iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 **Issue:** VIII **Month of publication:** August 2021

DOI: https://doi.org/10.22214/ijraset.2021.37339

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VIII Aug 2021- Available at www.ijraset.com

Land Use Land Cover Analysis using Geospatial Techniques

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Abstract: Remote sensing and Geographic information system (GIS) techniques can be used for the changing pattern of landscape. The study was conducted in Dehradun, Haridwar and Pauri Garhwal Districts of Uttarakhand State, India. In order to understand dynamics of landscape and to examine changes in the land use/cover due to anthropogenic activities, two satellite images (Landsat 5 and Landsat 8) for 1998 and 2020 were used. Google Earth Engine was used to perform supervised classification. Spectral indices (NDVI, MNDWI, SAVI, NDBI) were calculated in order to identify land cover classes. Both 1998 and 2020 satellite images were classified broadly into six classes namely agriculture, built-up, dense forest, open forest, scrub and waterbody. Using high resolution google earth satellite images and visual interpretation, overall accuracy assessment was performed. For land cover/use change analysis, these images were imported to GIS platform. Landscape configuration was observed by calculating various landscape metrices Images. It was observed that scrub land area had increased from 11 % to 14 % but a decrease in agriculture by 4.65 %. The increased value of NP, PD, PLAND, LPI and decrease in AI landscape indices shows that land fragmentation had increased since 1998. The most fragmented classes were scrub (PD - 3.32 to 5.18) and open forest (PD - 3.57 to 5.07). Decrease in AI for open forest, agriculture, built-up indicated that more fragmented patches of these classes were present. The result confirmed increase in the fragmentation of landscape from 1998 onwards.
Keywords: GIS, LULC, landscape metrics, Remote Sensing

I. INTRODUCTION

The Remote Sensing and GIS nowadays have become an integral part of landscape analysis. Lambin et al., (2003) in their study highlighted that the land use/cover change is a continuous process and is mainly because of humans. They had identified the unmeasured land-cover changes while summarizing the recent estimates changes in the cropland, agricultural intensification, tropical deforestation, pasture expansion, and urbanization. In their study, they had identified a restricted set of dominant pathways of land-use change. They argued that to uncover general principles for providing an explanation and prediction of new land-use changes, a study of local-scale land-use change over a timescale and systematic analysis of studies, must be conducted. Baan et al., in their study also showed that the land-use changes significantly affect the biodiversity. The chances of species extinction increase to several folds when there is a habitat fragmentation, which was studied and showed by Dirzo et al.,(2003), Zhang et al., (2017), Naha et al., (2018), Didham et al., (2012), Ghulam (2014) in separate studies over the years.
Therefore, geospatial techniques are used for landscape analysis.

A. Study Area

The study area are three districts of Uttarakhand, India-Dehradun, Haridwar and Pauri Garhwal. The area of Dehradun-3088 Km², Haridwar-2360 Km², Pauri Garhwal-5230 km². Figure 1 shows the study area map.

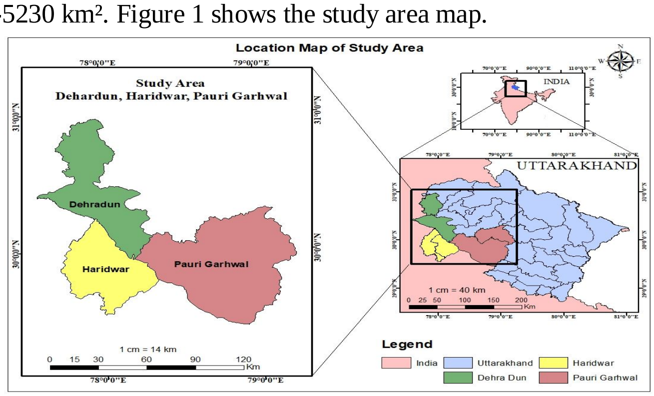

Figure 1 Study Area

B. Data and Tools

Satellite images and software used in this study are shown in Table 1.

Table 1 Data and Tools

Satellite Images	Path / Row	Resolution	Software
USGS Landsat 5 Surface Reflectance Tier 1 - Year 1998 USGS Landsat 8 Level 2, Collection 2, Tier 1-Year 2020	145 / 039, 146 / 039	30 m	ArcGIS 10.5, FRAGSTAT 4.2, Google Earth Engine
NASA SRTM Digital Elevation 30m			

II. METHOD

Google Earth Engine (GEE), a cloud-based platform is used for the landscape analysis. Using Landsat 5 Surface Reflectance Tier 1 for the year 1998, for the year 2020 Landsat 8 Level 2, Collection 2, Tier 1 and SRTM DEM at 30m resolution, land use/cover maps are prepared (Agarwal et al., 2019, Tassi et al., 2020). Six land cover classes identified namely as dense forest, open forest, agriculture, built-up, scrub and waterbody.

