
Title:
Valuation of Ecosystem Services Amidst Land Use Land Cover Change Dynamics in Kedarnath Wildlife Sanctuary, Uttarakhand

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Abstract

The Kedarnath Wildlife Sanctuary, situated in Uttarakhand, India, is a critical hub of ecological diversity and ecosystem services. However, rapid land use and land cover (LULC) transitions in the region have raised concerns regarding the sustainability of these services. This study presents a comprehensive assessment and quantification of ecosystem services in response to LULC changes over a 23-year period (2001–2024). Landsat images were classified into seven classes—forests, rangelands, cropland, waterbody, settlements, bare land, and snow cover—using a Random Forest classifier in Google Earth Engine. The classified LULC maps were used to estimate the ecosystem service value (ESV) using the Benefit Transfer Method (BTM). The results indicate that forested areas contribute the most to the total ESV, although they show a declining trend over time. Total ESV decreased from approximately USD 134.09 million in 2001 to USD 113.68 million in 2024. These findings underscore the urgent need for proactive conservation and sustainable land management strategies, particularly in ecologically sensitive regions like the Kedarnath Wildlife Sanctuary.

Keywords: Ecosystem Service Value (ESV); Random Forest Classifier; Benefit Transfer Method (BTM); Land Use Land Cover (LULC)

1. Introduction

The connection between humanity and the ecological world is increasingly evident as we collectively strive to address global objectives such as preserving biodiversity, combating climate change, fostering economic growth, and enhancing human welfare (UN, 2015). Every aspect of human existence is intertwined with, and reliant upon, ecosystems. These ecosystems offer valuable contributions, known as 'ecosystem services', to humanity. Conversely, the actions and behaviours of individuals and societies as a whole have a substantial influence on the quality and functioning of these ecosystems (Leviston et al., 2018). Hence, a comprehensive and profound investigation into the correlation between ecosystem services and human welfare has emerged as a crucial scientific matter within the domain of ecological economics (Xu et al., 2019). Enhancing our understanding of the intricate interdependencies between ecological and socio-economic systems is paramount for the continuous and sustainable operation of both anthropogenic systems and ecosystems (Millennium Ecosystem Assessment, 2003). Millennium Ecosystem Assessment, (2005) offers new insights into the connections between socio-economic systems and ecosystem services. This assessment was undertaken from 2001 to 2005 with the aim of evaluating the impact of changes in ecosystems on human welfare (Balasubramanian & Sangha, 2023). It sought to develop a scientific foundation for measures required to improve the preservation and sustainable utilization of ecosystem services. Ecosystem service can be described as "a human-centered utilitarian concept, where the value of the benefits provided by ecosystems depends on the usefulness that individuals gain from their use, either directly or indirectly" (Goldenberg et al., 2017; UNEP, 2011). These services encompass provisioning services, regulating services, habitat services, cultural services, and others (Li et al., 2022; Sharma et al., 2023). Ecosystem Service Value (ESV) is a comprehensive method used to quantify the market values of various ecological functions that often involve invaluable ecosystem services contributing significantly to the socio-ecological importance of naturally occurring processes integral in generating natural capital and enhancing green economy of the area (Millennium Ecosystem Assessment, 2005; Sannigrahi et al., 2020). In essence, ESV quantifies the value of natural resources or ecosystem services from an ecological standpoint, employing both ecological and economic research methodologies (Costanza et al., 1997).

Ecosystem services, despite their substantial contribution to both natural processes and human sustainability and survival, have experienced a significant global degradation across temporal and spatial dimensions (Gong et al., 2022). In the preceding half-century, anthropogenic influences have precipitated alterations in ecosystem services at a pace and range unparalleled in recorded human history (Scolozzi et al., 2012). Among the most significant consequences of anthropogenic disturbances on varied ecosystems is the modification in terrain utilization. This not only brings transformation in the configuration of vegetation and topography, but also influences the structure and operational dynamics of ecosystems (Hasan et al., 2020; Wang et al., 2022), consequently leading to transformations in ecosystem classifications, a progressive deterioration of Ecosystem Services, and a reduction in biodiversity, subsequently instigating alterations in Ecosystem Service Values (ESVs). Therefore, comprehending the influence and interplay of alterations in terrestrial use on the benefits of ecosystem services is of paramount importance (Yuan et al., 2019). Optimizing land use patterns to align with changes in ecosystem service values (ESVs) and holistically augmenting ecosystem services holds substantial importance for the preservation of environmental systems and ecological diversity (Wang et al., 2022). While global-level assessments of LULC diversions exist, these models often lack the specificity needed to capture critical landscape modifications occurring at more granular spatial resolutions, like sporadic tropical forest loss and forest regeneration. Models of a more refined scale are necessitated for the exploration of the responses of land cover transformations on environmental benefits at local and regional levels (Hu et al., 2008). Concurrent with socioeconomic progression, the overutilization of terrestrial resources by humans has remarkably damaged regional ecological systems (Tang et al., 2024). The degree and direction of LULC fluctuations have the potential to influence ecological phenomena such as energy transference, hydrological equilibrium, and biogeochemical rotations within and interconnecting ecosystems. These dynamics can cause additional changes in ESVs, increasing certain aspects while diminishing others, or potentially leading to ecological deterioration (Polasky et al., 2011). That is why, research focused on ESVs that are predicated on land utilization can provide the spatiotemporal impact of regional changes in land use. This understanding can clarify the repercussions these changes have on ESVs, thereby providing a theoretical foundation and benchmark for ecological reformation (Zuo et al., 2023).

