



ANALYSIS OF LAND USE AND LAND COVER CHANGE DETECTION BY USING REMOTE SENSING AND GIS TECHNIQUES IN 20 YEARS (1997_2000) IN MAZANDARAN, IRAN

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ABSTRACT

Satellite imageries provide a low-cost and up-to-date spatial database that can be used to derive useful information for landscape ecologists, policymakers, and scientists. A similar attempt has been made in this study, using open-source data and tools to define some of the environmental impacts due to LULC in Northern Iran. This study aims at measuring and assessing the hot spot areas, which are in direct as well as indirect consequences due to LULC change, therefore, providing a quantitative impact assessment approach. Two methodologies were adopted for this study. Supervised classification technique and Index integrated method. Both classification techniques are based on the spectral reflectance of the land cover, however, the former is composite classification and it is highly dependent on the number of sampling or pixel training involved. Despite many factors controlling the selection of suitable change detection approach from wide-ranging methods, the used approach in the present study proved very effective in fulfilling the objectives with successful implementation. To sum up, the present study shows great potential for decision makers to generate accurate LULC change detection by exploiting various sources of RS and techniques towards successful implementation of sustainable development, natural resource management, and safe land use planning.

Keywords: Land Use, Land Cover, Remote Sensing, GIS Techniques, Iran

1. INTRODUCTION

Land use and land cover (LULC) change is a major issue of global environmental change. Scientific research community called for a substantive study of land use changes during the 1972 Stockholm Conference on the Human Environment, and again 20 years later, at the 1992, United Nations Conference on Environment and Development (UNCED). At the same time,

the International Geosphere and Biosphere Programme (IGBP) and the International Human Dimension Programme (IHDP) co-organized a working group to set up a research agenda and promote research activity for LULC changes. Land use/ land cover mapping is the essential component where other parameters are integrated on a requirement basis to drive various developmental indexes for land and water resources. Land use refers to man's activities and the varied uses that are carried on over land and land cover refers to natural vegetation, water bodies, rock/soil, artificial cover, and others noticed on the land (NRSA, 1989). Land Cover, defined as the assemblage of biotic and biotic components on the earth's surface is one of the most crucial properties of the earth system. Land cover is that which covers the surface of the earth and land use describes how the land cover is modified. Land cover includes water, snow, grassland, forest, and bare Soil. Land Use includes agricultural land, built-up land, recreation area, wildlife management area, etc.

The Land cover reflects the biophysical state of the earth's surface and immediate subsurface, thus embracing the soil material, vegetation, and water. Land use refers to man's activities on land which are directly related to the land. Land use and land cover are dynamic. Changes may involve the nature or intensity of change but may also include spatial (forest abatement at the village level, or for a large-scale agro-industrial plant), and time aspects. Land use/ Land cover changes also involve the modification, either direct or indirect, of natural habitats and their impact on the ecology of the area.

Unplanned developmental activities, population growth, change in the service sector, urbanization, and economic development are coming at a high environmental and social cost in many of the urbanized and semi-urbanized areas in developing countries. There are many environmental concerns arise due to urban expansion which include climate change (Grimm et al., 2000; Satterthwaite, 2008; Nelson et al., 2009), deforestation (Jones, 2010), air pollution (Norström, 2010; Grimm et al., 2008; Brown et al., 2005), and the pollution of surface and underground water sources (Graniel et al., 1999). Subsequently, it leads to a decrease in the quality of life in urban areas. Many of the studies related to urbanization and LULC change revealed that urbanization will continue to grow at a global scale in the coming decades (Liu et al., 2005; Swyngedouw, 2002). At the same time, however, it is necessary to protect natural resources (Latif & Sarvestani, 2009). Moreover, it is imperative that any LULC planning in developing countries should focus on comprehensive evidentiary policies and models. Therefore, urban and regional planning in developing countries is now adopting the latest scientific tools and techniques to overcome, minimize, and mitigate the environmental impacts arising due to urbanization.

Over recent years sources, and satellite imagery have become an essential dataset in studying environmental issues such as LULC change, Climate Change, Soil Erosion, Habitat fragmentation, etc. (Dorji and Geneletti, 2009). Satellite imageries provide a low-cost and up-to-date spatial database that can be used to derive useful information for landscape ecologists, policymakers, and scientists. A similar attempt has been made in this study, using open-source data and tools to define some of the environmental impacts due to LULC in Northern Iran. This study aims at measuring and assessing the hot spot areas, which are in direct as well as indirect consequences due to LULC change, therefore, providing a quantitative impact assessment approach. Moreover, it is one of the initial studies that attempted to understand the human-induced impact in the northern province of Mazandaran. The major drawback of the study area is environmental database is not available easily and is also a poorly studied area. Therefore open-source databases were of immense use in developing the LULC database and assessing the LULC change due to human-induced developmental activities.

