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NDVI and NDMI indices based land use and land cover change analysis of Charaideu District, Assam, India.

Análisis de uso de la tierra y cambios en la cobertura de la tierra basados en los índices NDVI y NDMI del distrito de Charaideu, Assam, India.

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ABSTRACT

A transformation of natural environment to man-made environment causes Land use and Land cover change (LULC). These changes have been taking place due to human's unethical uses of natural resources. Remote Sensing and GIS are the essential techniques to identify land use land cover change in an area. Normalized Difference Vegetation Index (NDVI) and Normalized Difference Moisture Index (NDMI) indices have been used to study the Land use changes in Charaideu District. The objectives of this paper are to analyse the spatio-temporal LULC, NDVI and NDMI changes and the impact of LULC change in NDVI and NDMI. Three multi-temporal satellite imageries for the years 1995, 2010, and 2020 were acquired from the United States Geological Survey website to meet the study's aims.The supervised classification method has been applied to prepare land use and land cover maps using Maximum Likelihood Algorithm and also the NDVI and NDMI maps for depicting vegetation pattern and moisture condition of the study area. It is revealed from the study that the areas under built-up land and agricultural hand have been increasing during the period 1995-2020. On the other hand, area under dense vegetation has decreased due to increasing population which leads to changes in vegetation pattern and moisture condition in the study area

Keywords: Land use land cover, Remote sensing, Normalized Difference Vegetation Index, Normalized Difference Moisture Index, Supervised classification, Maximum likelihood algorithm.

RESUMEN

Una transformación del entorno natural en un entorno creado por el hombre provoca cambios en el uso de la tierra y la cobertura de la tierra (LULC, por sus siglas en inglés). Estos cambios se han producido debido al uso poco ético de los recursos naturales por parte de los seres humanos. La teledetección y los SIG son las técnicas esenciales para identificar el cambio de cobertura del suelo en un área. Se han utilizado los índices Normalized Difference Vegetation Index (NDVI) y Normalized Difference Moisture Index (NDMI) para estudiar los cambios de uso del suelo en el distrito de Charaideu. Los objetivos de este artículo son analizar los cambios espacio-temporales de LULC, NDVI y NDMI y el impacto del cambio de LULC en NDVI y NDMI. Se adquirieron tres imágenes satelitales multitemporales para los años 1995, 2010 y 2020 del sitio web del Servicio Geológico de los Estados Unidos para cumplir con los objetivos del estudio. también los mapas NDVI y NDMI para representar el patrón de vegetación y la condición de humedad del área de estudio. El estudio revela que las áreas bajo tierra edificada y mano agrícola han aumentado durante el período 1995-2020. Por otro lado, el área bajo vegetación densa ha disminuido debido al aumento de la población, lo que conduce a cambios en el patrón de vegetación y la condición de humedad en el área de estudio.

Palabras clave: uso del suelo, cobertura del suelo, teledetección, índice de vegetación de diferencia normalizada, índice de humedad de diferencia normalizada, clasificación supervisada, algoritmo de máxima verosimilitud.

INTRODUCTION

The changes in land use and land cover (LULC) have become a global ecological issue in recent times. Land use and land cover modification imply the changes in the earth's surface, primarily triggered by human interference. Land cover refers to natural features on the earth's surface, such as forests, water bodies. In contrast, land use refers to human-made modifications to the land surface such as agriculture, settlements, and other man-made structures. Hassan et al.(2016)mentioned that land use and land cover changes have intensified tremendously in the past several decades(Hassan et al. 2016). In the analysis of global change, the role of LULC is crucial. Changes in land use and cover are related to human population growth, which stimulates demand for land resources. The incompetence of agricultural, urban, and forest lands causes land use/land cover changes, resulting in serious environmental problems such as landslides, flooding, deforestation, habitat loss, global warming, and a rise in other natural disasters. Changes in land use/cover have resulted from unforeseen urbanization, especially in developing countries. Pawe et al. (2018) due to minimal or non-existent planning efforts compounded by rapid urban population growth, many Indian cities experience unplanned LULC transitions (Pawe et al. 2018). The impacts of LULC change can be well identified by using two important space data-based indices, viz. Normalized Difference Vegetation Index (NDVI) and Normalized Difference Moisture Index (NDMI). NDVI and NDMI both involve multispectral and multi-temporal satellite datasets pertaining to vegetation and available moisture content on vegetation. The present study attempts to analyze the changing pattern of land use and land cover of Charaideu District using NDVI and NDMI indices. The main objectives of the study are: 1) to generate spatio-temporal LULC ,NDVI and NDMI maps of the study area using multi-spectral imageries; 2) to find out the relationship between NDVI and NDMI; AND 3) to analyse the impact of LULC in changing NDVI and NDMI in the study area.