Ecosystem Services represent the actual flow from ecological systems to socio-economic structures, which are utilized within a defined time and space. In this context, various elements of ecological and socio-economic structures are essential to evaluate the actual transfer of services and understand the temporal changes (Hein et al., 2016; Vallecillo et al., 2019) . The significance of ecological advantages can be understood by the quantification of ecosystem services in economic units, as the management of entities without any assigned value creates intricate challenges. There is an escalating need to numerically evaluate the role of ecological systems in enhancing human welfare and economic prosperity (Vallecillo et al., 2019). There are a number of direct and indirect use methods to estimate and allocate the economic value to terrestrial ecosystem services, such as ‘contingent valuation method’, ‘hedonic price method’, ‘opportunity cost method’, ‘inferred willingness-to-pay’, ‘price-based market valuation’, ‘revealed preference technique’ and the ‘benefit transfer method (BTM)’ (Barbier et al., 2009; Chopra et al., 2022; Marta-Pedroso et al., 2018; Verma & Ghosh, 2023). Within the diverse array of methodologies for the quantification of ecosystem service value, the Benefit Transfer Method (BTM) has garnered extensive utilization due to its operational feasibility and inherent simplicity (Costanza et al., 1997, 2014; Dammag et al., 2024).

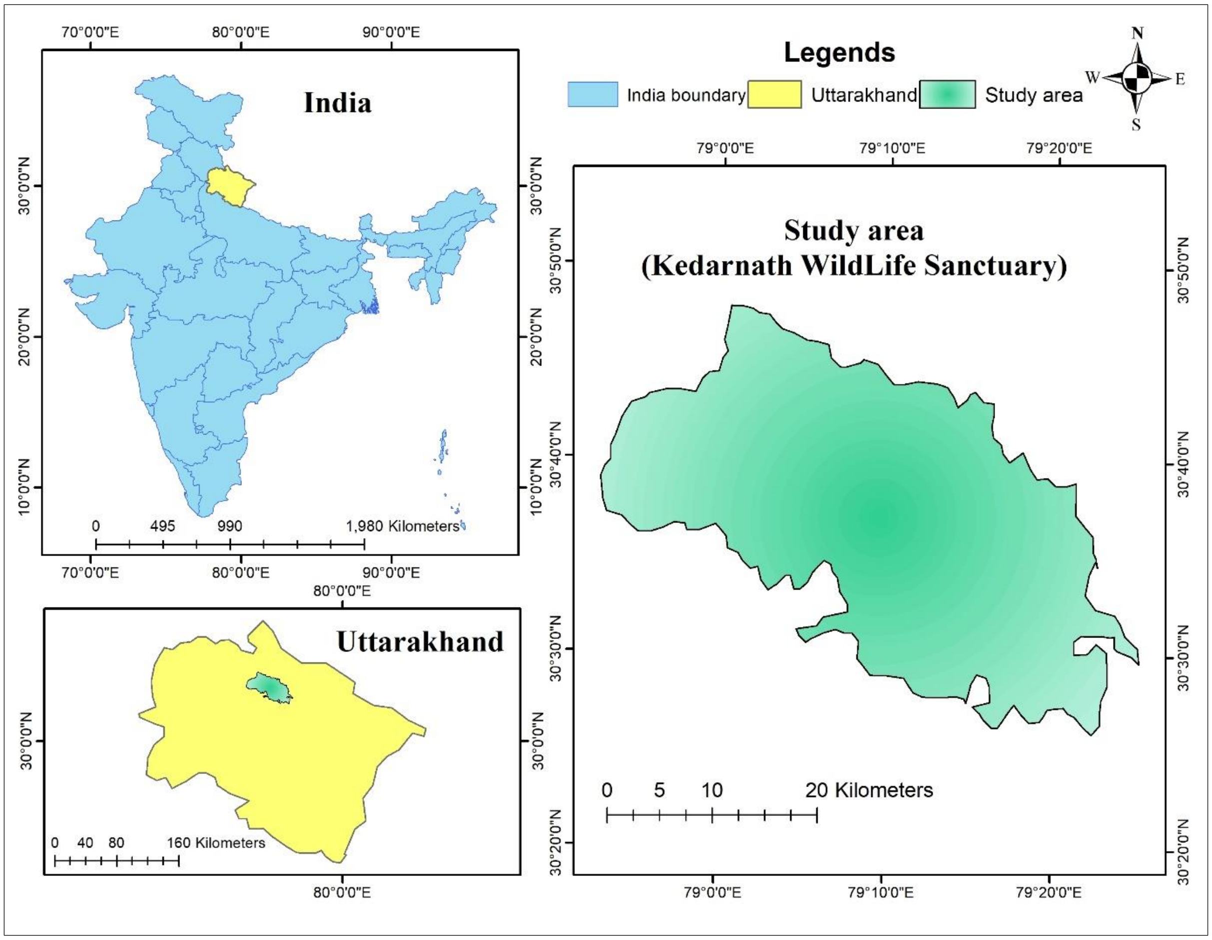
The present study has selected Kedarnath Wildlife Sanctuary (KWLS), the largest protected area (PA) in Indian Himalayan Region (IHR), situated in Uttarakhand, as the study area due to its ecological significance and fragile mountainous nature. In the last few decades, KWLS has witnessed extensive land transition due to natural and human disturbances such as extreme flood, landslides, forest fire, exploitative tourism, and excessive resource extraction (Manral, 2018). Studying the variations in monetary value of KWLS’s ecosystem services in response to the transition in LULC is crucial for raising awareness and implementing strict regulations by both national and regional managing authorities in order to stabilize climatic, socio-economic, and cultural vulnerabilities. The present study covering a longitudinal period of over two decades (2001-2024) utilises GIS & remote sensing technique and the BTM approach to assess the ESV of KWLS and encompasses the following objectives:

(i) To prepare the LULC classification map of Kedarnath Wildlife Sanctuary (KWLS) for the years 2001, 2014, and 2024 using random forest technique,
(ii) To conduct change detection analysis from 2001 to 2024.
(iii) To estimate the ecosystem service value (ESV) of KWLS for the period 2001, 2014, and 2024.

1.1 Study area description

The Kedarnath Wildlife Sanctuary, largest protected region in western Himalayas, nestled in the majestic Himalayan range of Uttarakhand, India, encompasses an area of approximately 975.20 km^2. Established under the Wildlife Protection Act of 1972, the sanctuary's primary purpose is to protect the endangered Himalayan musk deer. Its geographical coordinates range from approximately 30°25'–30°41' North latitude and 78°55'–79°22' East longitude (Fig. 1). Located in the Garhwal region of Uttarakhand, the sanctuary stretches across the districts of Rudraprayag and Chamoli. Situated at altitudes ranging from 1,160 meters (near Phata) to 7,553 meters (Chaukhamba peak) above sea level, this sanctuary is a haven for diverse flora and fauna, offering a unique ecosystem for scientific exploration and conservation efforts.

The sanctuary experiences a sub-tropical to alpine climate, characterized by cold winters and pleasant summers. Annual precipitation is about 3000 millimeters, with the majority occurring during the monsoon season from June to September. Snowfall is common in higher elevations (Alpine and temperate regions) during the winter months (December to February) (Thakur et al., 2011). The sanctuary's topography varies from gentle slopes to steep ridges and valleys, with the presence of numerous glaciers and perennial streams that serve as lifelines for the region's biodiversity. The main high peak mountains are Kedarnath (6940 m), Mandani (6193 m), and Chaukhamba (7553 m). Kedarnath Wildlife Sanctuary boasts a diverse array of vegetation due to its wide altitudinal range. It has vast alpine pastures in the northern region and numerous dense oak mixed forests in the southern area (Malik et al., 2014). The lower elevations are dominated by subtropical forests comprising species such as oak, pine trees, and rhododendron. As elevation increases, these forests transition into alpine meadows, coniferous forests, and eventually rocky bare landscapes. The reserve also serves as the origin of numerous significant rivers and their tributaries, such as the Mandakini, Alaknanda, and Bhagirathi rivers (https://wandersky.in/kedarnath-wildlife-sanctuary/). Alpine meadows adorn the higher altitudes, adding to the sanctuary's ecological richness. Owing to its unique geographical and ecological features, the Kedarnath Wildlife Sanctuary serves as an invaluable site for scientific research and conservation initiatives.