2. MATERIALS AND METHOD

2.1. Study area

Mazandaran Province is a Caspian province in the north of Iran Located on the southern coast of the Caspian Sea; it is bordered clockwise by the Golestan, Semnan, Tehran, Qazvin, and Gilan provinces. The province has an area of 23,842 km² and consists of five districts namely; Amol, Sari, Babol, Ghaemshahr, and Behshahr districts. Mazandaran province is geographically divided into the coastal plain and the mountainous area. The Alborz Mountain range surrounds the coastal strip and plains of the Caspian Sea.

2.2. INT

Satellite remote sensing technology has found its acceptance worldwide for rapid resource assessment and monitoring, particularly in the developing world. The National Aeronautical and Space Administration (NASA) of the USA has made the most significant contributions to satellite-based remote sensing. Since 1972, when Landsat-1 was launched, remote sensing technology and applications have undergone tremendous change in terms of sensor development, aerial flights with improved sensors, satellite design development, and operations including data reception, processing, interpretation, and utilization of satellite images. All these developments have widened the applicability of remotely sensed data in various areas *viz.* forest cover, vegetation type mapping, and their changes on a regional scale. These developments have indicated that if satellite data is judiciously used along with sufficient ground data, it is possible to carry out detailed forest inventories and monitoring of land use and vegetation cover at various scales.

In this study, I have used the open-source data from Global Land Cover Facility Mapping GLCF (<http://glcfapp.glcf.umd.edu:8080/esdi/index.jsp>). As earlier mentioned, one of the main objectives of the study is to generate a spatial database of the province, since it is the least studied area and lacks the primary spatial database.

2.3. Database

The details of primary data in the form of digital data were downloaded for interpretation and analysis and are given in Table 1. In this study, I am using multi-spectral and multi-temporal resolution to assess the LULC change in the Mazandaran province.

Table 1. Database used for land use/ land cover mapping

ID of imageries	Path/Row	Date	Sensor	Product	Type	Location
16-852	163/035	1987/06/14	TM	Earthsat	GeoTIF	Iran
16-869	164/035	1988/06/19	TM	Earthsat	GeoTIF	Iran
17-501	165/035	1987/06/28	TM	Earthsat	GeoTIF	Iran
37-941	165/035	2000/07/25	ETM	Earthsat	GeoTIF	Iran
38-123	165/035	2001/07/30	ETM	Earthsat	GeoTIF	Iran
38-175	164/35	2000/07/18	ETM	Earthsat	GeoTIF	Iran
203-771	165/035	1987/06/28	TM	USGS	GeoTIF	Iran
212-441	164/035	2000/07/18	ETM	USGS	GeoTIF	Iran
212-500	165/035	2000/07/25	ETM	USGS	GeoTIF	Iran
235-124	163/035	1987/06/14	TM	USGS	GeoTIF	Iran

235-210	165/035	1987/06/28	TM	USGS	GeoTIF	Iran
243-460	164/035	2000/07/18	ETM	GLCF	GeoTIF	Iran
243-519	165/035	2000/07/25	ETM	GLCF	GeoTIF	Iran

The mask of the entire Mazandaran province was not possible therefore only the central Mazandaran was used from the downloaded satellite imageries for the analysis of LULC. Earlier the study area was generated from the mosaic of three scenes of LANDSAT 7 ETM+ mosaics generated from the scenes of dates ranging from 1987 and 2006 generated from scenes of dates ranging from.

2.4. Methodology

Satellite Remote sensing technology is based on the Electromagnetic Spectrum. Earth's land surface reflects about three percent of all incoming solar radiation back to space. The rest is either reflected by the atmosphere or absorbed and re-radiated as infrared energy. The various objects that make up the surface absorb and reflect different amounts of energy at different wavelengths. The magnitude of energy that an object reflects or emits across a range of wavelengths is called its spectral response pattern. In other words, we can define spectral responses as a measurement of a light detector's signal or developed density of light-sensitive material when exposed to radiation of varying wavelengths. Two methodologies were adopted for this study. Supervised classification technique and Index integrated method. Both classification techniques are based on the spectral reflectance of the land cover, however, the former is composite classification and it is highly dependent on the number of sampling or pixel training involved. The latter one is based entirely on the spectral reflectance. In the Index integrated method, each of the land use/ land cover was extracted using several indices e.g., Normalized difference on Vegetation Index (NDVI), Normalized Difference on Built-up Index (NDBI) & Normalized difference on Snow Index (NDSI). All the indices generation and development will be discussed later.

2.4.1. Supervised Classification Technique

Before processing any image for image enhancement, transformation, or classification, pre-processing was done for band separation. Different bands were downloaded into the workstation using ILWIS 3.7, an open-source GIS software developed by ITC, Faculty of Geo-Information and Earth Observation, University of Delft, Netherlands. The images were checked for occasional shortcomings in the quality of radiometric and line dropouts. The registration of the image was performed using the nearest-neighbor resampling algorithm (Qian et al., 2007; Lilles and Kiefer, 2000).

