

Investigating the Effect of Urbanization on Environmental Quality Using RS and GIS.

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Abstract— The effect of urbanization on the environment are of major concern. Rapid urbanization has caused many environmental issues that risk human and animal health. The effects of urbanization on air and water quality, soil health, and biodiversity are particularly noteworthy. As urbanization continues to accelerate, it is imperative that we take proactive measures to mitigate its negative impact on the environment. Remote sensing (RS) and GIS techniques, which go beyond the limitations of traditional field monitoring tools, are critical for monitoring a complex and dynamic ecosystem. This method allows biologists to readily visualize and analyze geospatial data, which could be beneficial for a range of applications such as crop monitoring, forest categorization, water availability, climate change. The purpose of this study was to look at the influence of urbanization on land use efficiency (LUE) and ecosystem value (ESV) in Dehradun district, Uttarakhand, India, during the previous 20 years using RS and GIS techniques. According to our research, the quantity of built-up area increased continuously from 2001 to 2021, while the amount of water body, agricultural, and forest decreased. As a result, the total LUE of the examined area grew from 1.02 in 2001 to 1.3 in 2021, whereas ESV reduced by 27% from 2001 to 2021. This investigation shows that Dehradun's built-up area has increased substantially, especially in the city centre, where a smart city project is underway.

Index Terms— Remote sensing, Ecosystem system Value, Support vector machine, Urbanization, Google Earth Engine, LULC.

I. INTRODUCTION

The conventional method of mapping land cover is a laborious and ineffective means of monitoring intricate ecosystems. The employment of RS and GIS methodology is of utmost importance in the realm of monitoring, exploration, visualization, and analysis of geospatial data, as it offers a more efficient and expeditious approach. In pursuit of improved employment opportunities, enhanced health prospects, better education prospects, and superior living standards, individuals migrate from rural areas to urban centers. The outcome of this phenomenon is the transformation of previously lush forests, fertile agricultural lands, and pristine water bodies into urbanized, built-up areas. In order to effectively advocate for the city, policymakers must possess precise and current information regarding land use and land cover. This data is essential for detecting and monitoring climate change, managing disasters, tracking urbanization, classifying forests, preventing forest fires, maintaining crop health, and predicting changes in land use and land cover across the earth's surface [1-2].

The phenomenon of urbanization serves as a pivotal catalyst for the alteration of land use and land cover, thereby exerting a profound influence on the ecosystem services and values. The assessment of impacts and the evaluation of urban planning and management strategies are frequently conducted through the utilization of remote sensing and GIS techniques. The phenomenon of urbanization exerts a profound influence on the utilization and coverage of land, as it involves the transformation of once-agricultural land, wetlands, and forests into bustling urban centers [3]. The alterations have a profound impact on the Ecosystem services, leading to a decline in carbon sequestration and sediment retention, while simultaneously causing a surge in water runoff.

Ecosystems consist of a myriad of plant, animal, and microbial populations, in addition to the encompassing abiotic surroundings [4]. The phrase "ecosystem services" denotes the direct and indirect benefits bestowed upon individuals by the ecosystem [5]. The incorporation of Sustainable Development Goals (SDGs) is imperative for the effective and environmentally conscious urban planning of a multifaceted metropolis. The Ratio of Land Consumption Rate to Population Growth Rate (RLCRPGR) holds significant weight in the context of Sustainable Development Goals (SDG). It serves as a crucial parameter in assessing whether the underdeveloped urban areas are being developed at a pace that is either faster or slower than the current rate of population growth [6]. The present observation serves as an indication of the intricacies of urban ecology. Achieving equilibrium between the expansion of urban areas and the increase in population is contingent upon maintaining a Recreational, Living, Commercial, Road, Public, and Green Ratio (RLCRPGR) value that approximates unity. The significance of RLCRPGR lies in its ability to gauge the effects of land cover conversions to built-up areas on population expansion within the examined region [7].

The Support Vector Machine (SVM) is a type of supervised machine learning algorithm that is particularly useful for classification tasks, such as the classification of land use and land cover [8]. The SVM algorithm operates by identifying a hyperplane that optimally separates distinct categories of data points within a multi-dimensional space. Numerous studies have demonstrated the efficacy of SVM in GEE as a classification scheme for land use/land cover classification [9]. The selection of kernel function and other parameters is of utmost importance as it can greatly influence the accuracy of classification. It is imperative to exercise caution and choose these parameters judiciously, taking into account the unique features of the data and the classification task at hand [10].