MATERIAL AND METHODS

Study Area: Charaideu District is situated in the Upper Brahmaputra valley of Assam, India. Topographically, it is a plain area with an area of 1069.15 sq. km and elevation is 89.6 m above mean sea level. Geographically the study area extends from 26º65' N to 27º10'N latitudes and 94º60' E to 95º25' E longitudes. The district is surrounded by Sivsagar District in the west, Nagaland and Arunachal Pradesh in the south, and in the north, east, and north-west it is surrounded by Dibrugarh District of Assam.

Methods: The study makes use of multispectral satellite images which are collected from the United States Geological Survey's website. Three years of 30 m resolution Landsat series imageries have taken to find out spatio-temporal variation. From this satellite imageries research area have extracted and then combined with the WGS84UTM projection for additional analysis.

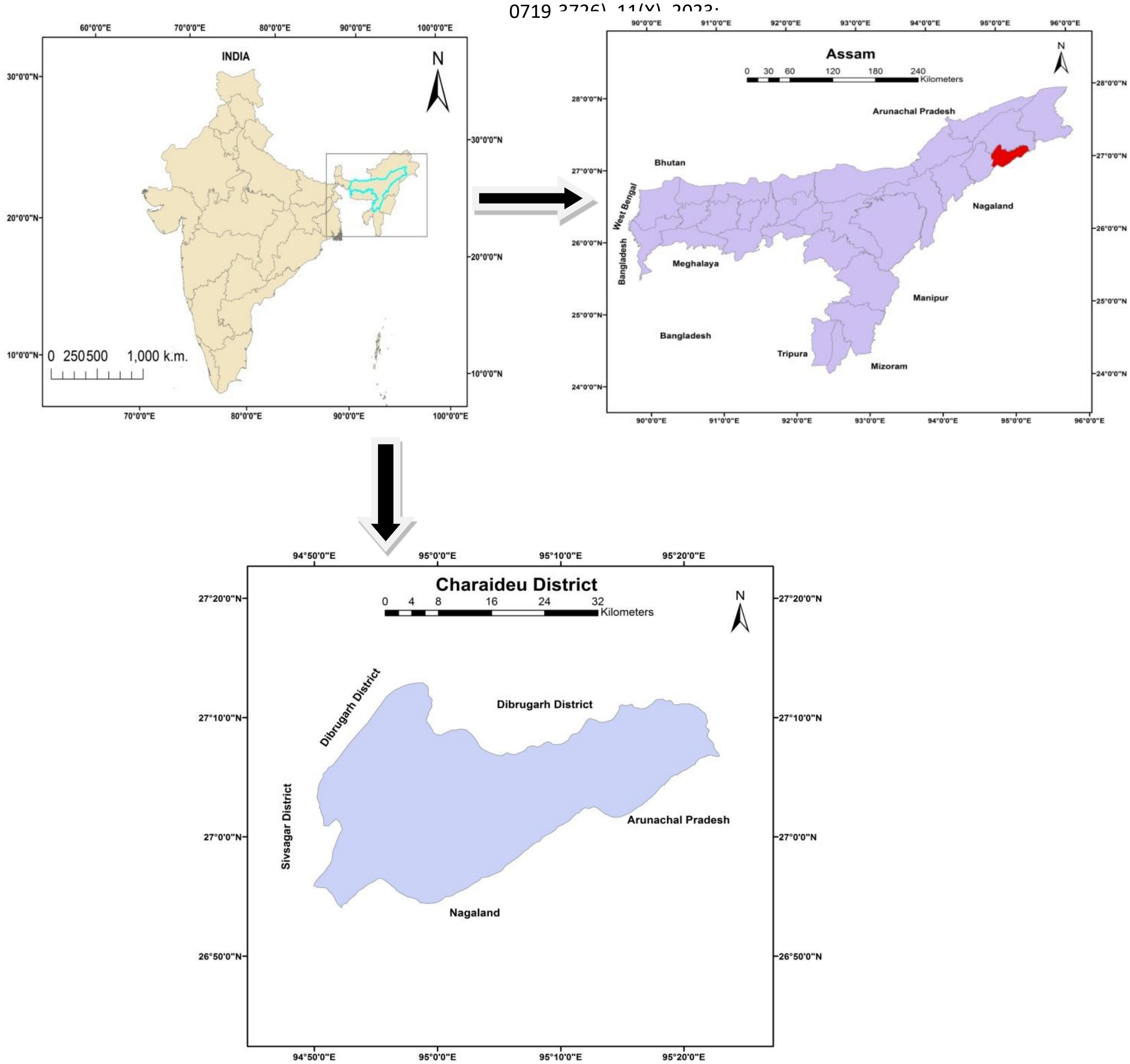

Fig. 1. Map of studied site.