LANDSAT 7 TM & ETM+ data was radiometrically corrected using the dark pixel subtraction technique. Sub-pixel image to map registration accuracy was achieved through repeated attempts. The image enhancement was performed by using different combinations for the best image contrast for the full dynamic range for each band employing enhancement techniques like edge detection, filters, manipulation of contrast and brightness, histogram equalization, etc. False Colour Composite (FCC) was prepared using enhanced data of Bands 2, 3, and 4 of LANDSAT 7 ETM+. The image was interpreted digitally using various digital image processing techniques. All operations were carried out using ILWIS 3.7 software.

To utilize the higher resolution of a panchromatic band of LANDSAT ETM+, image fusion was done to enhance the lower multispectral ETM+ images. For this purpose, a portion of the high-resolution PAN band that corresponds with an area of interest in the multispectral ETM+ images was extracted. Thereafter, both the images were co-registered and ETM+ images were resampled for merging with the PAN image. Merging or image fusion was done by the spatial

enhancement module of ERDAS Imagine 8.7.

The digital vector layer was downloaded from DIVA-GIS (<http://www.diva-gis.org/gdata>) of the Province of Mazandaran. The vector layers were then used as masks to extract the images for further processing. A mosaic image was prepared from two different ETM+ scenes. As the scenes were of different dates for a particular year, mosaicking was done by histogram matching using band by band matching tool of ERDAS IMAGINE 8.7. It was from these mosaic images, that the mask of the above-mentioned study area was extracted. From this mosaic image, masks of Mazandaran Province were extracted.

In the preliminary analysis, image classification was done by supervised classification method by performing ISODATA training. Pixel training was done for various sites and later spatial correlations of the pixel trained were plotted for all the pixels trained. It helped in assigning the classification of the image into land use categories. The doubtful areas or wrongfully interpreted areas owing to various physical features controlling the study area were marked for ground truthing (Field Visit and data collection were done in December 2012). The ground truth collected during the field surveys was used for the supervised classification for the preparation and identification of land uses resulting in accurate classification of the areas. The classified map was regrouped and merged. The same classification technique was followed for both the imageries downloaded for different years i.e., 1987 & 2006.

2.4.2. Classification Scheme

Two forest density classes were interpreted for the forest cover mapping. The forests with >70% canopy cover were delineated as very dense forests, with canopy density between 40-70% as moderately dense forests and between 10-40% crown density as open forests. Furthermore, degraded forests and scrubs were also delineated for erosion mapping. The cropland was also delineated. The non-forest land cover in the form of barren/ rocky land, glaciers, lakes, etc. was also delineated for the calculation of erosion intensity classification. The layers used for classification were relief, slope, aspect, landslides, and geological formations. An interpretation key was prepared based on the relationships between ground features and image elements like texture, tone, shape, location, and pattern. Image interpretation was done for the entire study area and interpreted details were then classified using the Maximum Likelihood classifier.

After image classification filtering is used. Filtering in GIS is the technique to minimize and rectify the redundancy after the image processing. In the filtering technique isolated single pixels are combined with the larger pixel classes. Patterns of sharp changes in scene illumination, which are typically abrupt rather than gradual, produce a relation that we express quantitatively as "spatial frequencies". The spatial frequency is defined as the number of cycles of change in image DN values per unit distance (e.g., 10 cycles/mm) applicable to repeating tonal discontinuities along a particular direction in the image. An image with only one spatial frequency consists of equally spaced stripes (in a TV monitor, raster lines). For instance, a blank TV screen with the set turned on, can have horizontal stripes. This situation corresponds to zero frequency in the horizontal direction and a measurable spatial frequency in the vertical, evidenced by line boundary repeats.

2.5. Integrated Classification Technique

In this classification technique, I have used two spectral bands separately to map the Land Use Land Cover. I have used the combination of two spectral bands to extract the Land Use Land Cover in this study viz. NDVI, NDBI & NDSI. Each of the indexes is discussed below along with the algorithm that has been used in the ILWIS 3.7 software.

2.5.1. Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is an index of plant “greenness” or photosynthetic activity and is one of the most commonly used vegetation indices. Vegetation indices are based on the observation that different surfaces reflect different types of light differently. Photosynthetically active vegetation, in particular, absorbs most of the red light that hits it while reflecting much of the near-infrared light. Vegetation that is dead or stressed reflects more red light and less near-infrared light. Likewise, non-vegetated surfaces have a much more even reflectance across the light spectrum.

By taking the ratio of red and near-infrared bands from a remotely sensed image, an index of vegetation “greenness” can be defined. The *Normalized Difference Vegetation Index (NDVI)* is probably the most common of these ratio indices for vegetation. The NDVI is an index that provides a standardized method of comparing vegetation greenness between satellite images.

The formula to calculate NDVI is:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

Where NIR is the near-infrared band value for a cell and RED is the red band value for the cell. NDVI can be calculated for any image that has a red and a near-infrared band. The biophysical interpretation of NDVI is the fraction of absorbed photosynthetically active radiation. Index values can range from -1.0 to 1.0, but vegetation values typically range between 0.1 and 0.7. Higher index values are associated with higher levels of healthy vegetation cover, whereas clouds and snow will cause index values near zero, making it appear that the vegetation is less green.