The swift proliferation of metropolitan regions has engendered notable alterations in the utilization of land, giving rise to a plethora of ecological and environmental consequences. The conversion of once-pristine natural landscapes into sprawling urbanized areas has resulted in the unfortunate depletion of biodiversity, degradation of soil quality, and alterations to the delicate balance of hydrological cycles. Furthermore, the process of urbanization has resulted in heightened levels of energy consumption and atmospheric pollution. With the surge in population and an increase in living standards, the demand for ecosystem services and the absorption of built-up land has witnessed a rapid escalation. Therefore, the economic valuation of ecosystem services and the absorption of land use are crucial considerations for decision-makers and urban planners in effectively mapping and monitoring a city.

Urbanization begets economic growth, yet it is not without its attendant predicaments. The Dehradun district, nestled in the heart of the Indian state of Uttarakhand, has undergone a swift metamorphosis in its land use and land cover (LULC) patterns, specifically in relation to the built-up area. This transformation can be attributed to the ongoing smart city initiative in the region. The scrutiny of Land Use and Land Cover (LULC) in Dehradun was primarily centered on the spatial transitions of diverse land uses and covers, as documented in reference [11]. Insufficient attention was given to the impact of urbanization on the value of ecosystems and the efficiency of land use, resulting in inadequate monitoring of natural land resources.

Human being relies on forests and agriculture for social and economic prosperity. Urban development has replaced some agricultural and forested land. Significant ecosystem concerns may cause this [12]. Therefore, there is a need to detect LULC changes and to determine land use efficiency and ecosystem value over a time of period for sustainable development of natural resources. The aim of this research is to detect LULC changes in the study area using support vector machine learning classifier in GEE and to provide answer of four specific research questions: i) What LULC changes have detected in study area from 2001 to 2021? ii) How do LULC shifts affect land use effectiveness in the research area? iii) What is the effect of LULC variations in the research region on the value of the ecosystem? iv) What elements are contributing to LULC changes?

II. MATERIALS AND METHODS

A. Research Area

The research was done in the Dehradun district of Uttarakhand, India, at the base of the Himalayas (Fig. 1). It is situated in the Garhwal region of the state of Uttarakhand's North-West direction. It serves as the capital and largest city of the Uttarakhand state, India. The overall geographical area of the district is 3088 km². Rice, wheat, maize, soy beans, pulses, as well as a variety of fruits and vegetables are the principal crops farmed in Dehradun. The study area lies amidst the latitudes of 30°01' and 31°2'N and longitudes of 77°34' and 78°18'E.