Table 1: Types of Satellite Data Used in the Study. Software used- ArcGIS 10.3 version , Google Earth Pro Source: USGS Earth Explorer

Satellite	Sensor	Year of Acquisition	Path/Row	Spatial Resolution(mts)
Landsat 5	Thematic Mapper(TM)	1995/11/7	135/41	30
Landsat 5	Thematic Mapper (TM)	2010/11/25	135/41	30
Landsat 8	Operational and Land Imager (OLI) and Thermal Infrared Sensor (TIRS)	2020/11/11	135/41	30

The methodology is followed by pre –processing stage, processing and classification stages in the ArcGIS 10.3 software. It helps to reduce noise and distortion of the images while capturing and also provides accurate data for efficient analysis. After that, visual image interpretation is conducted to analyse the different variables in the imagery.

Both the NDVI and NDMI indices are important in geospatial technology to analyse physical aspects of environment. NDVI and NDMI both are directly proportional to each other, higher the vegetation higher is the humidity or moisture.

Normalized Difference Vegetation Index (NDVI) - It is used for detection of healthy vegetation and vegetation greenness on the earth's surface. The value ranges from -1 to 1. Here -1 signifies bare ground and 1 signifies healthy vegetation. NDVI formula is:

For Landsat 5-7

$$\frac{\text{band4 (NIR)} - \text{band3(RED)}}{\text{band4 (NIR)} + \text{band3 (RED)}} \text{ ----------- (i)}$$

For Landsat 8

$$\frac{\text{band5 (NIR)} - \text{band4(RED)}}{\text{band5 (NIR)} + \text{band4 (RED)}} \text{------------(ii)}$$

Normalized Difference Moisture Index (NDMI) - NDMI indices are used for generating data regarding the level of moisture content present on the plants. The values are ranging from -1 to 1. Here, 1 signifies very high moisture and -1 represent very low moisture content present on plants. These values can be obtained from the following formula-

For Landsat 5-7,

$$\frac{\text{band4 (NIR)} - \text{band5(SWIR)}}{\text{band4 (NIR)} + \text{band5 (SWIR)}} \text{--------------(iii)}$$

For Landsat 8,

$$\frac{\text{band 5(NIR)} - \text{band6(SWIR)}}{\text{band 5 (NIR)} + \text{band6 (SWIR)}} \text{-----------(iv)}$$

Image Pre-processing and Classification – Radiometric and geometric adjustments are two types of pre-processing functions. Geometric correction is the process of transforming remotely sensed image into map with scale and projection attributes. After the completion of image pre-processing and visual image interpretation, the classification stages are started. Lillesand et al.(1994) mentioned that the process of categorizing all pixels in an image or remotely sensed raw satellite data to obtain a collection of labels or land cover themes is known as image classification. (Lillesand et al.1994). Different feature forms on the earth's surface have different spectral reflectance and remittance properties, and the classification process uses these to recognize them. Various classification approaches have been developed to create LULC classification images. This work is based on Supervised Classification by using the Maximum Likelihood Method. Hence, ground truth verification has been done by using Google Earth Pro Software and necessary GPS-based field survey to get proper accuracy results obtained for different land use categories. With the help of image interpretation, six land use classes have been identified such as dense forest, Water Body, Agricultural Land, Fallow Land, Sparse Vegetation, and Built-Up Area.

Accuracy Assessment: The accuracy assessment has been done using the Kappa Coefficient method for validating the level of accuracy of the supervised map. With the help of ground truth data or GPS locations, the supervised map of 2020 has been validated. The formula of Kappa Coefficient is mentioned below:

$$K= \frac{N(Xii)-(Xi)-(Xi+xX+i)}{N(Xi)-(Xi+xX+i)} \text{--------- (v)}$$

Where, X_{ii} is the number of observations correctly classified for a particular category, X_i+ and where in the formula X+I are the marginal totals for row i and column i associated with the category, and N is the total number of observations in the entire error matrix.

Table 2: Confusion (Error) matrix for 2020 LU/LC change map of Charaideu District of Assam. Source: Calculated by authors.

Land use/ land cover categories	User's Accuracy	Producer's Accuracy
Dense Forest	90%	90%
Water Body	100%	90.4%
Fallow land	96.7%	92.18%
Agricultural land	93.9%	88.57%
Sparse Vegetation	88.23%	90.90%
Built-Up Area	83.72%	97.29%
Overall Accuracy 91.81%		
Kappa Coefficient 0.90		

RESULTS

Land Use and Land Cover analysis: In recent decades, land use and land cover change have become one of the most important themes and issues to investigate the changes on the face of the earth. Turner Ii et al.(1995) mentined that the changing trend of land use and land cover triggers an alteration in terms of livelihood pattern, changes in biogeochemical cycles on the globe, effects on pre-existing atmospheric composition, and it also plays a vital role in the implications for sustainable growth (Turner Ii et al.1995). Amini et al.(2016) mentioned that the rapid changing of land use and land cover pattern triggers an urgent need for extract, identify, monitoring and framing out a probable trend of land use/ land cover alteration for a certain time period to prepare an efficient and reliable land use management and policies to ensure sustainable development measures(Amini et al. 2016).