Many factors affect NDVI values like plant photosynthetic activity, total plant cover, biomass, plant and soil moisture, and plant stress. Because of this, NDVI is correlated with many ecosystem attributes that are of interest to researchers and managers (e.g., net primary productivity, canopy cover, bare ground cover). Also, because it is a ratio of two bands, NDVI helps compensate for differences both in illumination within an image due to slope and aspect, and differences between images due to things like time of day or season when the images were acquired. Thus, vegetation indices like NDVI make it possible to compare images over time to look for ecologically significant changes.

Bands from the following satellite sensors can be used to calculate NDVI:

- Land sat MSS -- bands 5 (0.6-0.7 μm) and 6 (0.7-0.8 μm) or 7 (0.8-1.1 μm); bands 2, 3, and 4, respectively, for Land sat 4 and Land sat 5
- Land sat TM -- bands 3 (0.63-0.69 μm) and 4 (0.76-0.90 μm)
- Land sat ETM -- bands 3 (0.63-0.69 μm) and 4 (0.75-0.90 μm)
- NOAA AVHRR -- bands 1 (0.58-0.68 μm) and 2 (0.72-1.0 μm)
- Terra MODIS -- bands 1 (0.62-0.67), 2 (0.841-0.876)

NDVI can be used as an indicator of relative biomass and greenness (Boone et al., 2000; Chen & Brutseart, 1998). If sufficient ground data is available, the NDVI can be used to calculate and predict primary production, dominant species, and grazing impact and stocking rates (Ricotta et al., 1999; Oosterheld et al., 1998; Paruleo et al., 1997; Peters et al., 1997; Diallo et al., 1991). It is also highly correlated with climatic variables, such as the El Niño Southern Oscillation (ENSO) (Li and Kafatos, 2000; Boone et al., 2000) and precipitation (Schemidt and Karnieli, 2000).

2.5.2. Normalized Difference Built-up Index (NDBI)

The NDBI method is proposed aiming to automate the process of mapping built-up areas. It makes use of both the conventional Normalized Difference Vegetation Index (NDVI) measurement and the newly proposed Normalized Difference Built-up Index (NDBI). Beyond its high-standard performance in terms of classification accuracy, the NDBI method, as a decision tree classifier, possesses a non-parametric nature, and several attractive properties of simplicity, flexibility, and computational efficiency (Friedl and Brodley, 1997). The nonparametric property means that non-normal, non-homogenous, and noisy data sets can be handled. In addition, a decision tree classifier has a simple form and thus can be stored compactly and reused for new data sets.

The algorithm for calculation NDBI will be given hereby:

$$\text{NDBI} = (\text{TM5}-\text{TM4})/(\text{TM5}+\text{TM4})$$

The development of the index was based on the unique spectral response of built-up lands that have higher reflectance in the MIR wavelength range than in the NIR wavelength range. However, this is not always the case. Some studies showed that the reflectance for certain types of vegetation over the bandpass of TM5 increased as leaf water content decreased (Cibula et al., 1992; Gao, 1996). The drier vegetation can even have higher reflectance in the MIR wavelength range than in the NIR range (Gao, 1996), resulting in positive values in NDBI imagery for these plants. Therefore, using of SVAI (soil vegetation area index) has been suggested but in our study, we don't have access to the soil details of the study area.

2.5.3. Normalized Difference Barren Land Index (NDBaI)

Bare lands play an important role in the ecosystem. It is an important source of sandstorms. Bare areas could be divided into primary and secondary bare lands according to their economic characteristics. As the distribution of bare land could be changed with the conversion of seasons; bare soil areas could be classified into seasonal and permanent bare lands. It is important to monitor the seasonal bare soil areas using remote sensing data. However, it is not ideal to derive bare soil areas using existing methods, e.g. maximum likelihood classification method. Normalized spectral indices were proved to be a good way to recognize different land cover types.

As the humus content of primary bare land is lower than that of secondary bare land and its surface is flat, the reflectance in the field of the shortwave infrared band is higher than the radiation in the thermal infrared band but the radiation of cultivated soil is higher because of its lower thermal capacity. Therefore, a new index: the normalized difference bareness index (NDBaI) was proposed to recognize different types of bare areas as follows:

$$\text{NDBaI} = [d(\text{band5}) - d(\text{band6})]/[d(\text{band5}) + d(\text{band6})]$$

Where d represents the digital number value (DN) of corresponding bands, band 6 represents the DN of ETM+/band61 or TM/band6. The proposed index made it possible to distinguish primary bare lands, secondary bare lands, and fallow lands.

2.5.4. Normalized Difference Snow Index (NDSI)

The distribution of snow in space and time is an important parameter for a wide variety of reasons. Knowing the extent of the snow is valuable information in that it provides insight as to the amount of water to be expected from snowmelt available for runoff and water supply. In addition, the snow cover itself is a surface condition that affects radiation and water balance determinations that are input to the hydrological cycle and climate studies (see, for example,

Cohen & Entekhabi, 2001; Foster et al., 1996; Yang et al., 1999). Furthermore, the sub-grid variability of snow within numerical models of hydrological or atmospheric surface energy exchange processes calls for knowing the fractional snow cover and its distribution as accurately as possible (see, for examples, Liston, 1999; Liston, Pielke, & Greene, 1999). Given the importance of knowing the distribution of snow, there has been much progress since 1966 when the first operational snow mapping was done by NOAA, in utilizing space-borne sensors that provide daily, global observations to monitor the variability in space and time in the extent of snow cover (Frei & Robinson, 1998; Rango, Walker, & Goodison, 2000).