Source: Generated in ArcMAP 10.7.1

Fig. 1 Location map

1.2 Landsat image retrieval in Google Earth Engine (GEE)

Data acquired through remote sensing has been known as an important source of information for cartographic representation of terrestrial cover and for tracing changes in land cover over temporal scales, with Landsat serving as the predominant data repository. Google Earth Engine (GEE), a web-based cloud interface, provides access to archived Landsat data for users, including data from Landsat 5 TM (Thematic Mapper) covering the years 1985 to 2011, Landsat 7 ETM+ (Enhanced Thematic Mapper Plus) from the period of 1999 to 2014, and Landsat 8 OLI/TIRS (Operational Land Imager/Thermal Infrared Sensor) data from 2013 to till date. The spatial resolution of these Landsat images is 30m and the original source of image acquisition is USGS (United States Geological Survey) Earth Explorer website (*https://earthexplorer.usgs.gov/*). The present research work has utilised Landsat series images 05 TM and 08 OLI/TIRS to analyse terrestrial changes from 2001 to 2024 (Table 1).

Table 1 Satellite data sources information

S. No.	Landsat Data	Satellite ID	Year	Spatial resolution	Cloud cover (%)	Data source
1.	Landsat 05 TM	LANDSAT/LT05/C02/T1_TOA	2001	30m	1	USGS Earth Explorer
2.	Landsat 08 OLI/TIRS	LANDSAT/LC08/C02/T1	2014	30m	1	USGS Earth Explorer
3.	Landsat 08 OLI/TIRS	LANDSAT/LC08/C02/T1	2024	30m	1	USGS Earth Explorer

2. Research methodology

2.1 Satellite image processing

The selection of the satellite images was based on their availability, spatial resolution, and overall general quality, especially those with minimal cloud interference or obstructions in the scene. In order to reduce the effects of the wet season's fluctuation on vegetation and limit the cloud cover interference, all the obtained images were selected from the dry season (January to March) (Admasu et al., 2023). January to March is generally considered the dry season in Uttarakhand, India. During this time, the region experiences lower levels of precipitation compared to the monsoon season, which typically occurs from June to September. The dry season is characterized by clearer skies, cooler temperatures, and lower humidity levels, making it an ideal time for LULC assessment. Prior to the classification process, the images were transformed into an RGB colour composite. This was done to enhance the visibility of surface characteristics and to facilitate their clear identification during the classification stage (Kazakeviciute-Januskeviciene et al., 2020). For uniformity and compatibility, every image was projected to the UTM zone 44 N, using World Geodetic System 84 (WGS84) as the reference datum. After that, sub-setting and resampling process was performed in ERDAS IMAGINE and ArcGIS 10.7.1 software, respectively to match the extent and cell-size of all the three images.

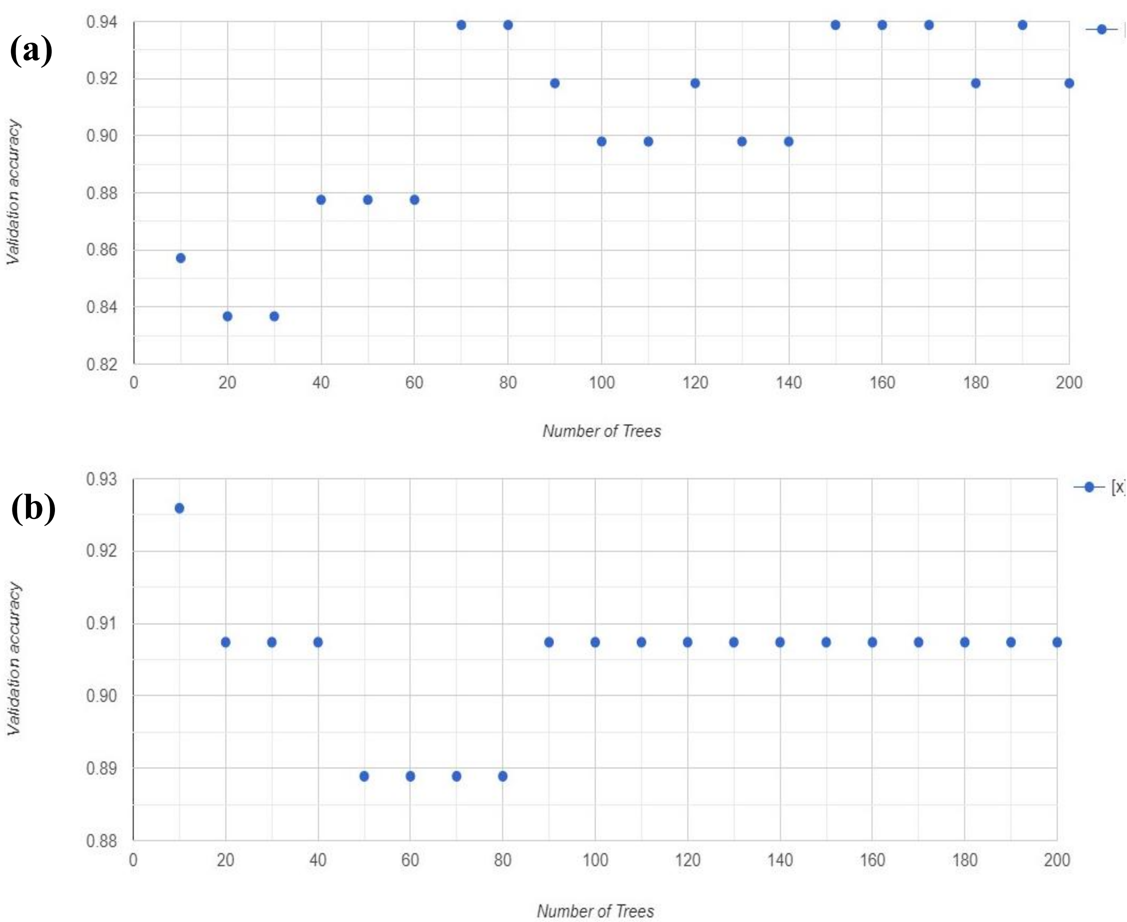
2.2 LULC classification using machine learning classifier