The forests are the lungs of the earth, and it is also known as the foster mother of agriculture. Forest determines the positive and negative environmental conditions of a country. Forest plays a vital role in maintaining ecological setup and provides basic human needs. In the land use and land cover change detection analysis, it has been revealed that the area under forest cover has been decreasing drastically. In 1995, the area under forest cover was 144.40 Km^2 (13.50%), and in 2010 it decreased to 122.13 Km^2 (11.42%).From 1995 to 2010, around 22.27 Km^2 (2.08%) of forest land got lost due to anthropogenic causes, and again in 2020, the total area under forest land was

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109.80 Km² (10.27%). Thus from 2010 to 2020, the forest area has decreased by 12.33 Km^2 (1.15%). Considering the entire period of study i.e. from 1995 to 2020, total forest land has decreased by 34.6 Km^2 accounting for 3.23% loss. Water bodies may be either natural or man-made features, including ponds, lakes, cannels etc. They support the aquatic ecosystem, and therefore, the quality of the water resource is very much essential. In the study area, from 1995 to 2020, considerable area under water body has decreased. In 1995, the total area under waterbody was 33.25Km^2 (3.10%), and in 2010, the area under the waterbody was reduced to 13.93 Km^2 (1.30%). From 1995 to 2010, the area under waterbody has decreased by 19.32 Km^2 (1.8%). In 2020, the area under waterbody was 12.23 Km^2 (1.14%). From 1995 to 2020, the area under water body has decreased by 21.02 Km^2 (1.96%). Agriculture is the main occupation in developing countries. With the increasing trend of population, the workforce participation in agriculture has been increasing tremendously, and it also impacts the natural landscape. In1995, the total area under agriculture was198.26 Km^2 (18.54%), and in 2010, it was 211.98 Km^2 (19.82%).The area under agricultural land has increased by 13.72 Km^2 (1.28%) from 1995 to 2010. In 2020, the area under agricultural land was 221.71 Km^2 (20.73%). From 1995 to 2020, the agricultural area has increased by 23.45 Km^2 (2.19%).

