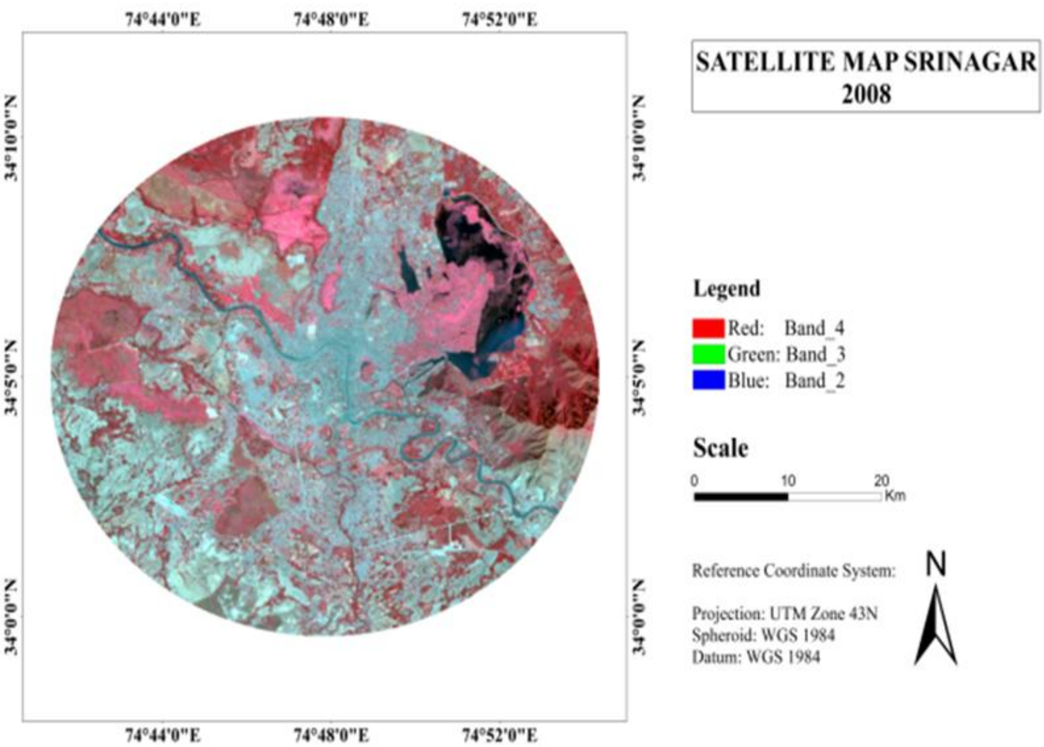

Figure2. Satellite map of Study Area

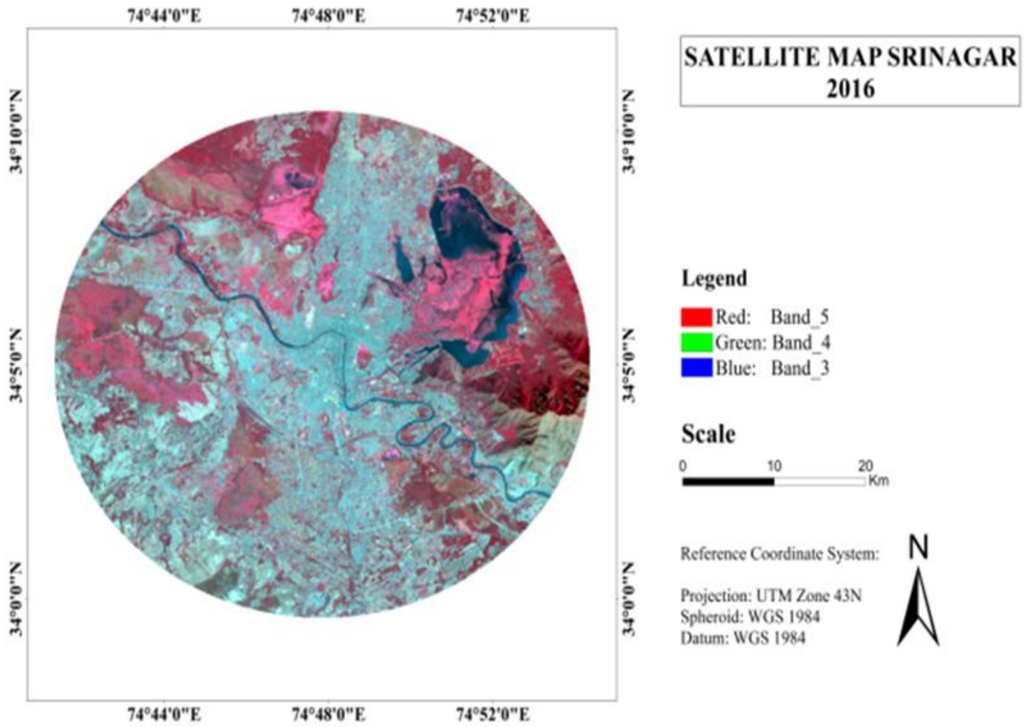

Figure3. Satellite map of Study Area

2. METHODOLOGY

This Study aims at quantifying the change in urban land cover for Srinagar (India) using maximum likelihood classification based techniques as a prime indicator of urban development in the Srinagar region. The overall methodology adopted for the study is shown in the flow diagram (Figure 4). The process has been studied using urban land cover pattern derived from Landsat 5 and Landsat-8 satellite data for two different years 2008 and 2016. Firstly, both the images are downloaded from the United States Geological Survey (USGS) Earth Explorer web portal and preprocessed using ERDAS (Earth Resource Data Analysis System) Imagine software. Images have been classified using supervised classification by maximum likelihood algorithm for the quantitative analysis. This classification technique classifies the data based on the training sets or signatures provided to software manually and these training sets lead the software to identify the types of pixels for the land cover type.

These classified images provide all the information of the five major land use land cover classes; (i) urban (ii) water (iii) barren land (iv) vegetation and (v) forest. For Accuracy assessment of the classified images, each classified image has been compared to the referenced data (considering random points and google earth as referenced data) in ERDAS Imagine software. Classified images further processed for urban extraction in ArcGIS 10.3.1 software using raster calculator tool and as a result urban has been generated for 2008 and 2016. Classified images again processed using LCM (Land Change Modular) tool in IDRISI software to generate the change in land cover.