Multi-temporal Landsat images for 2001, 2014, and 2024 were used to prepare the LULC map of KWLS. Before applying any method of classification i.e. supervised/unsupervised, understanding the nature and complex structure of the study location is an essential step (Shivakumar & Rajashekararadhya, 2018). Several band composites were analysed to identify the spectral separability of multiple land use features, where some classes were overlapped because of equal radiometric or spectral values knows as digital numbers (DN). Classification entails careful identification of spectral patterns for the extraction of good quality and accurate training samples, also referred to as signature gathering (Verma et al., 2024). The study area's landscape was segmented into seven possible major LULC categories: forests, rangelands, cropland, waterbody, settlements, bare land, and snow cover. To recognise the LULC class features in remotely accessed Landsat images, all the sample data were accumulated based on band combinations, manual visual interpretation, and high-resolution Google Earth imagery (Baidoo & Obeng, 2023). Mean pixel values of the spectral signatures were utilized in Google Earth Engine (GEE) to derive the sample training data. The signatures were collected employing two different band combinations, i.e. FCC (false colour composite), used for forest, cropland, rangelands and bare land recognition. In contrast, the natural colour composite was used for settlements and waterbody class identification (Sharma et al., 2023). For FCC, Landsat 08 used band composites: B5, B4, B3 and Landsat 05 used band composites: B4, B3, B2. Similarly, B5, B4, B1 band combinations were used to access 'nature-like' rendition in Landsat 05 and B7, B5, B3 bands combinations were used to access natural colour image with atmospheric removal. For each type of LULC classes, over 30-40 spectral signatures or values were collected. The sample size for each Land Use and Land Cover (LULC) type was decided based on its area proportion. The training data must adequately represent the whole area under study (Belay et al., 2022). Further, by utilizing GEE functions, the sample dataset was divided into 70% for training purposes and 30% for testing. Additionally, these sample datasets were utilised as a training test in order to classifying the LULC features using machine learning algorithms such as random forest (RF)

2.2.1 Random Forest (RF) classifier

A suitable classification model can establish the inherent relationship between the features (for instance, band data) and the targets (like the seven categories in this study) through supervised learning from training data. Once the model is trained, it can predict and assign class labels to new, unseen data. Various classification algorithms have been employed in scholarly works for supervised learning, such as Random Forests (RF), Support Vector Machines (SVM), nearest neighbour methods, decision trees, and neural networks. RF is frequently employed as an algorithm for categorizing land cover based on remote sensing data (Breiman, 2001).