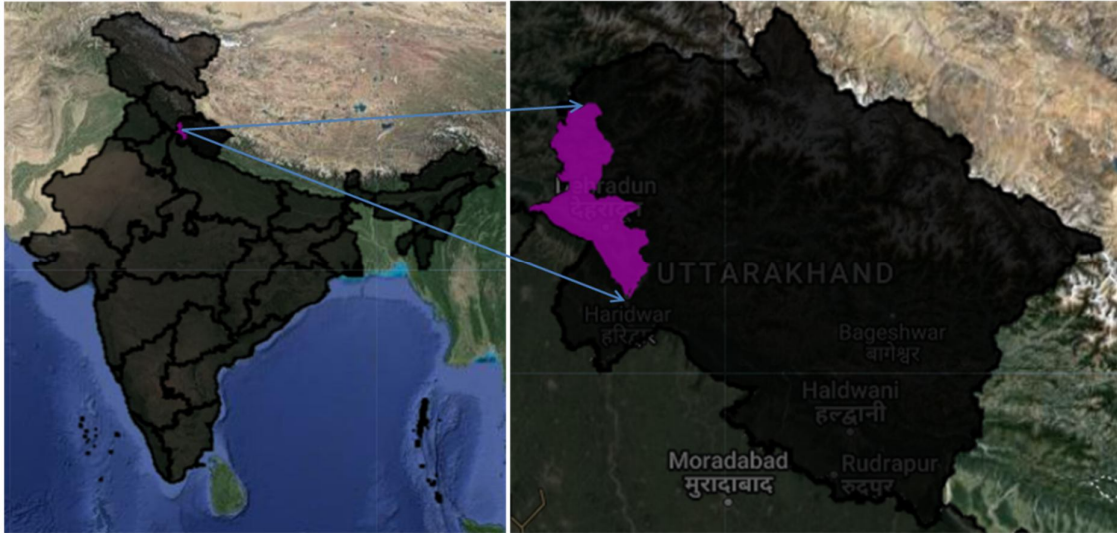


Figure 1. Study area

B. Data Used

USGS Earth Explorer provided the 2001, 2011, and 2021 LANDSAT 5, 7, and 8 images for the month of October. Path and row of LANDSAT image are 146 and 039 respectively (Table I).

TABLE I. DATA ACQUISITION AND TYPE OF SENSOR

Data type	ID	Source	Path and Row	Date of acquisition
Landsat 7	LE07_L1TP_146039_20011011_20200917_02_T1	USGS earth explorer	146 and 039	2001/10/11
Landsat7	LE07_L1TP_146039_20111023_20200909_02_T1	USGS earth explorer	146 and 039	2011/10/23
Landsat8	LC08_L1TP_146039_20211013_20211020_02_T1	USGS earth explorer	146 and 039	2021/10/13

C. Methodology

Fig. 2 presents the methodology that was used for the investigation. The images obtained from USGS Earth Explorer were classified in to 5 different land cover classes using support vector machine classifier. 60 percent of the training samples were put to use in support vector machine training process, whereas only 40 percent were put to use in the testing phase. The accuracy of the evaluation was determined by computing the kappa coefficient (KC) and the overall accuracy (OA). A post classification change detection approach was utilized in order to determine LULC shifts that occurred across a variety of time periods.

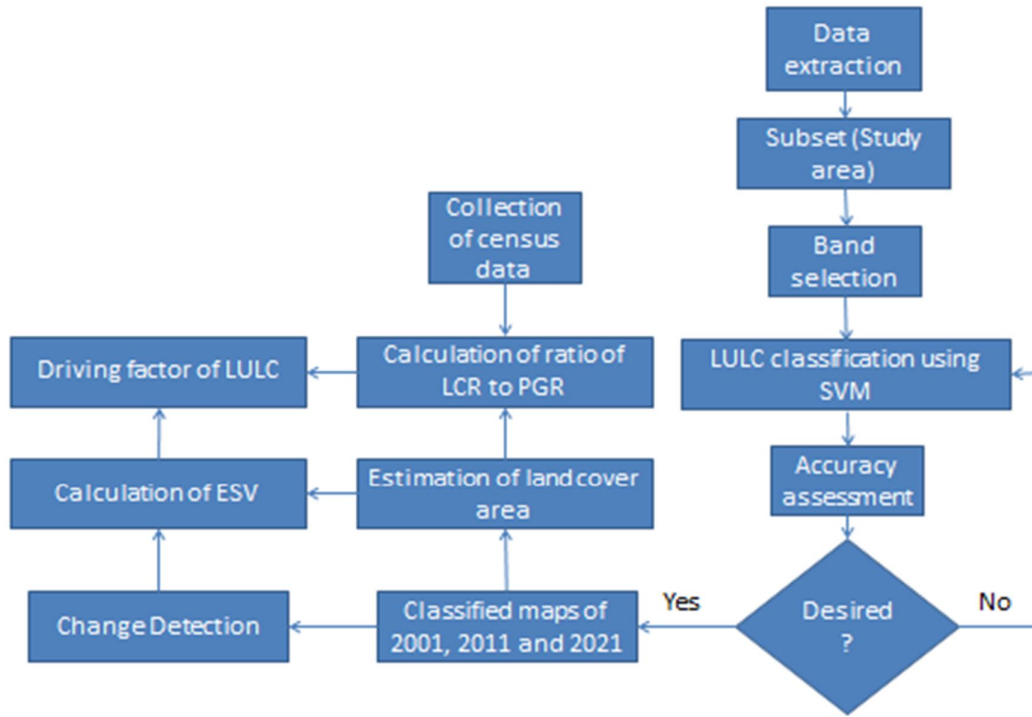


Figure 2. The research methodology adopted in this study.

