LAND USE / LAND COVER CHANGES MONITORED BY NDVI INDEX IN RANGAMATI, BANGLADESH FOR THE LAST FOUR DECADES

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Abstract

The study of land use/land cover dynamics has been increasingly important in the research of earth surface natural resources. The normalized difference vegetation index (NDVI) is a widely used method for observing land use/land cover change detection. The surface land resources are easily interpreted by computing their NDVI. This study aimed at analyzing Land Use/Land Cover (LULC) changes between 1977 and 2019 in the Rangamati district, Bangladesh using reclassify the NDVI values of the Landsat satellite image and identifying the main drivers to change LULC by household survey. Five different years of Landsat images were used to extract the NDVI values January of 1977, 1989, 2000, 2011 and 2019. The NDVI values are initially computed using the user define method to reclassify the NDVI map to create land use land cover map and change detection. The highest NDVI value was found in 1977 (0.88) which indicates healthy vegetation at that time and thereafter it followed a decreasing trend (0.79 in 1989, 0.74 in 2000, 0.71 in 2011 and 0.53 in 2019) which shows a rapid vegetation cover change in the study area. Analysis of the household survey revealed that population growth, migration from plain land, rapidly urbanization, Kaptai Dam, migration policy of government, high land price, unplanned development, development of tourism industry, firewood collection and poverty have been identified as the major drivers of LULC changes in the study area. Furthermore, analysis of NDVI confirms that the forest vegetation area is being decreased and settlement area and sparseness of vegetation are being increased. The accuracy of the NDVI-based classified images is assessed, using a confusion matrix where overall classification accuracy and Kappa coefficient are computed. The overall classification accuracy was 84% - 90% with corresponding Kappa statistics of 80% - 88% for TM and OLI-TIRS images, respectively. The study serves as a basis of understanding of the LULC changes in the southeastern part of Bangladesh.

Keywords: ETM+, LULC, Landsat, OLI, Remote sensing, TM

Introduction

Land use / land cover (LULC) represents the natural and physical cover of the earth as well as various human uses of land like settlement, agricultural land, reservoirs, transportation network, etc. The change detection of LULC is one of the significant techniques, which is broadly used for planning and managing land (Sahebjalal and Dashtekian, 2013). The multi spectral remote sensing image is the science and art of

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acquiring information and extracting the features in form of spectral, spatial and temporal about some objects, areas or phenomena, such as vegetation, land cover classification, urban area, agriculture land and water resources without coming in to physical contact of these objects (Karaburun and Bhandari, 2010). Remote sensing technique play an important role in many fields, such as air temperature estimation (Pelta and Chudnovsky, 2017), land cover monitoring (Restrepo *et al.,* 2017), fire incidence assessment (Alves and Perez-Cabello, 2017), drought prediction (Nichol and Abbas 2015) and monitoring of crop distribution (Zhong *et al.,* 2014). Several methods have been used for analyzing LULC, such as conventional image differencing, multi-date image classification, image differencing rationing, vegetation index differencing, principal component analysis, and change vector analysis (Lu *et al.,* 2005). The normalized difference vegetation index (NDVI) is one of the widely used significant classification methods in detecting land cover and land use changes (Aburas *et al.,* 2015). Remote-sensing and GIS technologies only identify the nature, extent, and rate of LULC changes on the landscape; however, they do not provide an explanation about the underlying causes of LULC dynamics on the landscape (Kindu *et al.,* 2013). Therefore, this study aims at quantifying and mapping land use land cover dynamics between 1977 and 2019 in Rangamati district using the NDVI index. The study also explores the local people's perceptions of major drivers of LULC changes in the study area. The outcome of the study would be useful to planners, environmentalists, resource managers, policymakers, and other stakeholders in formulating sound management and environmental planning strategies for conservation of natural resources in Rangamati district.