Spectral indices to identify land cover classes such as for vegetation Normalized Vegetation Index (NDVI) (Tucker, 1979), and Soil Adjusted Vegetation Index (SAVI) (Huete, 1988) highlights area with low vegetation, for open water surface Modified Normalized Water Index (MNDWI) (Xu, 2006), for built-up Normalized Built-up Index (NDBI) (Zha et al., 2003) were used (Jeevalakshmi et al., 2016, Shahfahad et al., 2020).

Supervised classification is performed by using stratified random sampling and random forest algorithm.(Zeng et al., 2020). The random forest classifier is an ensemble Machine Learning technique which uses tree bagging to form ensemble an of trees. It works by searching random subspaces for the data features and then splits the nodes by minimizing the correlation between the formed trees (Breiman, 2001). In land-cover mapping (Yu et al., 2014; Wang et al., 2015; Gong et al., 2019) and in crop type identification (Zhang et al., 2018; Singha et al., 2019; Tian et al., 2019) random classifier had been used. it has high efficiency and accuracy thus used for land cover classification (Breiman, 2001). Visual interpretation is a largely used approach for generating validation points (Bwangoy et al., 2010, Tassi et al., 2020). Total 258 validation points(point/polygon) were generated randomly Table 2. The overall accuracy and the kappa coefficient were calculated by using these validation points.

Table 2 The number of validation points for each LULC (class)

Class	Number of Validation Points
Agriculture	44
Built-up	35
Dense forest	46
Open forest	39
Scrub	34
Waterbody	52
Total	258

After preparing LULC for 1998 and 2020 in GEE platform. Landscape change and configuration analysis was done by calculating landscape indices in FRAGSTATS 4.2 software (Mcgarigal, 2015). The description about landscape indices is given in table 3. These metrices helps in understanding land cover changes (Lausch et al., 2002, Dewan et al., 2012 ,Zhang et al., 2017).

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Table 3 Landscape metrics

Name	Units	Description	Measure
Number of patch (NP)	-	Number of patches in the landscape of patch type (class)	Fragmentation
Patch density (PD)	Number per 100 hectares	Number patches per unit area	Fragmentation
Contagion Index (CONTIG_MN)	%	Measures both patch type interspersion (i.e., the intermixing of units of different patch types) as well as patch dispersion (i.e., the spatial distribution of a patch type)	Fragmentation
Aggregation Index (AI)	%	Patches (of the same class) are clumped or tend to be isolated	Aggregation
Interspersion and juxtaposition index (IJI)	%	Indicates decrease in the mixing of patches over time	Uniformity in class level configuration
Largest patch index (LPI)	%	Percentage of the total landscape area comprised by the largest patch	Dominance
Percentage of land (PLAND)	%	Proportional abundance of each patch type in the landscape	Habitat fragmentation and habitat loss
Edge Density (ED)	Meters per hectare	Edge length on a per unit area	Heterogeneity in the landscape

III. RESULT & CONCLUSION

Figures 2-4 shows LULC maps for 1998/2020 and LULC change. The overall accuracy and kappa coefficient for 2020 and 1998 land use/land cover were 89%,0.84 and 82%, 0.75 respectively. Land use change analysis based on statistics extracted from two land use/cover maps of 1998 and 2020. During the last two decades, it was observed that scrub land area had increased from 11% to 14%. Each dense forest and open forest overall area had increased by 1% while waterbody overall area by 2 %. There was reduction in agriculture and built-up areas from 25% to 20% and 6% to 4% respectively (Table 4). The increased value of NP, PD, PLAND, LPI and decrease in AI landscape indices shows that land fragmentation had increased since 1998. The most fragmented classes were scrub (PD- 3.32 to 5.18) and open forest (PD- 3.57 to 5.07). Increased LPI and ED value indicates the dominance and heterogeneity in the landscape. Open forest and scrub classes were highly fragmented. Landscape changes at class level can be understood in the study area (Table 5). The number of patches in open forest, scrub and waterbody increased that enhanced corresponding patch density. For agriculture land, NP increased from 86714 to 98266, indicating that the spatial heterogeneity to this class increased with the growing disturbances. Similar pattern was found in dense forest class. This implies that the increasing human pressure led to greater fragmentation in the recent past. Increase in LPI for agriculture, built-up and scrub intensifies decline in forest cover. Decrease in AI for open forest, agriculture, built-up indicates that more fragmented patches of these classes. The result confirmed increase in the fragmentation of landscape.