D. Classification

The classification of land use and land cover (LULC) through the support vector machine (SVM) method is a technique that involves the use of machine learning algorithms to identify and categorise different types of land use and land cover. Supervised learning trains the system to spot patterns and classify fresh data. SVM is effective for LULC classification because it can manage complex and non-linear correlations between input variables and output classes. By applying this method, it is possible to accurately map and monitor changes in land use and land cover over time, which can be valuable for a range of applications, including environmental management, urban planning, and natural resource conservation. The LANDSAT images captured in 2001, 2011, and 2021 were meticulously analysed and categorised into five discrete groups based on their land use and land cover characteristics. In order to train machine learning models, we have generated practise data for each of the land cover types found on Google Earth. The accuracy of the model is ascertained through the utilisation of the testing data, while its efficacy is assessed via the simulated data.

E. Value Estimation for Ecosystem Services

In this study, we utilised the modified ecosystem service value coefficients [13] that were specifically developed for 11 biomes in Ethiopia. Our aim was to determine the ESV from the five distinct LULC categories. Subsequently, the land use and land cover (LULC) categories within the examined research area were linked to their respective representative biomes, as outlined in Table II. The biomes that have been selected as a proxy for each LULC category are highly representative. These include cropland for agriculture area, the area where mostly trees that are taller than 5 meters for forest, urbanization-related construction projects for urban area and soil-exposed land for the barren land.

TABLE II. LAND COVERS CLASSES AND THEIR EQUIVALENT ESV COEFFICIENT [13]

Land Cover Class	Description	ESC (USD Ha ⁻¹ Yr ⁻¹)
Water bodies	Includes all rivers, canals, wetlands, lakes, etc.	8498
Agriculture	The place used to grow crops, such as farmland, pasture, nurseries, etc.	92
Forest	The area is mostly trees that are taller than 5 meters.	986.7
Urban area	Urbanization-related construction projects (roads, homes, buildings, industrial zones, etc.)	0
Barren Land	Soil-exposed land.	0

$$ESV_k = A_k * VC_k \quad (1)$$

$$ESV_t = \sum A_k * VC_k \quad (2)$$

$$ESV_f = \sum A_k * VC_{fk} \quad (3)$$

ESV_k, ESV_t, and ESV_f reflect the ESV for a k-type land cover category, the overall ESV, and a specific ecosystem service function, respectively; A_k is the area of k-type land cover, and VC_k is the service value coefficient in USD Ha⁻¹Yr⁻¹. VC_{fk}, in US dollars per hectare per year, is the function coefficient for land use category k [14].

F. Land Use Efficiency

It is determined by RLCRPGR. RLCRPGR is land consumption to population growth rate. The SDG indicator RLCRPGR illustrates how fast the remaining urban land is developing compared to population growth. This measures urban sustainability. This metric is crucial for assessing how various land cover classes being converted into built-up areas *affect population growth in the research region*.

$$RLCRPGR = \frac{\ln\left(\frac{A_2}{A_1}\right)}{\ln\left(\frac{P_2}{P_1}\right)} \quad (4)$$

In this scenario, ln stands for a natural logarithm, A₂ and A₁ are the total built-up areas at the past and future times, respectively, and P₂ and P₁ are the populations of the study region at the past and future times, respectively. Stability, robustness, and ecology are part of the Sustainable Development Goals (SDG 11) for towns and urban growth, so SDG 11.3.1 is essential for the efficient and sustainable development of a city a human settlement [15].

III. RESULTS AND DISCUSSIONS

A. LULC Classification

For land use land cover classification, the most commonly used metrics are the overall accuracy and kappa coefficient. These metrics are used to evaluate the accuracy of a land use land cover map by comparing it to reference data, such as ground truth samples or high-resolution imagery. Many investigations have shown that the accuracy of traditional supervised and unsupervised classification methods, suffered from a variety of limitations such as each classifier being area dependent and having varying accuracy for a particular land use / cover class [16-17]. However Random Forest and SVM provides highest accuracy for heterogeneous type LULC classification. SVM in Google Earth Engine was used to classify LANDSAT photos from 2001, 2011, and 2021 into five land use/land cover classes. Table III shows overall accuracy and kappa coefficient found were more than 92 percent (Table III) in each image classification showing that the classification of the LANDSAT photos was almost accurate. Simulated classified maps are shown in fig. 3.