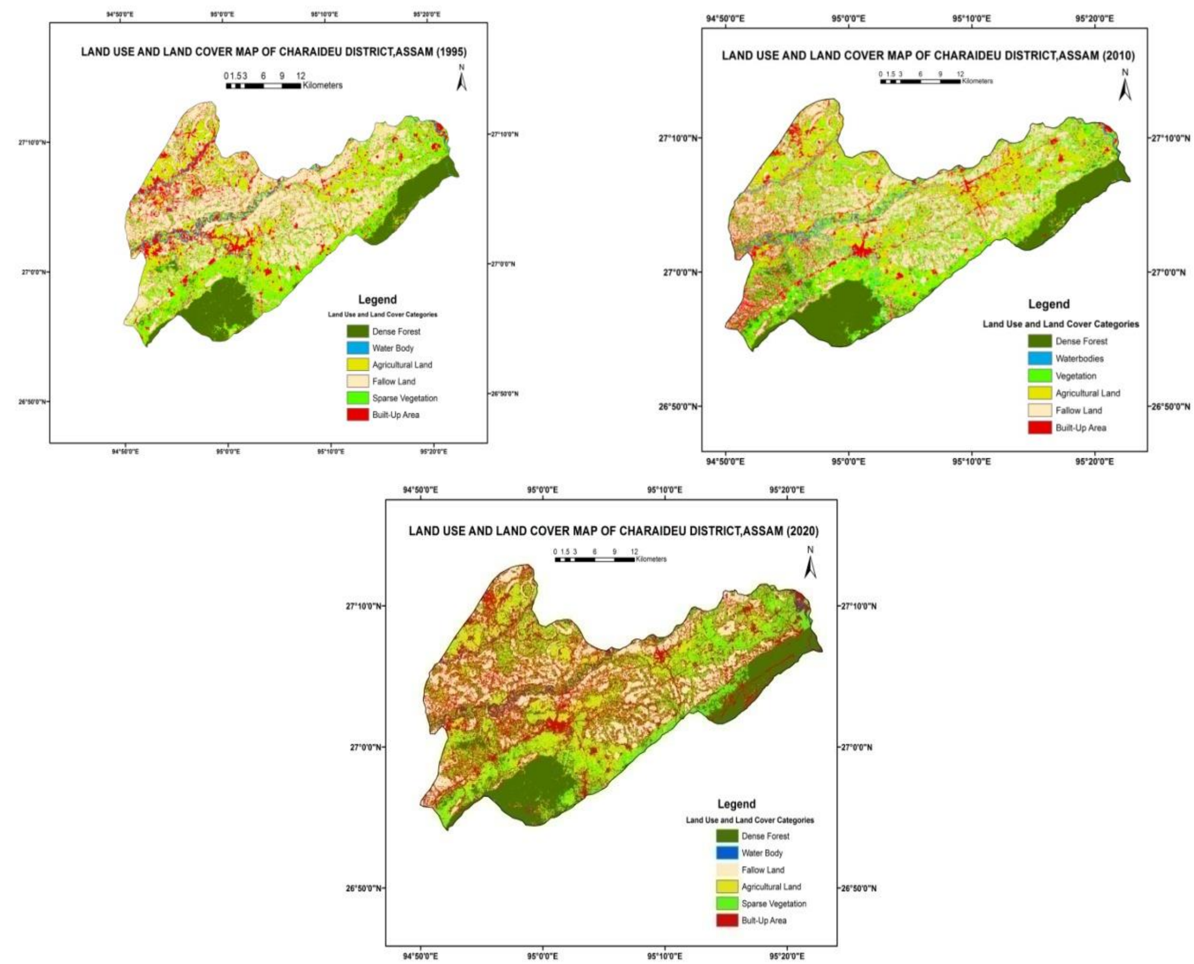

Figure 2: Land use Land cover Map of the study area during 1995, 2010 and 2020.

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Table 3: Land use and Land cover statistics 1995, 2010 and 2020. Source: Calculated by authors

Categories	1995(in Km^2)	1995 (in %)	2010 (in Km^2)	2010 (in %)	2020 (in Km^2)	2020 (in %)	Net Change(1995-2020)	Remark
Dense Forest	144.40	13.50	122.13	11.42	109.80	10.27	-0.23	Decrease
Water Body	33.25	3.10	13.93	1.30	12.23	1.14	-0.63	Decrease
Agricultural Land	198.26	18.54	211.98	19.82	221.71	20.73	0.11	Increase
Fallow Land	382.97	35.82	294.03	27.50	187.03	17.49	-0.51	Decrease
Sparse Vegetation	174.21	16.29	236.63	22.13	247.91	23.18	0.42	Increase
Built-Up Area	136.06	12.72	190.46	17.81	290.46	27.16	1.17	Increase
Total	1069.15	100	1069.15	100	1069.15	100		

The fallow land is the cultivable land that is not seeded for less than five years. In the study area, the area under fallow land has been decreasing remarkably. In 1995, the area under fallow land was 382.97 (35.82%) Km^2 and in 2010 it has decreased to 294.03 Km^2 (27.50%).From 1995 to 2010, 88.94 Km^2 (8.32 %) of fallow land has been converted to other land use categories. Again in 2020, the total area under fallow land was 187.03Km^2(17.49%). From 2010 to 2020, the fallow area has decreased by 107 Km^2 (10.01%). From 1995 to 2020, total fallow land has decreased by 195.94 Km^2 (18.33%). Vegetation is one of the most significant natural constituents and decreasing rate of vegetation area denotes that the ecological setup is under stress, and necessary steps are required for revival. In the study area, the area under sparse vegetation has been decreasing tremendously from 1995 to 2020. In the year 1995, the area under sparse vegetation was 174.21 Km^2 (16.29%), and in 2010, it was 236.63 Km^2 (22.13%). The area under sparse vegetation decreased from 1995 to 2010 was 62.42 Km^2 (5.84%). In 2020, the area under sparse vegetation was 247.91 Km^2 (23.18%). From 1995 to 2020, the area under the sparse vegetation has decreased by 73.7 Km^2 (6.87%). With the increase in population, the demand for built-up areas has been growing tremendously. In the study area also, the increasing population size also triggers an increase in built-up area. In 1995, the area under built-up was 136.06 Km^2 (12.72%), and in 2010, it was 190.46 Km^2 (17.81%). The area under built-up has increased by 54.4 Km^2 (5.09%) from 1995 to 2010. In 2020, the area under build-up was 290.46 Km^2 (27.16%). From 1995 to 2020, the area under built-up land has increased by 154.40 Km^2 (14.44 %).

Derivation of NDVI and NDMI: NDVI scale is used to assess the state of a certain area's vegetation. It is capable of detecting and quantifying the presence of living green plants. It's also useful for determining the amount of green vegetation present and detecting changes in vegetation. In this context, to understand the vegetation condition of the study area three NDVI maps are produced with multi-temporal data.The pixels' of NDVI values vary from -1 to 1. The NDVI value of no vegetation area ranges from -0.58 to 0.11 in 1995, -0.36 to 0.19 in 2010, and -0.19 to 0.13 in 2020 .NDVI value for low to medium vegetation cover is 0.11-0.34 in 1995, 0.19-0.42 in 2010 and 0.13-0.26 in 2020. In case of medium vegetation the value is 0.34-0.46 in 1995, 0.42-0.52 in 2010 and 0.26-0.33 in 2020. In medium to high vegetation category the NDVI value is 0.46-0.56 in 1995, 0.52-0.59 in 2010 and 0.33 to 0.39 in 2020. For high to very high category of vegetation cover the NDVI value is 0.56-0.95 in 1995, 0.59-0.75 in 2010 and 0.39-0.54 in 2020 as revealed after preparing NDVI maps.