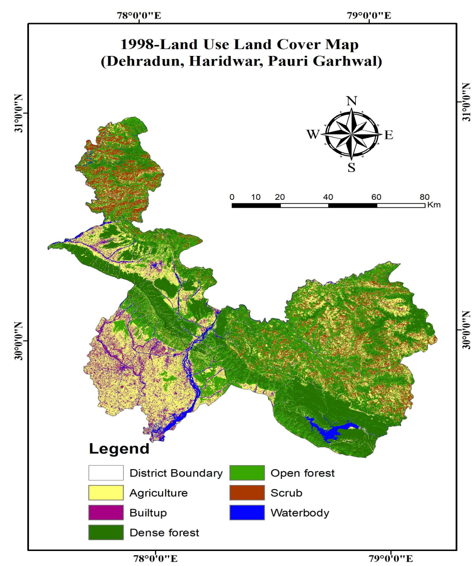

Figure 2 1998-Land Use Land Cover Map

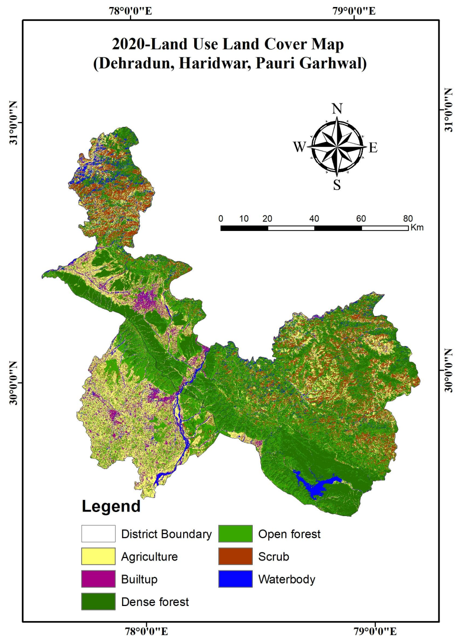

Figure 3 2020-Land Use Land Cover Map

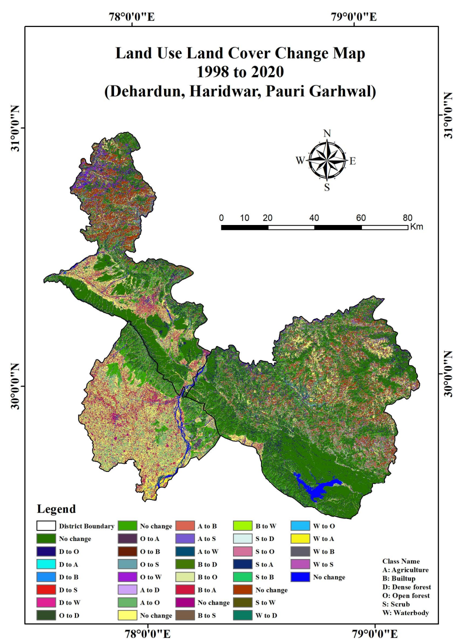

Figure 4 Land Use Land Cover Change Map

Table 4 Land use statistics from 1998 to 2020

Class	Year-1998		Year-2020		Overall area change (%)
	Area(km^2)	Area(%)	Area(km^2)	Area(%)	
Agriculture	2695.42	24.65	2186.51	20.00	-4.65
Built-up	643.78	5.89	483.03	4.42	-1.47
Dense forest	2847.13	26.04	2972.08	27.18	1.14
Open forest	3130.07	28.63	3225.78	29.51	0.88
Scrub	1223.62	11.19	1481.72	13.55	2.36
Waterbody	392.77	3.59	583.67	5.34	1.75

Table 5 Landscape metrics

Class	NP	PD	PLAND	LPI	IJI	ED	AI	CONTIG_MN
Year-1998								
Agriculture	86714	3.22	10.03	1.62	81.87	33.49	74.68	0.19
Built-up	79909	2.97	2.39	0.06	29.93	14.71	66.93	0.16
Dense forest	66675	2.48	10.60	2.21	18.43	23.49	83.37	0.18
Open forest	95951	3.57	11.65	1.46	68.39	42.20	72.80	0.18
Scrub	89290	3.32	4.55	0.12	58.74	18.05	53.93	0.14
Waterbody	24947	0.92	1.46	0.45	76.70	4.26	77.96	0.13
Year-2020								
Agriculture	98266	3.65	8.14	2.27	85.00	34.23	68.41	0.17
Built-up	73059	2.72	1.79	0.17	54.32	10.78	55.02	0.14
Dense forest	68148	2.53	11.06	2.12	24.09	26.80	81.83	0.19
Open forest	136362	5.07	12.01	1.85	77.88	51.91	67.55	0.18
Scrub	139104	5.18	5.51	0.19	54.53	23.25	68.37	0.13
Waterbody	66757	2.48	2.17	0.26	85.91	9.91	65.69	0.16