B. LULC Changes in Study Area from 2001 to 2021

Table III shows that the study region's water body fell by 43.6%, farm area decreased by 28.8%, and forest area decreased by 4.6% between 2001 and 2022. From 2001 to 2021, the water body has shrunk due to slum development along rivers like Rispana and Bindal etc. During the course of more than two decades, forest and agricultural land of studied area have been reduced as a result of clearing vegetation for the construction of roads and buildings. Urban area expanded particularly in the city's centre, where a smart city initiative is taking shape by 115.8% from 2001 to 2021, rising from 26912 ha in 2001 to 58075 ha in 2021.

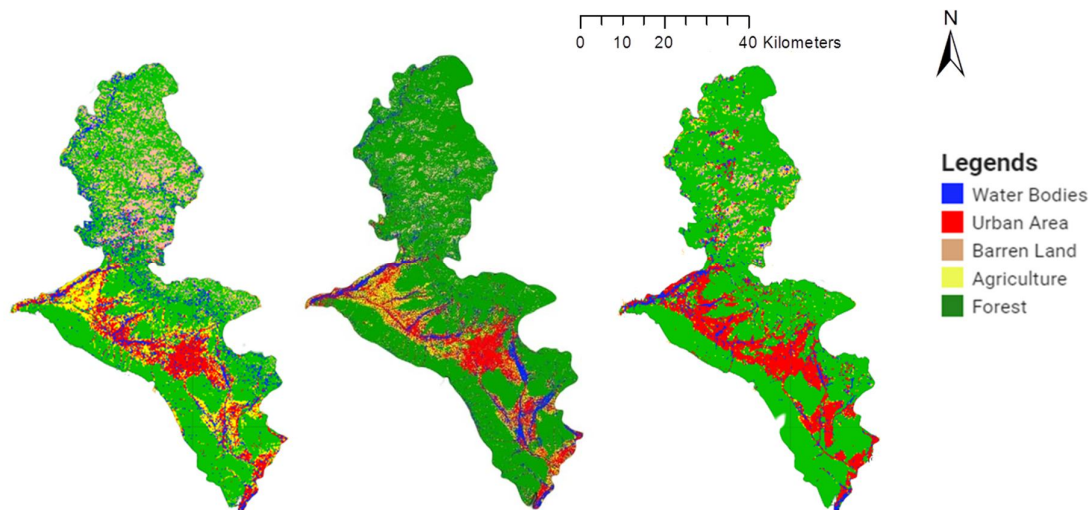


Figure 3. Simulated classified maps for (a) 2001, (b) 2011 and (c) 2021`

TABLE III. AREA ESTIMATION USING SVM

LULC classes	2001		2011		2021		Area change in %
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)	
Water bodies	36879	11.94	27945	9.04	20805	6.73	-43.63
Urban area	26912	8.71	35854	11.6	58075	18.8	115.8
Barren land	35788	11.58	38250	12.38	42980	13.91	13.07
Agriculture	44790	14.5	47726	15.45	31896	10.32	-28.88
Forest	164431	53.24	159060	51.5	156814	50.78	-4.62
OA and KC	92.13 and 0.91		93.45 and 0.92		94.75 and 0.93		

C. Ecosystem Value Change

Ecosystems offer society a variety of products and services. In the study area due to their dominance as a land cover type and high ES value per hectare, forests and water body account for the largest portion of the overall ESV. ESV substantially dropped from 479.75 USD Million $\text{Ha}^{-1}\text{Yr}^{-1}$ to 334.44 USD Million $\text{Ha}^{-1}\text{Yr}^{-1}$ (Table IV) over a 20-year period (from 2001 to 2021) as a result of the loss of forests, water bodies, and agricultural land. This degradation of ESV could be due to other land cover such as water body, forest and agriculture land have been transformed into urbanization-related construction projects (urban area). The study periods revealed a significant decrease in total ESV, with the primary cause being the depletion of forest cover and water bodies, as indicated in Table IV and illustrated in Fig. 4.