Materials and Methods

Study area and its geographic location

Rangamati is the largest district of Bangladesh by area. It is a district of natural beauties & cultural heritage. It is located at 22° 00' 27"& 23° 00' 44" N and 91° 00' 56" & 92° 00' 33" E. It is surrounded by Tripura of India at the north, Bandarban at the south, Mizoram of India at the east, and Khagrachari & Chittagong at the west (Fig. 1). It is under Chattogram Division and is a part of the Chittagong Hill Tracts. It consists of 10 upazilas, 2 pourashavas, 50 unions, 1349 villages and 159 mouzas. It became a subdivision in 1891 and was upgraded to a district in 1983. Rangamati district occupies an area of 6116.13 sq. km ; its population is 6,20,214 . Rangamati district has a long history and heritage of a very rich culture of tribal & Bengali people. Rangamati is famous for cashew nut, watermelon, Bangla banana, fresh fishes of Kaptai lake. The district has a hydraulic Power Plant at Kaptai and Terrestrial Earth Satellite at Betbunia, Kawkhli. The main economic activities in the study area are intensive tourism, hydroelectric power, agriculture, fisheries, and forest resources.

Primary and secondary data collection tools

Household surveys

Semi-structured household questionnaires were used in face-to-face interviews in this study employing a random sampling method to select respondents for the household interviews. The questionnaire was pretested by 20 households and then modifications were made before the actual interviews of the sampled households (Munthali *et al.,* 2019). The questionnaire was administered to 300 households during April 04-30, 2019.

Moreover, the questionnaire was administered to respondents who were aged between 25 to 87, and the mean age was 48.41; 73.3% of the Rangamati Sadar residents are permanent residents and 26.7% are migrants but not settlers. Most of the respondents were decision-makers in the household. But in the absence of a family head, it was made with appropriate representatives and knowledgeable members of the household. The questionnaires consisted of both open and closed-ended questions to gather data about the socio-economic and environmental impacts of changing land use patterns of the study area. So, the drivers of LULC changes were extracted by the significant related part of the questionnaire.
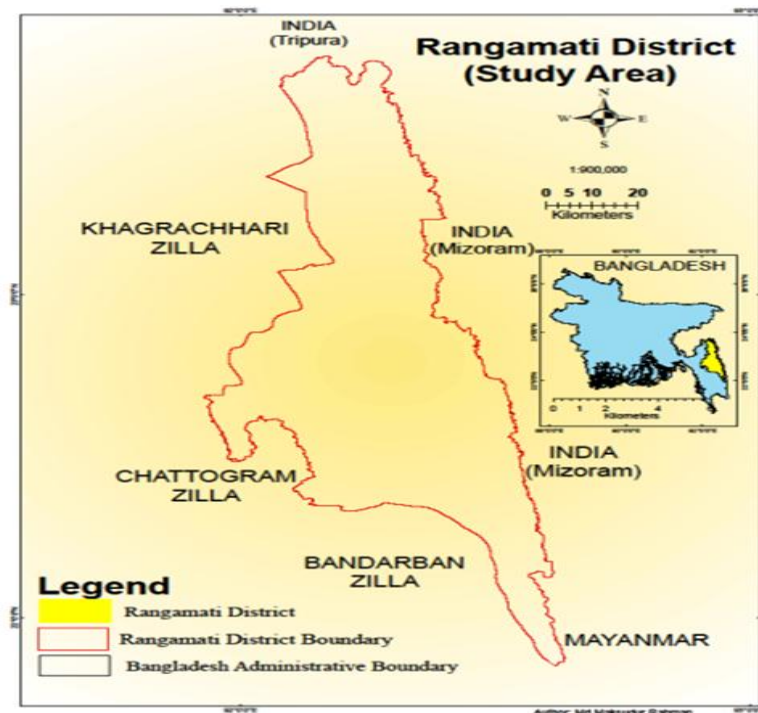

Fig. 1. Rangamati district map as study area (source: author)