RF is a classification algorithm based on ensemble learning which creates numerous decision trees during the training phase. The ultimate outcome is a composite of the classifications derived from each separate decision tree. This approach can prevent overfitting and is significantly more reliable than a single decision tree. Previous studies also indicate that the RF technique can deliver high precision, strong robustness, and reduced computational burden (Belay et al., 2022; Zhang et al., 2021). That is why, this study utilized the RF algorithm in GEE to perform LULC classification using selected sample points. The LULC classification was executed by calling the ee. smileRandomForest function within the GEE. In RF approach, some hyperparameters i.e., Ntree (number of trees) and Mtry (variablesPerSplit) are required to be tuned so that a robust classification performance could be achieved. In this study, Mtry parameter was kept at default setting and only Ntree was tuned, where iterations were ranged from 10 to 200 with an interval of 10 from that the Ntree value giving the maximum overall accuracy (OA) was selected for each year. Fig. 2 reflects the optimal Ntree values that are (a) 70, 80, 150, 160, 170 and 190 for the LULC 2001, (b) 10 for the LULC 2014, and (c) 30 for the LULC 2014.



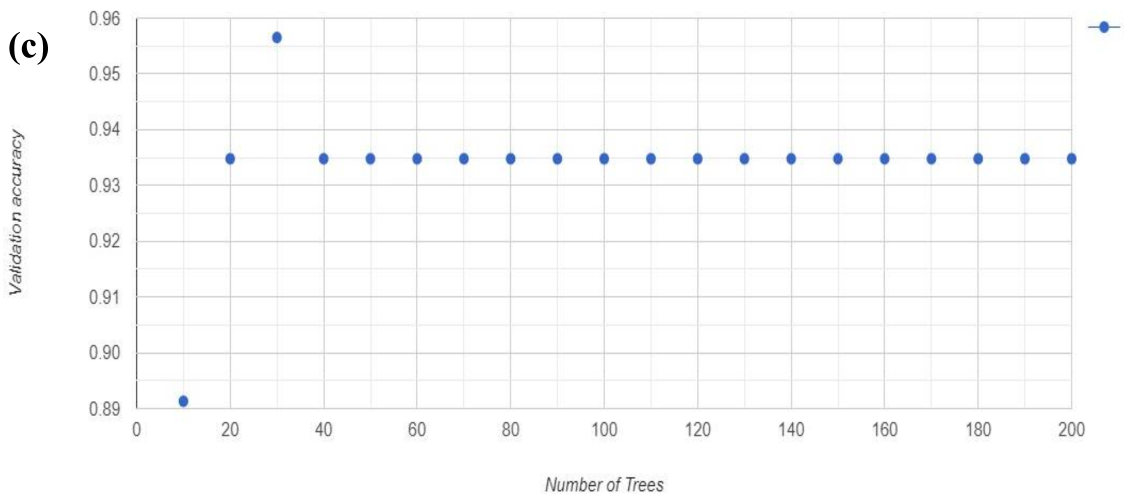


Fig. 2 Hyperparameter tuning for the number of trees: (a) 2001, (b) 2014, (c) 2024

To determine the accuracy of classification, various accuracy statistics were calculated, which include Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA) and Overall, Kappa Accuracy (KIA). This study has achieved OA values of 93.87%, 92.59%, and 95.65% for the years 2001, 2014, and 2024, respectively and KIA statistics of 0.92, 0.91, and 0.91 for the years 2001, 2014, and 2024, respectively (Table 2) which fall within the acceptable range of accuracy assessment. The LULC maps are presented in Fig. 3 for all the specified years.

Table 2 LULC Accuracy Assessment

LULC Classes	200		2014		2024	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
Forests	100	100	100	100	100	100
Rangelands	90	90	88	100	100	100
Cropland	100	83.3	100	100	100	100
Waterbody	100	85.7	100	90	100	83.3
Settlements	77.7	100	80	67	75	75
Bare land	100	100	71	100	83.3	100
Snow cover	100	100	100	83.3	100	100
Overall Accuracy (OA)	93.87%		92.59%		95.65%	
Kappa Coefficient (KIA)	0.92		0.91		0.91	