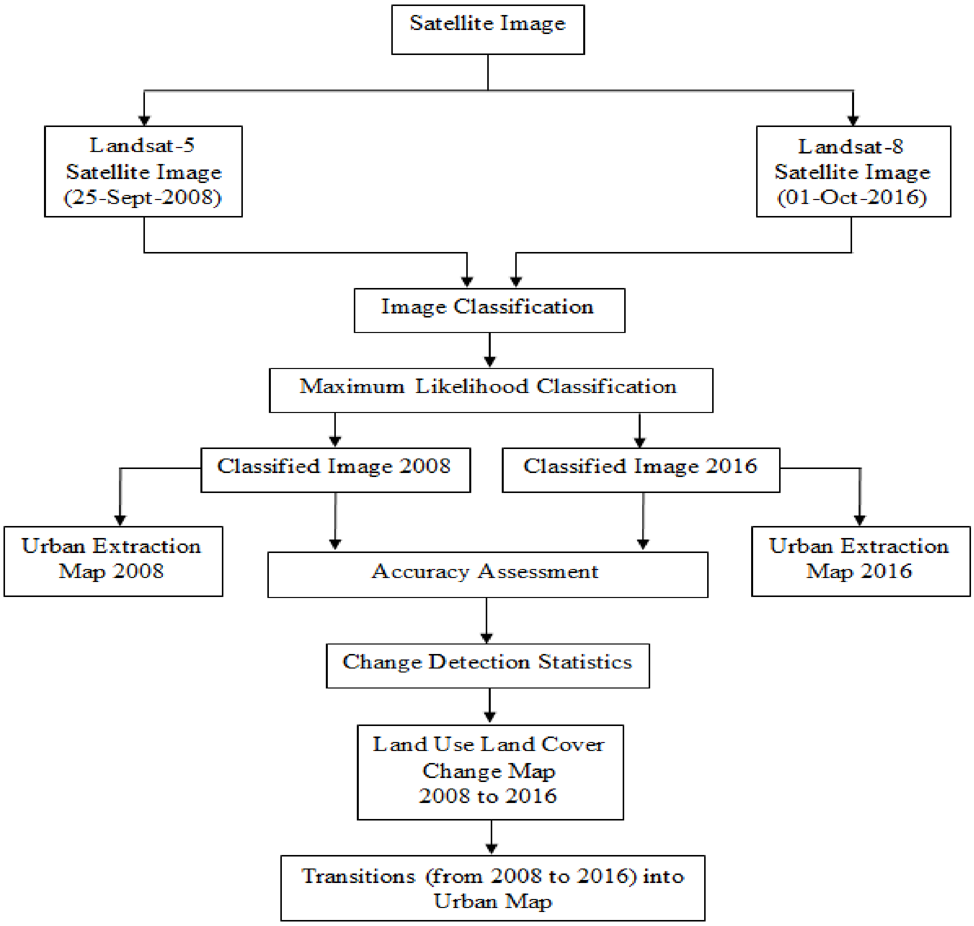

Figure4. Workflow diagram of the study area

2.1 Maximum Likelihood Classification

Maximum likelihood is one of the most popular supervised classification method used with remote sensing image data (Benediktsson et al., 1990). The classifier can generate the most accurate classification results if accurate training data is provided (Asmala, 2012).

This classifier is based on Bayesian probability theory (Hord, 1982). Once classifier receives training data it computes means and variances for each band of each class, which are Gaussian in nature and can be described by the mean vector and covariance matrix. From this information, the statistical probability is computed for a given pixel value being a member of particular land use and land cover class. Beside means and variance, the variability of brightness values in each class is also considered while defining membership. Now for every unknown pixel as per the equation 1 distance is calculated using the mean of a class and the probability of occurrence of that pixel in the class, class having minimum distance to the pixel is assigned to the that pixel in the class, the class having minimum distance to the pixel is assigned to the pixel.

$$\mathbf{D_{Max}(m_{ij}) = \ln P(w_i) - \frac{1}{2}\ln|Cov_c| - \frac{1}{2}\sum_j^{nb}(m_{ij} - k_j)Cov_c^{-1}(m_{ij} - k_j)} \text{-----Equation 1}$$

Where: i = the i^{th}class, x = n-dimensional data (where n is the number of bands), $P(w_i)$= probability that a class occurs in the image and is assumed the same for all classes, $|Cov_c|$= determinant of the covariance matrix of the data in a class, Cov_c^{-1}= the inverse of the covariance matrix of a class, m_{ij}= mean vector of class i and band j.

Equation 1 assumes that probabilities are equal for all classes, and the input bands have normal distributions. If this is not the case, we may have better results with parallelepiped or Minimum distance decision rule.

2.1.1 Accuracy Assessment

Accuracy assessment is the most accurate way of determining the reliability of the classification technique and its thematic results. A large number of accuracy assessment indicators have been developed for supervised image classification methods. In the current study overall accuracy and kappa coefficient with 57 ground control points are used to measure the error present in the results. A detailed description of these accuracy assessment methods and their significance as follows:

2.1.1.1 Overall Accuracy
The overall accuracy of the classified image compares how each of the pixels is classified versus the actual land cover conditions obtained from their corresponding ground truth data. It can be calculated by dividing the total number of correctly classified pixels by the total number of reference pixels.

2.1.1.2 Kappa Coefficient
Kappa Coefficient measures the difference between how much agreements are actually present (“observed” agreement) compared to how much agreement would be expected to be present by chance alone (“expected” agreement).