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Table 4: Changing NDVI and NDMI threshold values. Source: Calculated by authors

NDVI categories	NDVI values 1995	NDVI values 2010	NDVI values 2020	NDMI categories	NDMI values 1995	NDMI values 2010	NDMI values 2020
No Vegetation	-0.58-0.11	-0.36-0.19	-0.19-0.13	Very Low Moisture	-0.8- -0.09	-0.36-0.17	-0.19-0.13
Low to Medium vegetation	0.11-0.34	0.19-0.42	0.13-0.26	Low Moisture	-0.09-0.009	0.17-0.41	0.13-0.26
Medium Vegetation	0.34-0.46	0.42-0.52	0.26-0.33	Medium	0.009-0.084	0.41-0.51	0.26-0.33
Medium to Dense vegetation	0.46-0.56	0.52-0.59	0.33-0.39	High Moisture	0.084-0.15	0.51-0.58	0.33-0.39
Dense to very dense vegetation	0.56-0.95	0.59-0.75	0.39-0.54	Very High Moisture	0.15-0.78	0.58-0.75	0.39-0.54

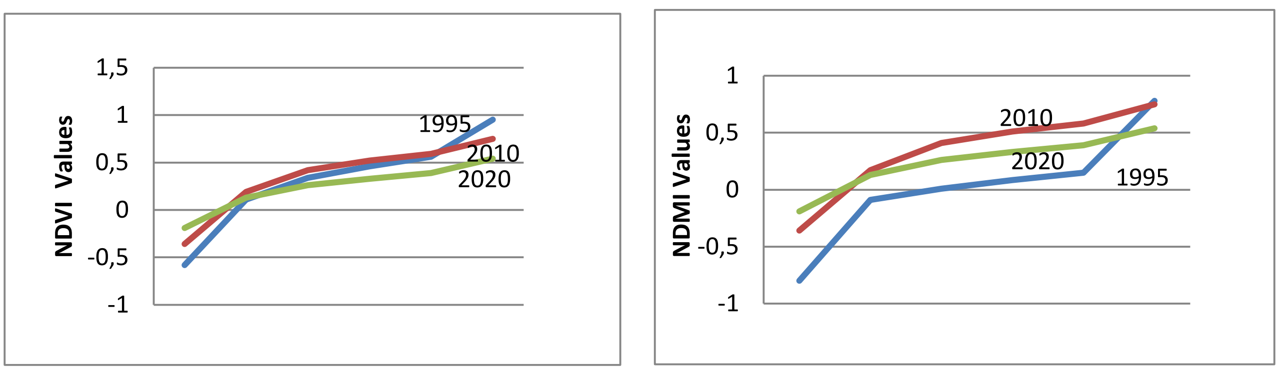

Figure 3: Changing trend of NDVI and NDMI values.

The NDMI indices provide information regarding presence of water content in plants and also give an idea about the chance of occurring drought condition in an area. Here, three NDMI maps have prepared for deriving moisture condition of the study area at three different times, i.e. 1995, 2010 and 2020.

The standard value of NDMI is -1 to 1. The prepared maps depict that the NDMI value is -0.8 to -0.09 in very low moisture for the year 1995, while in 2010 the NDMI value is changed to 0.36 to-0.17 and in 2020 the NDMI value for very low moisture is -0.19-0.13. For low moisture the NDMI value is -0.09-0.009 in 1995, 0.17-0.41 in 2010 and 0.13-0.26 value in 2020. In case of medium moisture category the NDMI value is 0.009-0.084 in 1995, 0.41-0.51 in 2010 and 0.26-0.33 in 2020. In high moisture category, the NDMI value is 0.084-0.15 in 1995, 0.51-0.58 in 2010 and 0.33-039 in 2020. For very high moisture category, NDMI value is 0.15-0.78 in 1995, 0.58-0.75 in 2010 and 0.39-0.54 in 2020 NDMI value as estimated.