TABLE IV. CALCULATED ESV (USD MILLION $\text{Ha}^{-1}\text{Yr}^{-1}$) VALUE IN DIFFERENT TIME

LULC classes	2001		2011		2021	
	ESV	ESV (%)	ESV	ESV (%)	ESV	ESV (%)
Water bodies	313.39	65.32	237.47	59.54	176.8	52.8
Urban area	0	0	0	0	0	0
Barren land	0	0	0	0	0	0
Agriculture	4.12	0.85	4.39	1.1	2.93	0.876
Forest	162.24	33.8	156.94	39.35	154.71	46.25
Total	479.75	100	398.8	100	334.44	100

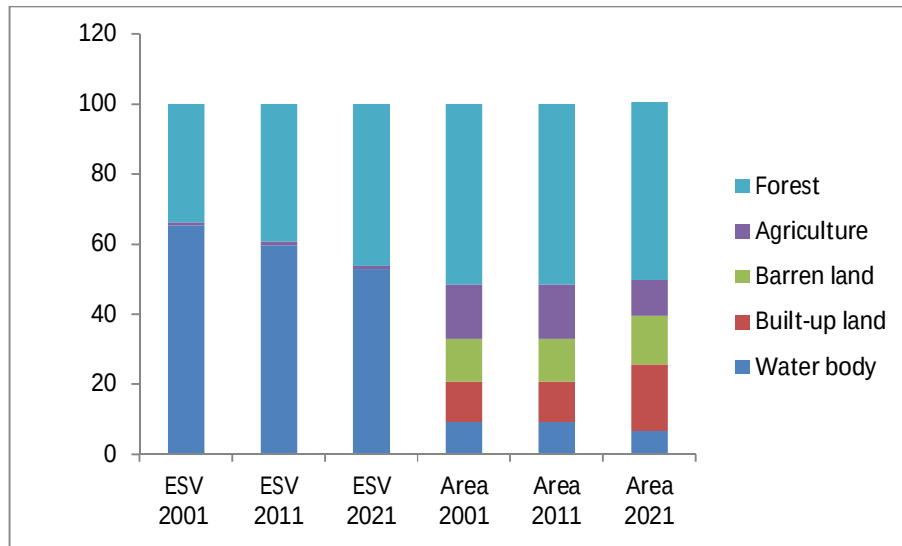


Figure 4. LULC (%) and ESV (%) from 2001 to 2021 in the research area

D. Land Use Efficiency in Different Time Periods

The population of the Dehradun district was estimated to be 1.282 million during the census taken in the year 2001, 1.696 million during the census taken in the year 2011, and about 2.3 million during the year 2021/2022 (as census of 2021 has been postponed or cancelled). The RLCRPGR experienced a considerable shift, going from 1.02 in the period 2001-2011 to 1.3 in the period 2011-2021. The RLCRPGR experienced a shift of 27.55 percentage points over the course of 20 years, from 2001 to 2021 (Table V). It is possible that this is due to the smart city project, as the population in the urban region has increased at a faster rate than that of the study area.

TABLE V. CALCULATED LUE

SDG PARAMETER	2001 to 2011		2011 to 2022	% change from 2001 to 2021
RLCRPGR	1.02		1.31	27.55

E. Driving Factors Affecting ESV and LUE due to LULC Changes

Over the course of two decades, our findings have revealed a concerning trend: the expansion of urban areas has come at the expense of vital agricultural land, forests, and water ecosystems. As a result, the total LUE of the studied region has surged from 1.02 in 2001 to 1.3 in 2021, while the ESV has experienced a sharp decline of 30 percent over the same period. The preponderance of the total ecological services value (ESV) lies in the forests and water bodies, underscoring the criticality of preserving these natural resources to prevent any further erosion of ESV. The burgeoning population and economic activities in the study region have led to notable reduction in water bodies and agriculture area. The transformation of land use and land cover (LULC) is a complex phenomenon that arises from a multitude of driving factors, commonly referred to as drivers that operate within a given region. Through careful analysis, it is evident that the smart city project, population growth, road network expansion, and the establishment of slums near rivers are the primary driving forces behind the observed land use and land cover (LULC) changes.

IV. CONCLUSIONS

Using RS and GIS methods implemented in Google Earth Engine, this study reveals how alterations to LULC affect the value of ecosystem services and the efficiency of land use. We found that between 2001 and 2021, total LUE of examined area grew from 1.02 in 2001 to 1.3 in 2021, while ESV reduced by 30%. This is due to the considerable rise of urban areas at the expense of agriculture land, forest, and aquatic ecosystems. Since

forests and water body's account for the vast majority of ESV, protecting them is essential in preventing further declines in this precious resource. Compared to a perfect score of 1, the RLCRPGR value of 1.3 from 2011 to 2021 indicates inefficient use of urban land. This could be because the population in the urban region covered by the smart city project has risen at a faster rate (115.8%) than the overall population in the study area. Policymakers and decision-makers must make methodical effort to prevent urban spread of the researched region for sustainable development of ecosystems and monitoring of environmental changes.