Satellite data acquisition

Landsat is the Earth Observatory System (EOS) satellite series that has been providing data since the 1970s (Almazroui *et al.,* 2017). Landsat satellites are considered a valuable source of observation and monitoring of global changes because of the medium spatial resolution and the availability of long term data (Masek *et al.,* 2008). Most of the Landsat satellite data is available free of charge to users via the internet. Landsat satellite data can be acquired via the FTP (File Transfer Protocol) system from the USGS or the GLOVIS (USGS Global Visualization Viewer) website (http://glovis.usgs.gov/). In this study, Landsat time series of LULC data sets were produced from the imagery of MSS, TM, and OLI_TIRS, which were acquired from January 1977, 1989, 2000, 2011 and 2019. The selected five years and their

corresponding months and days have been determined to get the near accurate changes of the temporal changes. Because of the images of the same month and day in a same gap of cloud and noise free are the most useful and reasonable for understanding the maximum changes. The selected images of this study cover most of these features.

The dry season was selected because there is less cloud cover affecting the Landsat images (Tovar, 2011). All images were geometrically corrected and acquired in level 1T (L1T). In addition, the time gap between all the Landsat satellite images was more than 16 days, because of cloudiness or noise-free scenes. Two criteria were followed to choose the satellites images in this study, agreeing to (Sun *et al.,* 2009): (1) the satellite images must have less than 10% cloud coverage (if possible, cloud free); (2) the satellite images should be available for a long time series. Table 1 shows the summary information of the remotely sensed data.

Table 1. Detailed information of Landsat Images used in this study

Year	Date of acquisition	WRS Path	WRS Row	Cloud Cover	Image Quality	Sensor Id	Spatial Resolution
1977	02/01/1977	146	44	0	5	MSS	60
	02/01/1977	146	45	0	5	MSS	60
	01/01/1977	145	45	2	7	MSS	60
1989	13/01/1989	136	44	0	9	TM	30
	13/01/1989	136	45	0	9	TM	30
	10/02/1990	135	45	0	7	TM	30
2000	28/01/2000	136	44	0	9	TM	30
	12/01/2000	136	45	0	7	TM	30
	23/01/2001	135	45	0	9	TM	30
2011	26/01/2011	136	44	0	7	TM	30
	26/01/2011	136	45	0	7	TM	30
	04/02/2011	135	45	0	7	TM	30
2019	16/01/2019	136	44	3.18	9	OLI_TIRS	30
	01/02/2019	136	45	.03	9	OLI_TIRS	30
	09/01/2019	135	45	1.27	9	OLI_TIRS	30

Data preprocessing

This study comprehensively employed GIS and Remote Sensing techniques. There are several methods for detecting seasonal changes in vegetation through satellite images, one method of which is to apply vegetation indices relating to the measurement of greenness (Chuvieco, 1998). NDVI is one of the most extensively used indices in remote sensing of vegetation (Wheeler and Dietze, 2019). It is also used in a variety of observations including that of phenological change (Loveland *et al.,* 2003), land cover classification (Loveland *et al.,* 2000), land cover change (Lunetta *et al.,* 2006), vegetation

cover degradation (Pettorelli *et al.,* 2005), environmental change (Jacquin *et al.,* 2010) and fire damage (Fernandez *et al.,* 1997).

The study considered the spectral index NDVI and classification using NDVI to explore and identify estimating land cover changes. (Akter and Ahmed, 2017). Several data sets (Table 1) were prepared by ERDAS IMAGINE 2014 and ArcGIS 3.4.1 software and field survey data prepared by the statistical software of SPSS 20 and spread sheet. Three Landsat time-series imagery of Level 1 MSS, TM, and OLI_TIRS were acquired and used to evaluate LULC changes by "Defined Interval" method of reclassifying NDVI values for this study. The range of threshold value or greenness value is divided into discrete classes by partitioning the range of NDVI values into five ranges by fixing the thresholds for NDVI classification (Table 2). The downloaded images were layer stalked first and then radiometric corrected, mosaicked and subset using ERDAS IMAGINE 2014. The NDVI values were generated using ArcGIS 10.4.1.