The TM4/TM5 ratio is cited by Chang et al. (1987) as effective for discriminating the ice and snow facies in glaciological studies, particularly through areas of shadow. The NDSI helps distinguish snow from similarly bright soil, rock, and cloud (Dozier and Painter, 2004). Normalized Difference Snow Index is calculated through multispectral imageries arithmetic using the following relationship:

$$\text{NDSI} = (\text{TM2} - \text{TM4}) / (\text{TM2} + \text{TM4})$$

3. RESULTS AND DISCUSSION

3.1. Accuracy Assessment

Before using the classification result from satellite images for change detection, it is important to test the result against any reference data or ground truth data. In some cases, if the satisfaction is not up to the mark, the classification needs to be repeated or updated (Shamaoma, 2005). The most common way of accuracy assessment for any application of remote sensing is by creating an error matrix or confusion matrix (Foody, 2002).

3.2. Classification result

Since the change detection method adopted here is completely dependent on individual classification, it is imperative to display the classification result from each classification method. These results from all the classifications have further been used for the calculation of change detection information. Two approaches were used to show the result. At first, the classified images have been displayed immediately after the classification (Figures 1-4). LULC change in percentage over 13 years (1987 -2000). It is to be noted that those classified images are the primary result of classification. This is a visual impression of the classification result, which should not be considered explicitly for accuracy judgment. Secondly, the classification output in the form of a table is given in Tables 2 and 3.

3.3. Change detection

Post classification change detection method was applied for the present study. The post-classification method is the most widely used and has been adopted here for the following reasons:

- The accuracy of change detection is dependent on the accuracy of individual classification which can be reclassified or updated easily whenever necessary.
- Pre-classification method provides the change information by attribute of “change or no change” only.
- To avoid the problems that arise due to different properties of multi-source images and due to co-registration since each image has been classified independently.
- Individual classification of time-series images produced a historical set of LULC data which can be used for some other applications as well.

The method of post-classification consists of overlaying the classified images, using the cross operation, to be compared for change detection. The cross-operation using two classified images from different times allows the interpreter to know the extent and nature of changes in LULC transition between different land cover classes and the corresponding area of change. Since the final change classes resulting from cross-operation are quite numerous and time-consuming as well as slight differences in co-registration between data might result in misinterpretation of changes, it has been decided to confine the change analysis to the perspective of area change for each class where area of each class have been calculated individually to show the area change for each class. Moreover, the study is more focused on the suitability of the applied change detection method instead of the result of change detection. The detailed change detection analysis has been provided in Tables 2 and 3. The classification result indicates that the study area is mostly covered by dense forest, 28% of the province is prevalent with dense forest in 1987. The area is also prevalent with barren land towards the southern part of the province. However, towards the northern part i.e., in the coastal zone settlement (urban fabric) and heterogeneous agriculture are more prevalent. For further detail please see Table 2 and Figure 3. Similarly, in the LULC map of 2000, dense forest is also prevalent with 26.5 % of the total province, followed by barren land and arable land. For further detail please refer to Table 3 and Figure 4.