Kappa = (observed accuracy - expected accuracy)/ (1 - expected accuracy)

$$\mathbf{k = \frac{P_o - P_e}{1 - P_e}}$$

2.1.2 Change Detection Analysis
Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh 1989). Change detection analysis explains and determines differences between images of the same scene at different times. Classified images of two years are used to evaluate the area of different land use land covers and obtain the change in each class, for the selected study area. For change detection analysis, comparison of classified images is evaluated after processing them in IDRISI (Land Change Modeler) and the results for change in land use land cover area (Area gain, area loss or the area having no change) is obtained. This analysis is helpful to identify various changes appearing in different classes of land use land cover i.e. increase in land use area or decrease in land cover.

3. RESULTS AND DISCUSSION
In this study Land Use Land Cover (LULC) classification is performed using a supervised classification method with maximum likelihood algorithm in the Software ERDAS Imagine. Image classification resulted in five LULC classes: Urban, Forest, Vegetation, Water, and Barren land. LULC map for both the year is presented in figure 5 and figure 6, whereas figure 7 and figure 8 show the urban map of the study area. LULC mapping of Srinagar study area for both the year indicates a continuous increase in built-up areas that comprises of urban, suburban and rural built-up. It is observed that the urban area which was 84.68 square kilometers in 2008 is increased up to 124.17 square kilometers in 2016. Vegetation and Forest areas are 36.83 square kilometers and 84.50 square kilometers respectively in 2008 are also increased up to 53.12 square kilometers and 85.21 square kilometers respectively in 2016. The Barren land and Water areas were 85.55 square kilometers and 24.07 square kilometers respectively in 2008 are decreased up to 50.61 square kilometers and 21.86 square kilometers respectively in 2016 shown in Table 2.

Table2. Land use Land cover statistics of the study area

Year	Urban Area (sq. Km.)	Forest Area (sq. Km.)	Vegetation Area (sq. Km.)	Barren land Area (sq. Km.)	Water Area (sq. Km.)
2008	084.68	84.50	36.83	85.55	24.07
2016	124.17	85.21	53.12	50.61	21.86

Accuracy assessment result for the LULC classification shown in Table 3.

Table3. Accuracy assessment for 2008 and 2016

S.No.	Year	Overall Accuracy	Kappa coefficient
1.	2008	78.01%	0.61
2.	2016	82.72%	0.78

Whereas different statistics of the urban area shown in Table 4.

Table4. Urban statistics in 2008 and 2016

Year	2008	2016
Urban Area (sq. Km.)	084.68	124.17
Year	2008	2016

Figure 9 represents the map of transition into the urban area for each class and Table 5 indicates the statistics for the transition into urban from 2008 to 2016.

As a result, it can be seen that the transition from the area of Water, Forest, Vegetation and Barrenland i.e. 0.33, 10.11, 6.57 and 22.48 square kilometers respectively changes into the urban area in the year 2016.

Table5. Transition into urban statistics from 2008 to 2016

Transition	Urban to Urban	Water to Urban	Forest to Urban	Vegetation to Urban	Barren Land to Urban
Urban Area (sq. km)	84.68	0.33	10.11	6.57	22.48