PA: Producer's Accuracy, UA: User's Accuracy

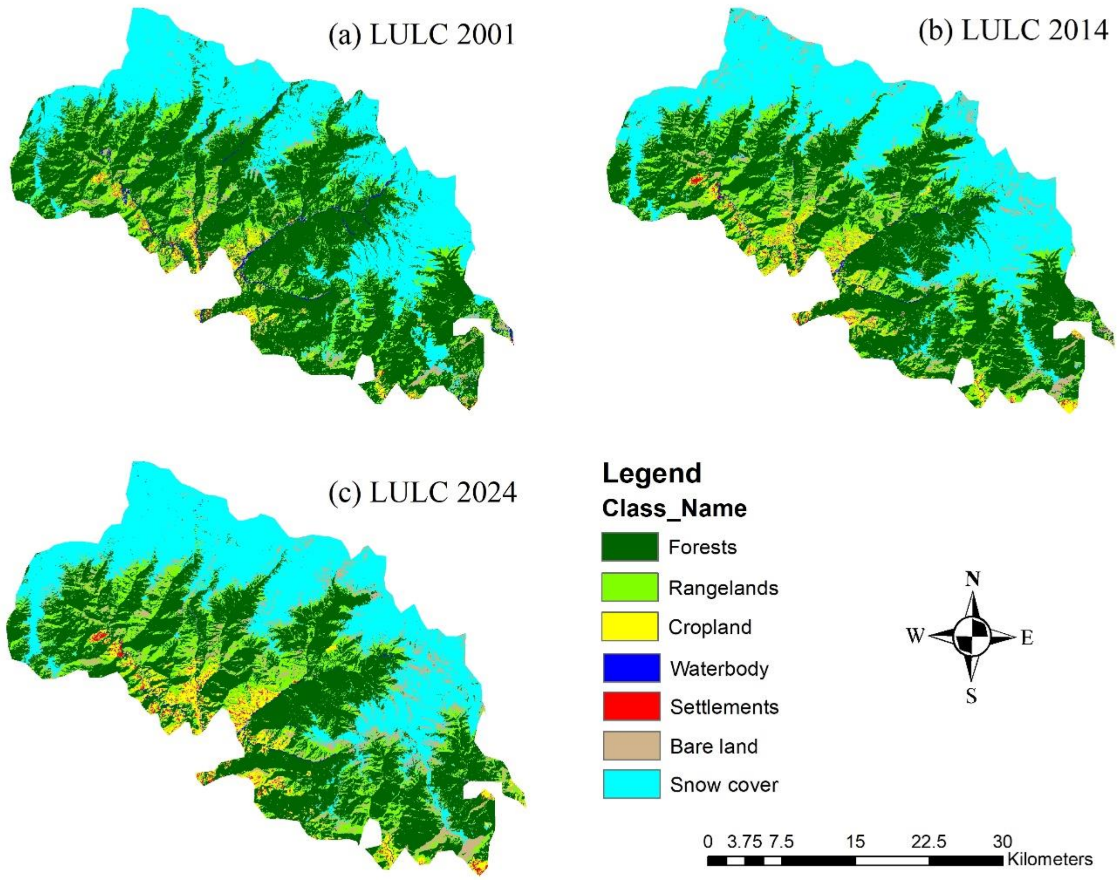


Fig. 3 LULC maps of Kedarnath Wildlife Sanctuary for the specified years: (a) 2001, (b) 2014, and (c) 2024

2.4 Assessment of ecosystem service valuation

The well-being of humanity and the smooth functioning of the global economy rely on the services provided by ecosystems. However, these services are at risk due to the complicated relations between people and the ecological system, leading to the deterioration of ecosystems and a decrease in biodiversity (Muche et al., 2023). Most the Earth's environmental services have been altered due to the interference of human activities. These activities include changes in landscape cover, deforestation, and exploitation of natural resources, which have significantly increased and are now unavoidable. Among all the factors causing these changes, LULC is considered to be the most significant (Sannigrahi et al., 2020). Moreover, quantifying ecological benefits in financial value is becoming increasingly common. This approach aims to promote awareness among individuals, offer evidence for decision-makers, calculate the potential restoration expenses, and ease the process of compensating for ecosystem services. The assessment of environmental benefits and their values has been in progress since the 1970s. However, accurately evaluating the values of the Earth's environmental services is challenging due to the absence of a related theoretical framework and methodology. Lately, the assessment of ecosystem service functionality and value has emerged as a focal point of research.

Ecosystem valuation model was first established by (Costanza et al., 1997; Millennium Ecosystem Assessment, 2005). Costanza et al., (1997) provided significant information and methodologies for the valuation of ecosystem services by calculating 17 ecological services supplied by 16 global biomes with an average annual value exceeding US$33 trillion. This incentivise a comprehensive exploration of Ecosystem Service Value (ESV) across various levels by global and local researchers. Nonetheless, the findings put forth by Costanza and his colleagues in 1997 have faced criticism and their valuation approach has been questioned due to its inherent uncertainties and limited applicability at diverse scales (Kindu et al., 2016; Kusi et al., 2023). In response to this, (Costanza et al., 2014) revised and modified the global values of ecosystem benefits. They took into account an extensive array of case studies (more than 300) from around the globe to tackle some major uncertainties. Upon examining multiple locations, (Costanza et al., 2014) asserted that the models and data utilized in their assessment have the potential to be implemented at diverse scales for evaluating changes in ESV. There are several studies (Kindu et al., 2016; Tolessa et al., 2017; Xie et al., 2003) which have also employed updated monetary value estimated by (Costanza et al., 1997, 2014). (Xie et al., 2003) performed the ecosystem service valuation assessment per unit area of the various land use classes based on Costanza's global ecological service valuation tachnique in the Tibetan Plateau in which an updated benefit transfer method (BTM) was used to evaluate the variations in the value of ecosystem benefits due to changes in land uses on ESVs.