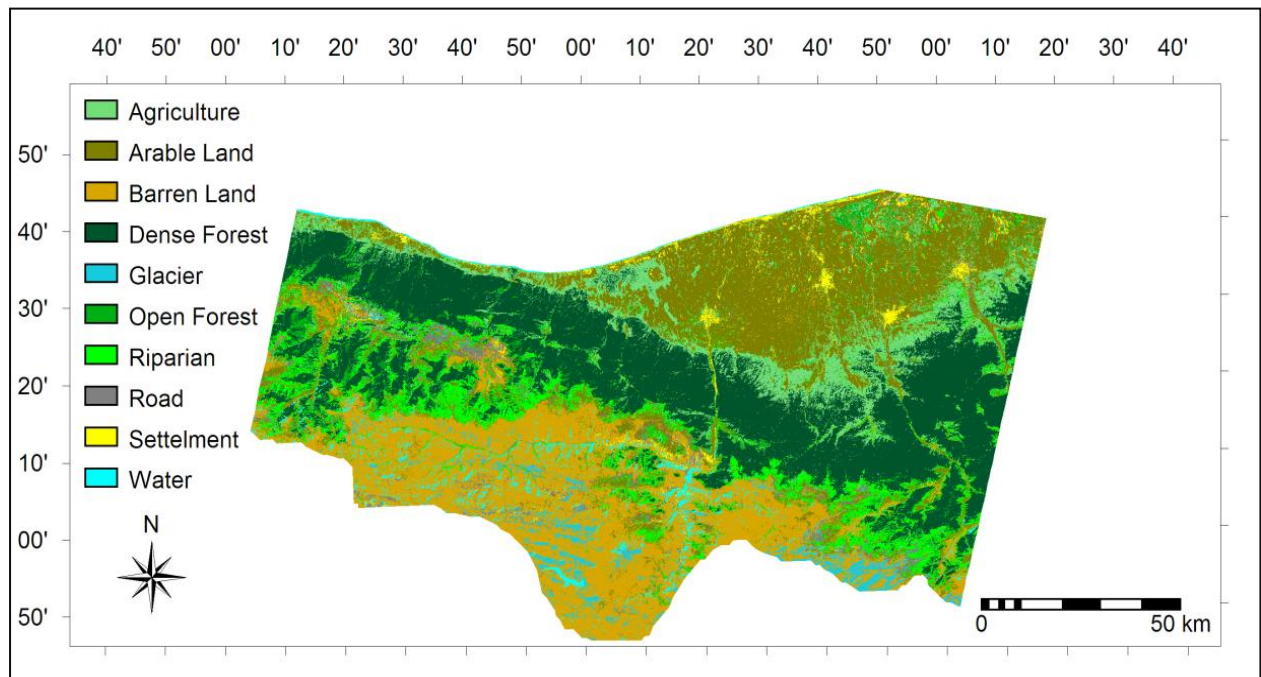


Figure 1. Land Use/ Land Cover Change Map of Year 1987.

The result of the change detection analysis exhibits significant changes in LULC in the study area in two different periods (from 1987 to 2000). There is no change in area for the class of water bodies through time, however, a little change in aerial extent has been noticed after cross-operation between results. In all other classes, changes have been noticed but, in some cases, changes are too small which can be generalized as “no change”. As, for the change in water bodies for the period of 1987-2000; the change is 0.05% which is very negligible, and thus can be considered as “no change”. This observable fact is sometimes the effect of automatic classification. The pixels of one particular class do not follow the same way between multi-date images. However, this is not the case in visual interpretation where analysts keep the classification result from previous images as a background layer when interpreting another temporal image of the same study area to check the change in real-time interpretation and thus update the land cover classes in the present image.

The class of urban fabric has increased through time; it is highly noticeable between the period of 1987 and 2000 is 0.06% whereas the road has increased to a higher amount by 5% (see Figure 5). Farming land witnesses a small amount of decrease both in the case of arable land and heterogeneous agriculture. Likewise, there is a drastic change in the barren land with an increase of 7%. Similarly, there is a decrease in the dense forest class by 2%. For further LULC change over 13 years please refer to Figure 5 and the change in LULC is also given in Table 4.

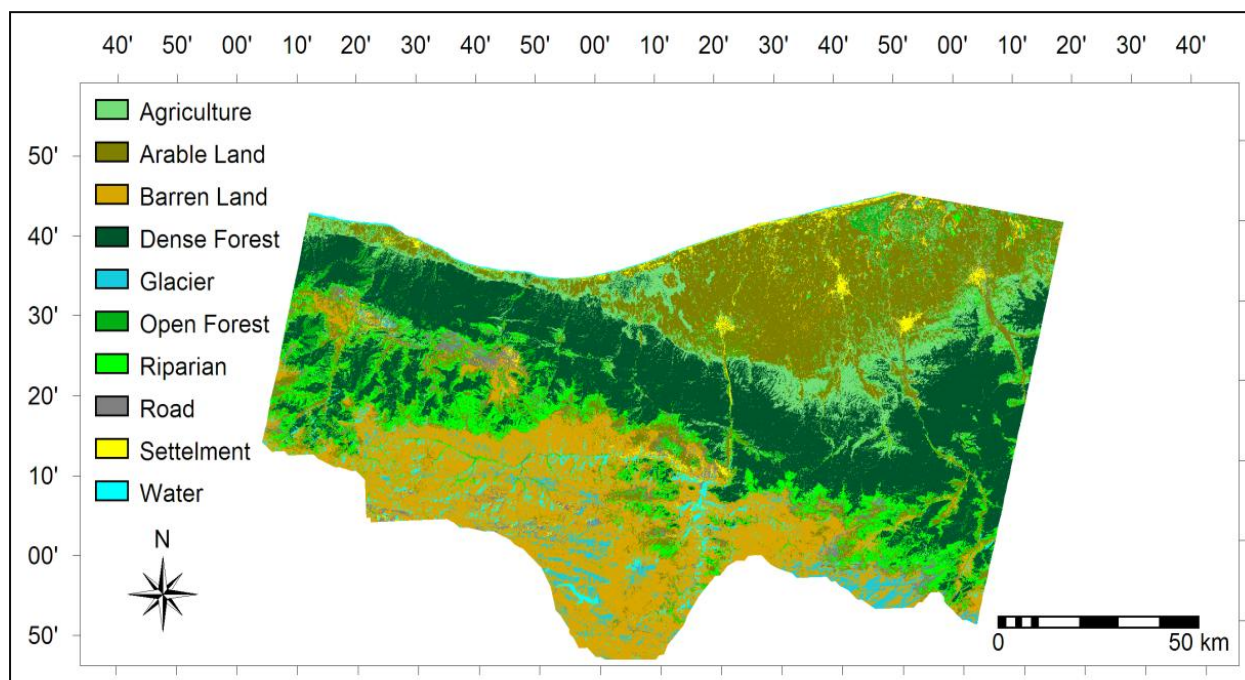


Figure 2. Land Use/ Land Cover Change Map of Year 2000.