The area under each vegetation and moisture category are presented in fig 6 .It is revealed from the data that the areas under no vegetation, dense to very dense and medium to dense vegetation have been decreasing during the period 1995-2020, while low to medium and medium categories of vegetation show an increase during the period of 1995-2020. The data depict that the area under low moisture has been decreasing since 1995 to 2020. But, in case of low moisture area and medium moisture area, the areas have decreased in 2010, but again increased in 2020, however, not more than that in 1995. In the case of high moisture area and very high moisture area, the areas have Increased in 2010, but again decreased in 2020. Figure 4: NDVI and NDMI maps for 1995, 2010 and 2020

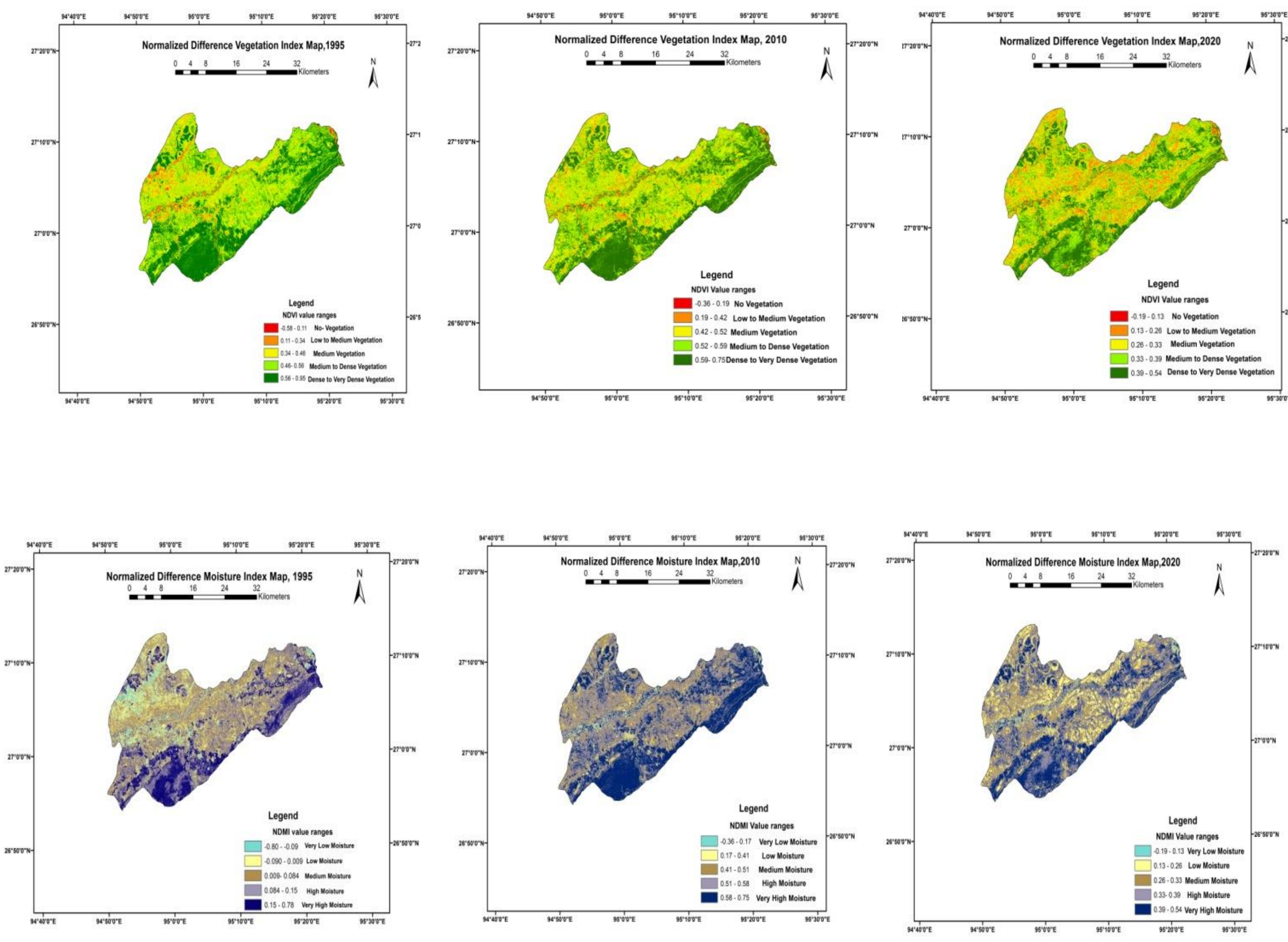

Figure 4: NDVI and NDMI maps for 1995, 2010 and 2020

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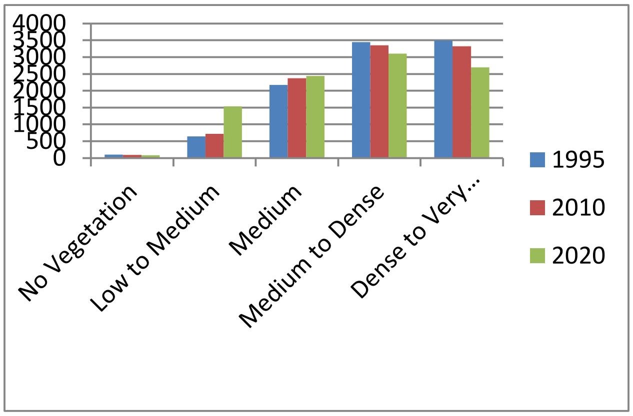