Spectral band 5 as visible Red band and spectral band 6 as visible Near Infrared band for Landsat(1-3) MSS (Multispectral Scanner) with 60 m spatial resolution; Spectral band 3 as visible Red band and spectral band 4 as visible Near Infrared band for Landsat TM sensor with 30 m spatial resolution; and spectral band 4 as visible Red band and spectral band 5 as visible Near Infrared band for Landsat OLI TIRS sensor with 30 m spatial resolution were used for the development of NDVI (Akter and Ahmed, 2017).

Landsat (1-3) MSS spectral Band 5 has wavelength from 0.6 to 0.7 μm and band 6 has wave length from 0.7 to 0.8 μm. Landsat TM spectral Band 3 has wave length from 0.63 to 0.69 μm and Band 4 has wave length from 0.76 to 0.90 μm. Land6sat OLI TIRS spectral Band 4 has wave length from 0.636 to 0.683 μm and Band 5 has wave length from 0.851 to 0.879 μm [http://glovis.usgs.gov].

The NDVI spectral index equation (Rouse et al.1973) is given below –

NDVI = (Near Infrared Band − Red Band) / (Near Infrared Band + Red Band)

The NDVI should be larger for greater chlorophyll density. It takes the (NIR-Red) difference and normalizes it to balance out the effects of uneven illumination such as shadows of hills or trees or clouds (Gandhi *et al..* 2015). Table 2 presents the threshold value used in the NDVI classification.

Table 2. Threshold value used in NDVI classification

LULC type	Threshold Value				
	1977	1989	2000	2011	2019
Water body	-0.9 -0	-0.45-0	-0.45-0	-0.5-0	-0.09-0
Bare land	0-0.1	0-0.1	0-0.1	0-0.1	0-0.1
Settlement	0.1-0.15	0.1-0.15	0.1-0.15	0.1-0.15	0.1-0.15
Sparse vegetation	0.15-0.25	0.15-0.25	0.15-0.25	0.15-0.25	0.15-0.25
Forest/Dense vegetation	0.25-0.9	0.45-0.8	0.45-0.75	0.45-0.75	0.45-0.55

Accuracy assessment

Satellite imagery-based classification and analysis accuracy depend on different climatic conditions, cloud cover, haze, leaf pattern, chlorophyll content and moisture content including sample selection procedures (Foody, 2008; Gaur and Chouhan, 2017). The information of ground truth data was compared to the classified image in order to check the accuracy. The accuracy of user and producer was carried out to measure the classification accuracy (Singh, 2012; Taufik *et al.,* 2017). Generally, classification accuracy refers to the extent of correspondence between the remotely sensed data and reference information (Congalton, 1991). The classification process is incomplete unless accuracy assessment is performed on it (Lillesand, 2004). For this, the 50 stratified random samples of testing pixels were selected from each (2000, 2011 and 2019) classified image and their classes compared with the land use/land cover field reference and in Google map (Thakkar *et al.,*2014), but accuracy assessment is impossible of others (1989 and 1977) previous images because of vague Google map or noisy Google image. The results were recorded in a confusion matrix. A non-parametric Kappa test was also used to measure the classification accuracy as it accounts for all the elements in the confusion matrix rather than just the diagonal elements (Rosenfield and Fitzpatirck-Lins, 1986).

Land use type

The NDVI value-based statistics are categorized in the following types i.e., water body, bare land, settlement area, sparse vegetation and forest or dense vegetation. Description of these LULC types are given in Table 3.