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REFERENCES

- [1] H. S. Pokhariya, D. P. Singh and R. Prakash, "Investigating the impacts of urbanization on different land cover classes and land surface temperature using GIS and RS techniques," *International Journal of System Assurance Engineering and Management*, vol. 13(2), pp. 961-969, 2022.
- [2] M. Hussain, D. Angela, C. Wei and H. Stanley, "Change detection from remotely sensed images: From pixel-based to object based approaches," *ISPRS J. Photogramm. Remote Sens.*, vol.80, pp.91–106, 2013.
- [3] S. Sharma, S. Hussain, and A. N. Singh, "Impact of land use and land cover on urban ecosystem service value in Chandigarh, India: a GIS-based analysis," *Journal of Urban Ecology*, vol. 9, pp.1, 2023.
- [4] "Assessment ME. Ecosystems and human well-being: a framework for assessment," Jan 2003.
- [5] S. Jacobs, N. Dendoncker, et al. "A new valuation school: Integrating diverse values of nature in resource and land use decision," *Ecosystem services*, vol. 22, pp. 213-220, 2016.
- [6] Y. Wang, H. Chunlin, F. Yaya, Z. Minyan, and G. Juan, "Using earth observation for monitoring SDG 11.3. 1-ratio of land consumption rate to population growth rate in Mainland China," *Remote Sensing*, vol. 12(3), pp. 35, 2020.
- [7] M. Laituri, et al., "SDG Indicator 11.3. 1 and secondary cities: an analysis and assessment," *ISPRS International Journal of Geo-Information*, vol. 10(11), pp. 713, 2021.
- [8] C. Huang, L.S. Davis and J.R.G. Townshend, "An assessment of support vector machines for land cover classification," *Int. J. Remote Sens.* Vol. 23, pp. 725–749, 2002.
- [9] M. K. Ridd and J. Liu, "A Comparison of Four Algorithms for Change Detection in an Urban Environment," *Remote Sensing of Environment*, vol. 63, no. 2, pp. 95-100, 1998.
- [10] A. E. Maxwell, T. A. Warner and F. Fang, "Implementation of machine-learning classification in remote sensing: An applied review," *International Journal of Remote Sensing*, vol. 39(9), pp. 2784-2817, 2018.
- [11] A. Agarwal, K. K. Soni and M.S.S. Rawat, "Monitoring Land Use Land Cover Change for Dehradun District of Uttarakhand from 2009-2019," *International Journal*, vol. 8(1), pp. 3106-3113, 2019.
- [12] D. Zhang, et al., "Impacts of Urban Expansion on Ecosystem Services in the Beijing-Tianjin-Hebei Urban Agglomeration, China: A Scenario Analysis Based on the Shared Socioeconomic Pathways," *Resources, Conservation and Recycling*, vol. 125, pp. 115–30, 2017.
- [13] R. Costanza, et al., "The Value of the World's Ecosystem Services and Natural Capital," *Nature*, vol. 387, pp. 253–60, 1997.
- [14] M. Kindu, T. Schneider, D. Teketay and T. Knoke, "Changes of ecosystem service values in response to land use/land cover dynamics in Munessa- Shashemene landscape of the Ethiopian highland," *Sci. Total Environ*, vol. 547, pp. 137–147, 2016.
- [15] Y. Wang, H. Chunlin, F. Yaya, Z. Minyan, and G. Juan, "Using earth observation for monitoring SDG 11.3. 1-ratio of land consumption rate to population growth rate in Mainland China," *Remote Sensing*, vol. 12(3), pp. 35, 2020.
- [16] R. Manandhar, I. O. Odeh and T. Ancev, "Improving the accuracy of land use and land cover classification of Landsat data using post-classification enhancement," *Remote Sens.*, vol. 1, pp. 330–344, 2009.
- [17] C. Yang, G. Wu, K. Ding, T. Shi, Q. Li and J. Wang, "Improving land use/land cover classification by integrating pixel unmixing and decision tree methods," *Remote Sens.*, vol. 9, pp. 1222, 2017.