Table 2. LULC in the year 1987.

Land use classes	Area (Sq.km)	Percentage
Agriculture	1302.61	8.95
Arable Land	3083.34	21.19
Barren Land	3012.14	20.70
Dense Forest	4151.91	28.54
Glaciers	310.98	2.14
Open Forest	369.08	2.54
Riparian	1382.07	9.50
Road	340.02	2.34
Settlement	271.45	1.87
Water	325.21	2.24

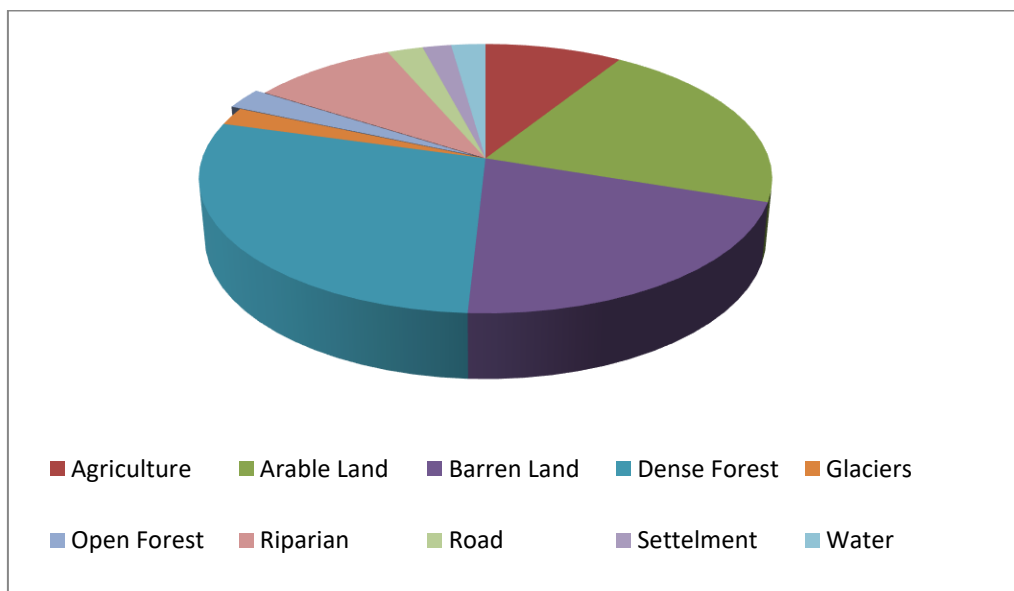


Figure 3. Pie Chart of LULC (1987).

Table 3. LULC in the year 2000.

Land use classes	Area (sq\ km)	Percentage
Agriculture	1162.81	8.05
Arable Land	2374.49	16.44
Barren Land	4246.69	27.4
Dense Forest	3834.63	26.54
Glaciers	188.85	1.3
Open Forest	365.97	2.53
Rapiran	578.60	4.005
Road	1097.31	7.6
Settlement	278.78	1.93
Water	317.61	2.199

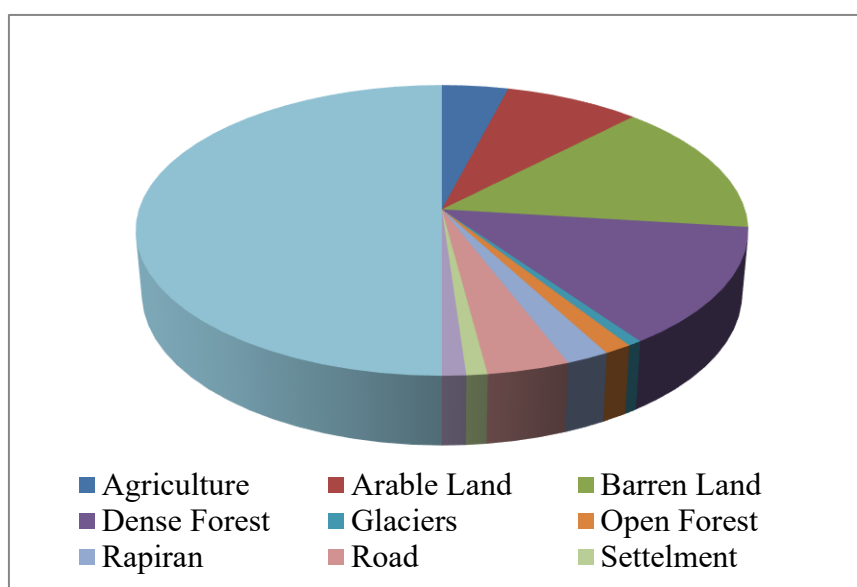


Figure 4. Pie Chart of LULC of the year 2000.