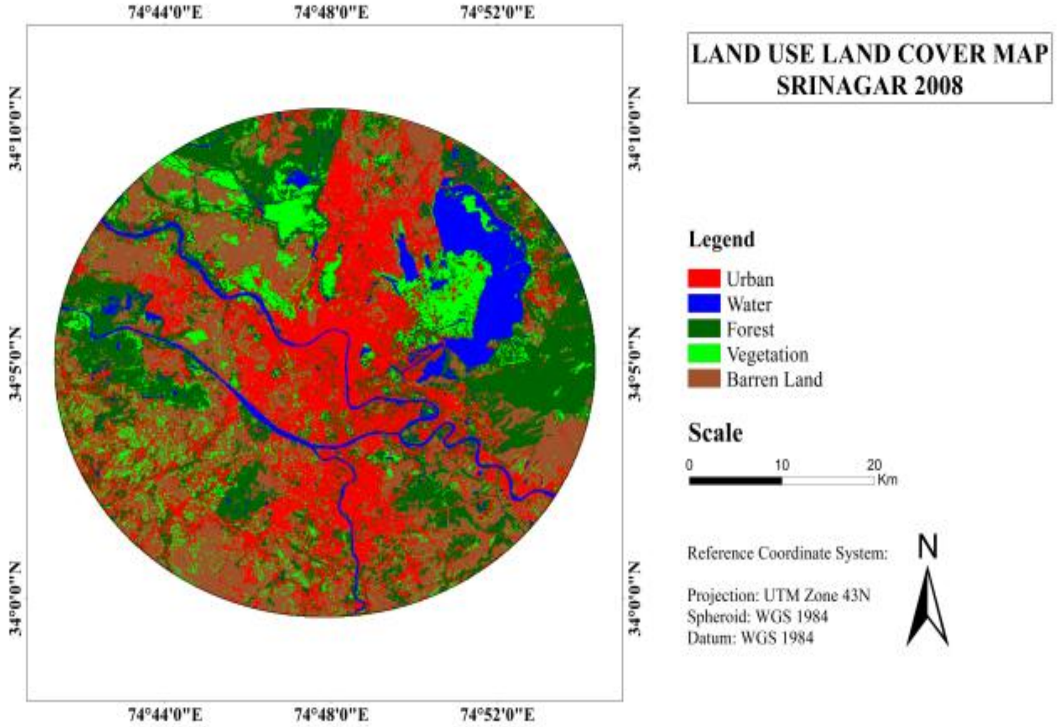

Figure5. Land use Land cover map of the study area for year 2008

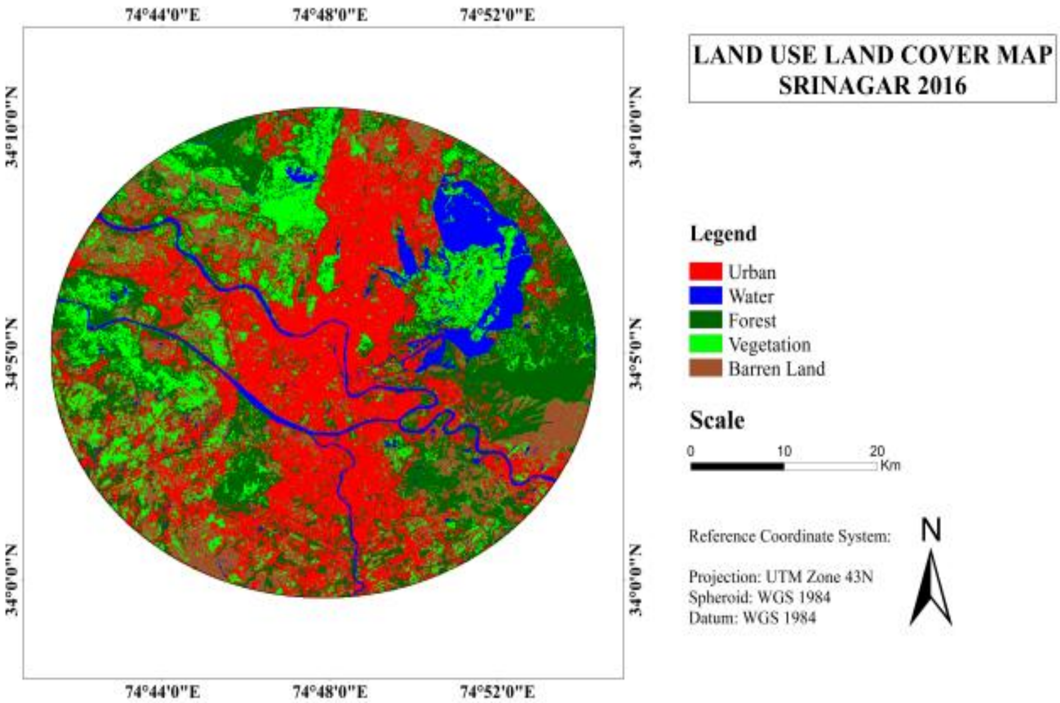

Figure6. Land use Land cover map of the study area for year 2016

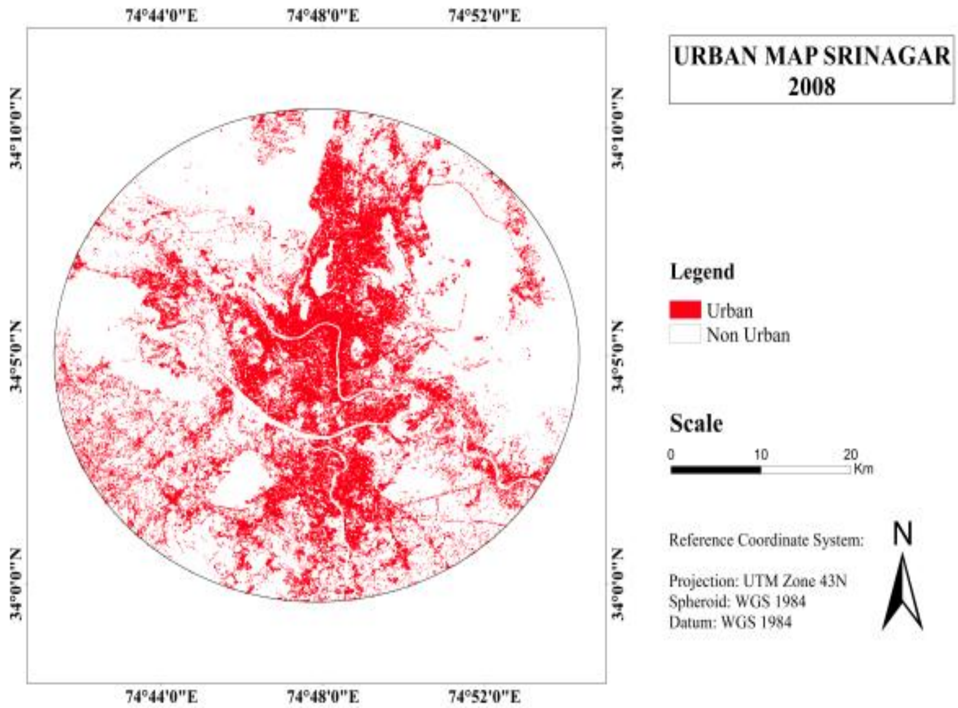

Figure7. Urban map of the study area for year 2008

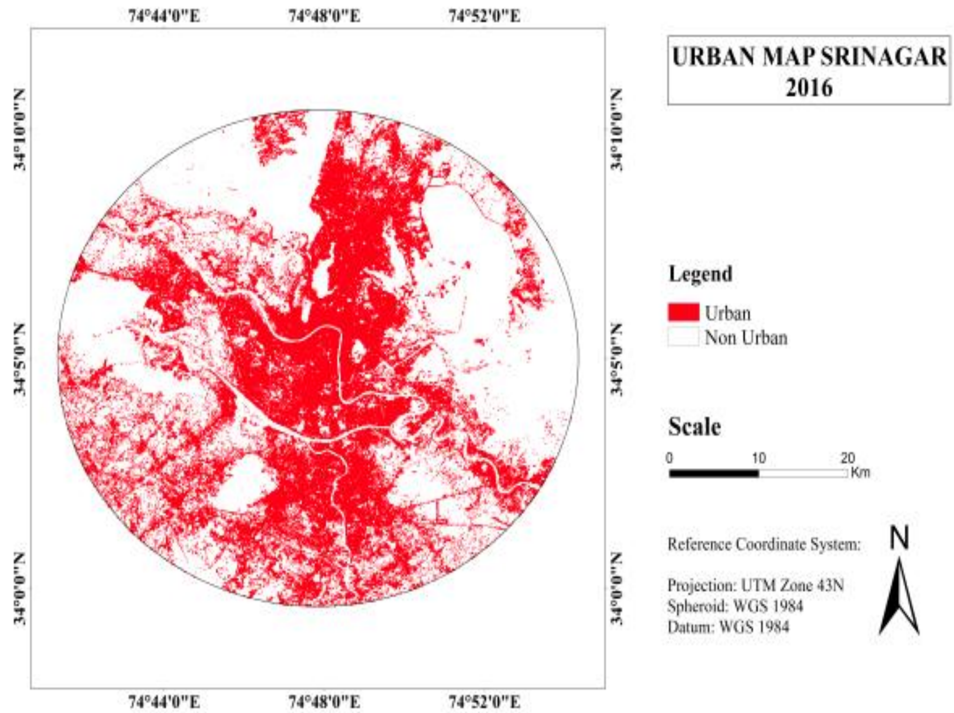

Figure8. Urban map of the study area for year 2016