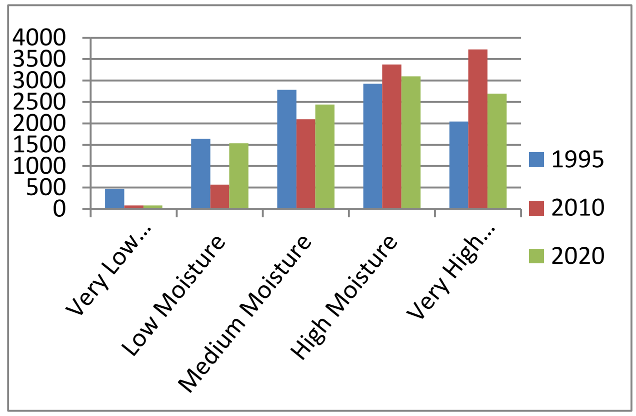

Figure 5. Changing pattern of areas under NDVI and NDMI categories.

Relationship between NDVI and NDMI: In remote sensing, NDVI and NDMI are essential metrics. There lies positive association between NDVI and NDMI. When the NDVI value drops, the NDMI value drops as well. Present study depicts positive correlation between these two variables

Table 5: NDVI and NDMI values

Years	NDVI values ranges	NDMI values ranges
1995	-0.58 – 0.95	-0.8 – 0.78
2010	-0.36 – 0.75	-0.36 – 0.75
2020	-0.19 – 0.54	-0.19 – 0.54

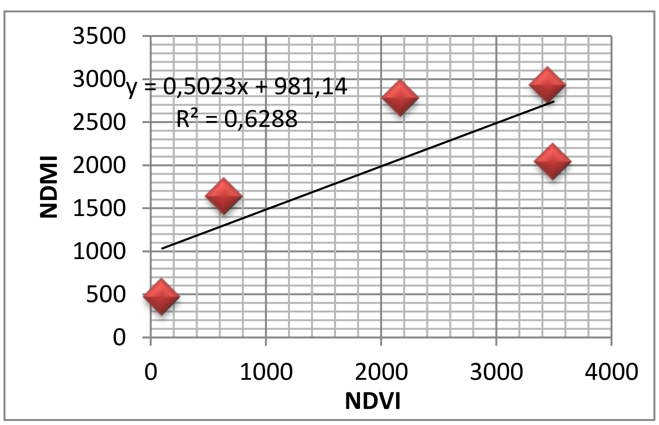

Figure 6: Correlation between NDVI and NDMI

The figure 6 shows the positive correlation between NDVI and NDMI. X axis represents NDVI values and Y axis represents NDMI values. After the analysis the equation has found y=0.502x+981.1, R2=0.628

DISCUSSION

The variations in NDVI and NDMI are strongly influenced by changes in LULC. The current analysis reveals that the study area's land use categories have changed significantly. As a result, it has put a significant impact on the study area's vegetation pattern and moisture condition. Agriculture is reliant on the availability of water. If moisture levels drop, agriculture may experience a drought like situation.

There is a critical link between LULC, NDVI, and NDMI. The analysis has found that between 1995 and 2020, the area under built-up area rose by 136 Km^2 to 290 km^2, while the area under agriculture increased by 198 Km^2 to 228 Km^2. However, owing to enhanced anthropogenic pressure on land, the area under dense forest has shrunk from 144 Km^2 to 108 Km^2 between 1995 and 2020. Such change in land use categories have has a significant impact on the study area's vegetation and moisture levels. NDVI values of the study area have changed from -0.58 to 0.95 in 1995, -0.36 to 0.75 in 2010, and -0.19 to 0.54 in 2020. Similarly, in 1995, the NDMI value ranged from -0.8 to 0.78, while in 2010, the NDMI value ranged from -0.36 to 0.75, and in 2020, the NDMI value ranges from -0.19 to 0.54. Because of the high pace of population growth, urban expansion, developmental activities like road construction, bridge construction etc. several changes have occurred. To alleviate food scarcity in the study area, fallow lands and dense forest area are converted to agricultural land. Furthermore, due to a lack of available housing, people have ruined significant woodland areas and encroach upon wetlands for settlements and agricultural purposes.

As conclusion, using multi-temporal satellite data, the study has carried out NDVI and NDMI based Land Use and Land Cover Change Analysis of Charaideu District for the years 1995, 2010, and 2020. It has been noted that the land area covered by deep forest and sparse vegetation has decreased dramatically, while agricultural land and the built-up areas have increased at the cost of vegetative coverage. The pattern of NDVI and NDMI is also influenced by alteration in LULC. This is well attributed to man's pressure on land and varieties of anthropogenic activities that have substantial impact on the natural landscape. Land cover categories are impacted adversely as population density rises. It has a negative impact on the study area's ecological setup. As a result, now is the pressing time to take the required steps to prevent nature from becoming suffocated in the future.

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