Table 3. Land use/land cover classes used in this study

LULC type	Description
Water body	All source of water (like river, stream, lake, pond, creek) which able to detect by RS in the study area.
Bare land/Char land	Areas with no vegetation cover, including exposed soils, char land, fallow land and landfill sites also included.
Settlement area	Residential, commercial and services, Industrial, Transportation, Roads, Mixed urban and all buildup area like Stadium, shop, office, school, college, Factory etc.
Sparse vegetation	All cultivated lands area, permanent and seasonal grasslands along lake, river, stream, marshy land and swamps. Which vegetation surrounding the buildup areas are included this class. Crop fields, agricultural land fallow land and vegetable land also included.
Forest/Dense vegetation	Reserve forest, plantations, deciduous forest, mixed forest, palms, conifer and scrubs

Results

Change detection

Fig. 2 shows the spatial representation of LULC types from 1977-2019 and Fig. 3 shows the different NDVI ranges of Rangamati district of selected years. Table 4 presents
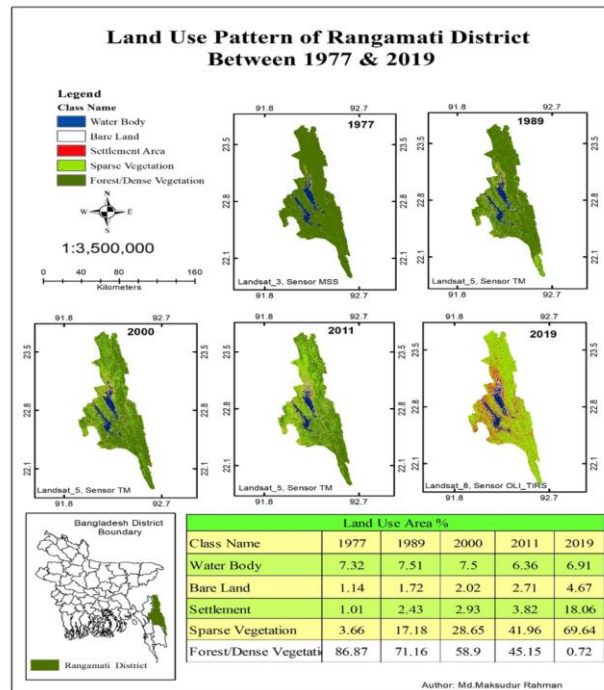
Fig. 2. NDVI derived classified map of Rangamati district for five different years (1977-2019), Source: Based on Satellite image processing (1977-2019)

the percentages of each class of different year out of total area of the study area. The area percentage of each class is calculated by converting those pixels value of each class after classification. The proportionate coverage area of each of the five classes extracted in Rangamati from 1977-2019 of LULC change trends are summarized in Table 5 and Fig. 2. The NDVI is a dimensionless index, so its values are between -1 and +1 (Munthali *et al.,* 2019). Higher NDVI values indicate a healthy vegetated area, while lower NDVI values indicate unhealthy vegetation, close to zero but not negative values indicate settlement, bare land, rock, sand beach respectively and negative values represent the absence of green vegetation (Tovar, 2011). The remote sensing data is broadly used for large area vegetation cover change monitoring (Nath and Acharjee, 2013).

Table 4. Decadal land use land cover area (%) of Rangamati district during 1977-2019