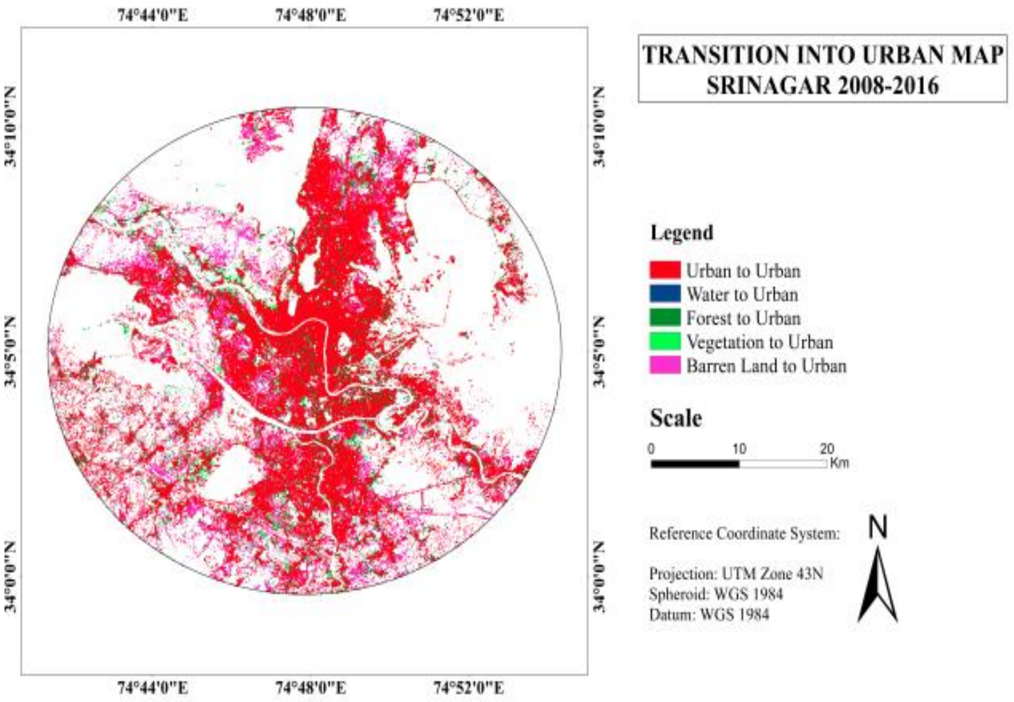

Figure9. Transition into the urban map of the study area

4. CONCLUSION

All major cities of India have been facing some serious issues nowadays, such as Urbanisation, various kinds of pollution and exploitation of available Natural Resources. As Srinagar is the summer capital of state it has also experienced the transformation from some decades in terms of economic, political and social aspects. Analysis of land use land cover transformation is very important to understand the potential threats for ecological communities, agricultural practices and accurate planning for urban development. Expansion of urban and agriculture has been highlighting the intensive economical practices.

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