The landscape change analysis over the last 2 decades showed the various transformation of different landscapes into one-another. The spatial pattern of land-use and land-cover change indicated highest overall area percentage change for the scrub area class. In both the years, open forest area was the maximum. Although, the agricultural and built-up areas showed a decrease, there was an increase in the overall fragmentated areas.

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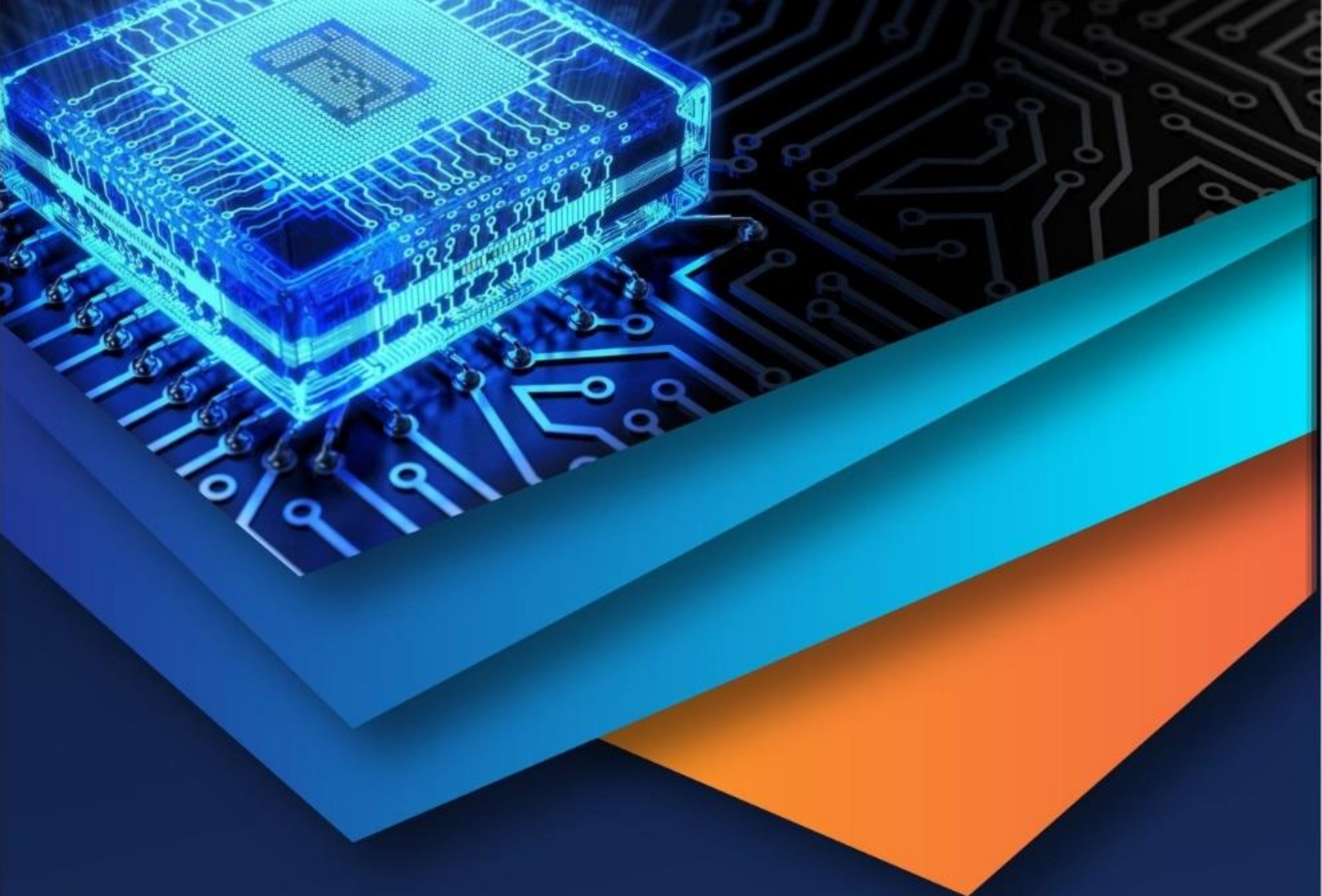

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