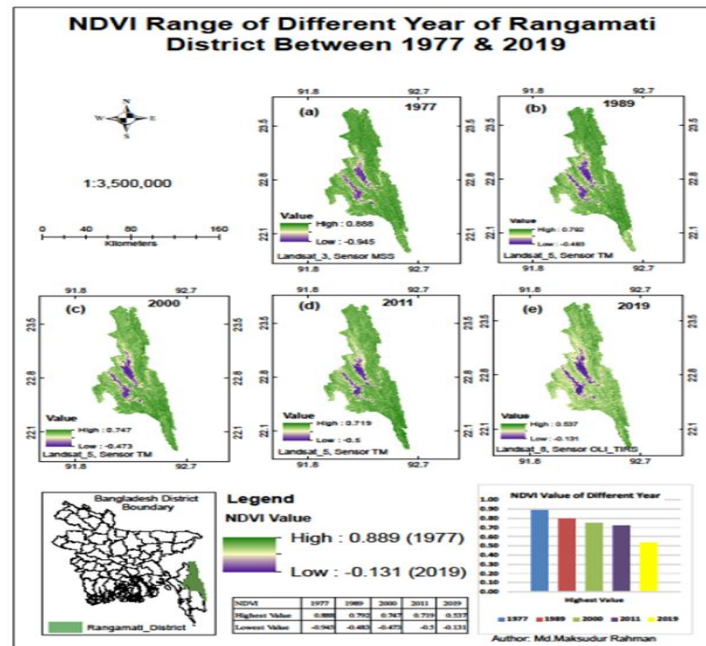| LULC type	Area (%)				
	1977	1989	2000	2011	2019
Water body	7.32	7.51	7.5	6.36	6.91
Bare land/Char land	1.14	1.72	2.02	2.71	4.67
Settlement area	1.01	2.43	2.93	3.82	18.06
Sparse vegetation	3.66	17.18	28.65	41.96	69.64
Forest/Dense vegetation	86.87	71.16	58.9	45.15	0.72
Total %	100	100	100	100	100

Fig. 3. NDVI range of Rangamati district for five different year (1977-2019), Source: Based on Satellite image processing (1977-2019)

Table 5. Land use change area %

LULC type	Change Area (%)			
	1977-1989	1989-2000	2000-2011	2011-2019
Water Body	0.19	-0.01	-1.14	0.55
Bare Land/Char land	0.58	0.3	0.69	1.96
Settlement Area	1.42	0.5	0.89	14.24
Sparse Vegetation	13.52	11.47	13.31	27.64
Forest/Dense Vegetation	-15.71	-12.26	-13.75	-44.43

Source: Authors' calculation based on Satellite image processing, (1977-2019)

Results of accuracy assessment

The NDVI derived and use classes overall accuracy were 84 to 90% and with corresponding Kappa statistics of 80, 88 and 87.5%, respectively (Table 6), corroborating the standard accuracy of 85-90% for LULC mapping studies as recommended (Anderson *et al.,* 1976).

Table 6. Results of accuracy assessment of land use/cover map produced from Landsat TM and OLI_TIRS data

LULC type	2000		2011		2019	
	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)
Water body	90.91	100	90.91	100	83.33	100
Bare land	88.89	80	100	90	80	80
Settlement	77.78	70	88.89	80	90	90
Sparse vegetation	66.67	80	75	90	100	90
Forest	100	90	100	90	100	90
Overall accuracy	84%		90%		90%	
Kappa Coefficient (T) 80%	80%		88%		87.50%	

Source: Based on Satellite image classification calculated by author, (2000, 2011 & 2019)

Major drivers of LULC changes

The major drivers of LULC changes are demographic factor, economic growth, land use policy factor, industrialization, housing and tourism. The annual population growth rate was 7.11% between 1974 -1981, 3.1% between 1981 -1991 and 4.1% in 1991- 2001 in Rangamati district shown in Fig 4.

The field survey was conducted in the rural, semi-urban, and urban areas. The majority of respondents agreed to the point that population growth, urbanization, unplanned development, and increase in economic activities are the factors for changes in the land use pattern over the past few decades (Fig. 5).
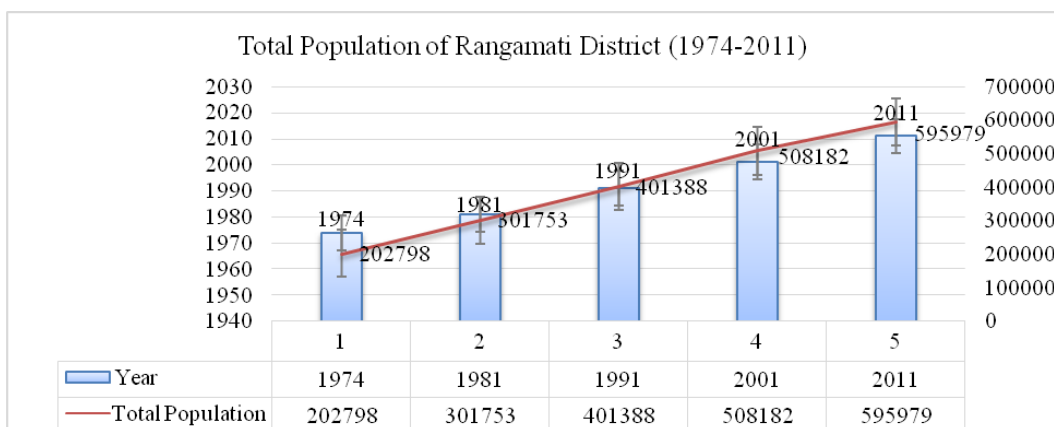