Table 4. Areas (%) of Different Land use in years 1987and 2000.

Land use classes	Area % (1987)	Area % (2000)
Agriculture	8.95	8.05
Arable Land	21.19	16.44
Barren Land	20.7	27.4
Dense Forest	28.54	26.54
Glaciers	2.14	1.3
Open Forest	2.54	2.53
Rapiran	9.5	4.005
Road	2.34	7.6
Settlement	1.87	1.93
Water	2.24	2.199

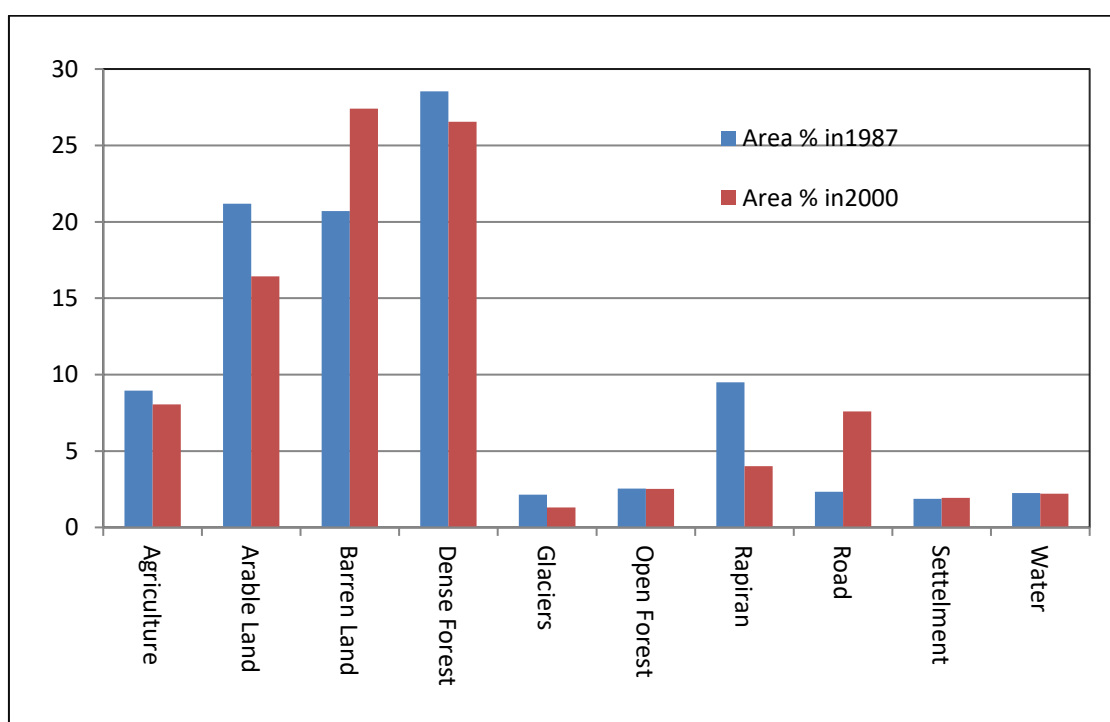


Figure 5. LULC change in percentage over 13 years (1987 -2000).

4. CONCLUSIONS

Despite many factors controlling the selection of a suitable change detection approach from wide-ranging methods, the used approach in the present study proved very effective in fulfilling the objectives with successful implementation. To support this viewpoint, the following conclusions can be illustrated as observed from the analysis of the result: The classification result clearly shows that the employ of satellite images was very helpful for extracting LULC for change detection. It is nonetheless to state that there is a great impact of spatial resolution (and spectral resolution as well) on any kind of remote sensing (RS) application. This impact of resolution was also evident in this study. The classification accuracy was fairly related to the resolution of the image.

The study explores the successful use of the classification technique approach for LULC change detection. The technique for the classification of LULC and its change detection has

proven very efficient as it offers multiple tools in GIS. It proved effective for the satellite images like Landsat ETM. However, this technique and due to low spatial resolution classes below minimum mapping unit (like canals and roads) could not be identified in this study. Post classification technique has been found a suitable method for the study. This method was applied for quantitative change detection after the classification images by comparison of results. The change is quantified by differencing classification results. The classification technique approach and post-classification turned out better accurate results when compared to simple image differences where the change is based on “change / no change” information.

The approach of studying change detection identified a significant amount of changes in two time periods. However, those changes have some inaccuracies as well. However, since each classification achieved a higher level of accuracy, the derived change information is acceptable. However, it is quite obvious that more accurate change information could be obtained if the ‘change layer’ for each classification was used instead of the classification result itself. The extent and spatial pattern of class change is different in two time periods whereas the rate of change per year is almost consistent throughout time.

To sum up, the present study shows great potential for decision makers to generate accurate LULC change detection by exploiting various sources of RS and techniques towards successful implementation of sustainable development, natural resource management, and safe land use planning.

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