Fig. 4. Population trend of Rangamati district (1974-2011), Source: Population Census of various census years of BBS (Bangladesh Bureau of Statistics).
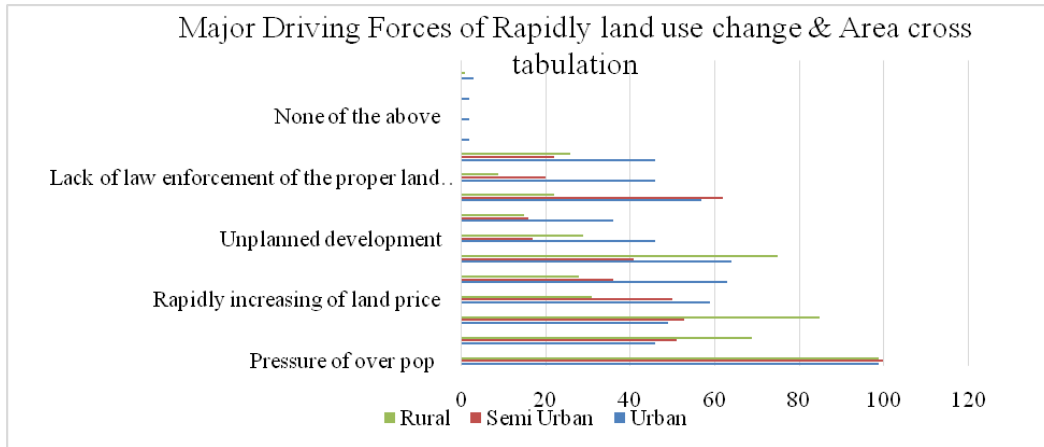
Fig. 5. Major driving forces for rapidly land use changes. Source: Field Survey, Rangamati 2019

Causes of forest degradation

Forest is a very vital renewable resource in Rangamati. It provides materials like timber, pulp, pole, fuel wood, food and medicine, habitat for wildlife, and primary base for biodiversity. It also influences the precipitation and sustained water yield in the river systems etc. But the pattern of our LULC map shows that the forest of Rangamati is degrading year by year which is alarming news to all. This research work also worked on the major causes of Rangamati forest degradation. In Fig. 6, the field study result shows that poverty is the major cause of all the other factors which is affecting the environmental sustainability of Rangamati District.
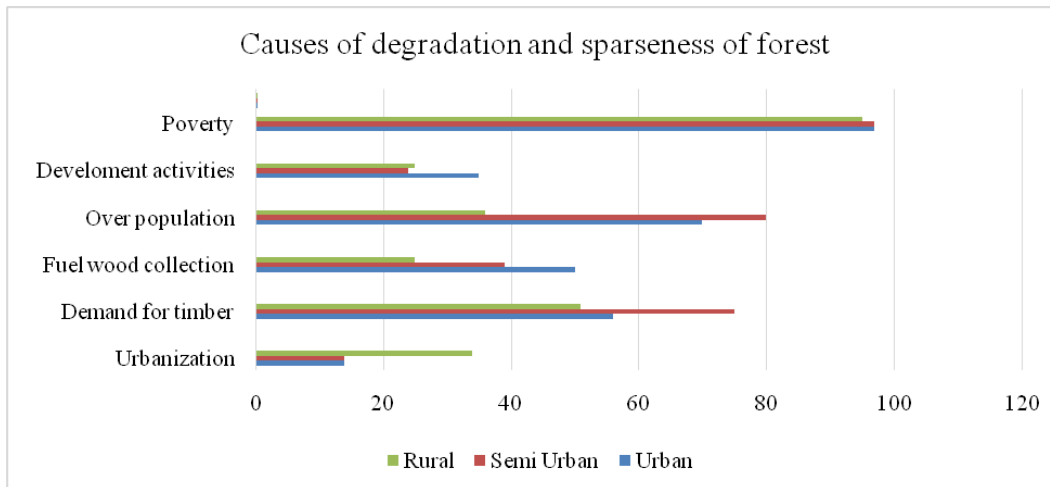

Fig. 6. Causes of degradation and sparseness of forest, Source: Field Survey, Rangamati 2019

Discussion

The NDVI values of these land use land cover classes differ significantly from 1977-2019. Figure 3 shows that the highest NDVI value was found in 1977 (0.88) which represents healthy vegetation at that time and after 1977, the highest NDVI value shows a decreasing trend (0.79 in 1989, 0.74 in 2000, 0.71 in 2011 and 0.53 in 2019) which represents a rapid vegetation cover change in the study area. Slightly changed or an irregular change trend observed in the Kaptai lake and water body area due to the seasonal variation (Table 4 & 5, Fig. 3) of water like scarcity and availability. Results confirmed that the forest or dense vegetation area is decreased rapidly and on the other hand bare land settlement area are increased gradually, and sparseness of vegetation are increased rapidly (Table 4 & 5), which may be considered as a great threat regarding proper ecosystem functioning and climate change.

Figs. 2 & 3 and Tables 4 & 5 show the spatial representation of LULC types from 1977 to 2019. The trend is changing land-use patterns is a dynamic process. It depends on different time and space. This research has found a major variation of settlement area and sparse vegetation and forest area were changed rapidly. The bare land area was changed gradually and the water body was found slightly irregular changed due to seasonal variation of water body. Dense forest & sparse vegetation were played a major role in many conversions to settlement and bare land area. This conversion could be related to the rapid increase of population (Fig. 4) and faster economic development in Rangamati district.

The major drivers of land use change and causes of degradation of forest interprets the environmental degradation of Rangamati over the decades which is alleviating the true beauty of landscape in Rangamati district. It is believed that eco-tourism could be an alternative mechanism for environmentally sustainable development without depleting the forest resources and its habitat.

Conclusion

The settlement area, bare land and the vegetation sparseness area have increased and dense forest area has decreased rapidly in the study period of 1977 to 2019. Slightly changed or an irregular change trend observed in the Kaptai lake and total water body area due to the seasonal variation of water like scarcity and availability. Thus the present study explains the temporal land-use trend of the Rangamati district, which is very important for sustainable land use planning decisions and also forecasting possible future changes in growth patterns.

Considering all these, results of this study have shown that remote sensing and GIS are important tools in land-use change studies. Based on the findings of this study, the followings are recommended as future research directions:

- Expansion of settlement should be regulated.
- Sustainability of environmental aspects should be focused.
- Deforestation must be stopped and the afforestation program should be undertaken.

- The use of high-resolution imageries such as IKONOS and Quick Bird is important in generating good quality of land use maps. Because urban areas have complex (especially hilly urban area) and heterogeneous features, high-resolution imagery provides better information by mapping these areas.

- Consistent multi-temporal Landsat satellite data for each year provides a detailed comparison of images.

- Incorporating socio-economic environmental data, land policy, biophysical and human factors (population density, technology, political) could improve the performance of land use analysis for future predictions.

Acknowledgment

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