The Benefit Transfer Method (BTM) presumes uniformity across space and allows the transfer of an equivalent value coefficient from one location to other regions that are similar in terms of ecology and socioeconomic dynamics (Kindu et al., 2016; Sannigrahi et al., 2020). The BTM approach, which relies on global value coefficients or modified value coefficients, has been a commonly employed strategy, particularly in regions lacking sufficient data (Munthali et al., 2023). The present study adopts the equivalent coefficient table provided by (Xie et al., 2003) since it has been also applied by studies like (Rai et al., 2018; Zhilong et al., 2017) which encompasses nearly similar bioma types as the present study.

The most indicative biome was utilised as a proxy for each LULC class including: (1) forests for tropical forests, (2) rangelands for Shrubland (3) cropland for cropland (4) waterbody for lakes/rivers (5) settlements for urban (6) bare land for desert and (7) snow cover for snow/glacier (Table 3).

The Ecosystem Service Values (ESVs) for each LULC category were determined by multiplying the area (in hectares) of each LULC type by its respective value coefficients, as per the formula provided below in equation 1 and the total ESV of the landscape for each reference year was calculated by adding up the values for the LULC types in each respective year.by using equation 2.

$$ESV_k = (A_k * VC_k) \qquad \text{Equation 1}$$

$$ESV_t = \sum(A_k * VC_k) \qquad \text{Equation 2}$$

Where,

ESV_k = Estimated ecosystem service value for individual LULC class

ESV_t = Total ecosystem service value

A_k = The area (in ha) for LULC type k

VC_k = The value coefficient (in US$/ha/year) for LULC type k

Table 3 Ecosystem services value (ESV) coefficient respective to each LULC classes

LULC Classes	Equivalent biome	Ecosystem services value (ESV) in USD/ ha/year
Forests	Tropical forests	2168.84
Rangelands	Shrubland	1089.19
Cropland	Cropland	699.37
Waterbody	Lakes/Rivers	6552.97
Settlements	Urban	0
Bare land	Desert	0
Snow cover	Snow/glacier	0

Source: (Xie et al., 2003)

3. Data analysis and results

3.1 Change detection analysis (2001-2024)

Land use pattern and formation has experienced significant diversification in the past 23 years. To analyse the trajectories of LULC transitions, a change analysis of seven LULC classes has been performed based on study period 2001, 2014 and 2024. The LULC year-wise area proportion (in ha) of all the seven major classes (forests, rangelands, cropland, waterbody, bare land, settlements, and snow cover) is presented in Fig. 4 and their change dynamics from 2001 to 2024 are provided in Table 4 (2001-2014) and Table 5 (2014-2024) to explore the variations occurred among all the LULC types over time. The land use classes like forests, rangelands, waterbody, and snow cover are the naturally formed landscapes, while the other remaining three classes represent human-modified landscapes resulting from the transformation of forests, rangelands, waterbody, and snow cover into cropland, settlements and bare land. The overall land coverage of LULC classes in all the reference periods shows significant domination of forests coverage followed by snow cover, rangelands, bare land, cropland, waterbody, and settlements. Despite of being the dominant land use class, forested area has witnessed down fall over the time i.e., 51640.11 ha in 2001 > 45779.49 ha in 2014 > 42511.14 ha in 2024 with the area difference of -5860.62 ha (2001-2014) and -3268.35 ha (2014-2024), however this down fall has happened with decreasing rate as demonstrated in Fig. 4 and Table 4, 5. The second most dominant landscape feature is snow cover which indicates up and down trajectory since it has increased from 33176.61 ha in 2001 to 34917.57 ha in 2014 with the area difference of 1740.96 ha which makes 5.25% increment in the class cover which further falls with the area difference of -350.01 ha, an decrement of -1.01%. The third most occupied land cover rangelands has shown increment in area coverage from 2001 (13438.89 ha) to 2014 (14352.3 ha) that is 6.80% increase, but it has remain almost persistent during 2014 to 2024 with percentage increase of only 1.25. Bare land has witnessed only increment over time with the area difference of 2319.39 ha (in 2001 to 2014) and 1814.49 ha (in 2014 to 2024). Cropland has also drastically increased with the percentage difference of 63.28 (in 2001 to 2014) and 49.47 (in 2014 to 2024). Waterbody and settlements have the least area coverage where waterbody has shown decreasing trend and settlements has shown increasing trend from 2001 to 2024.

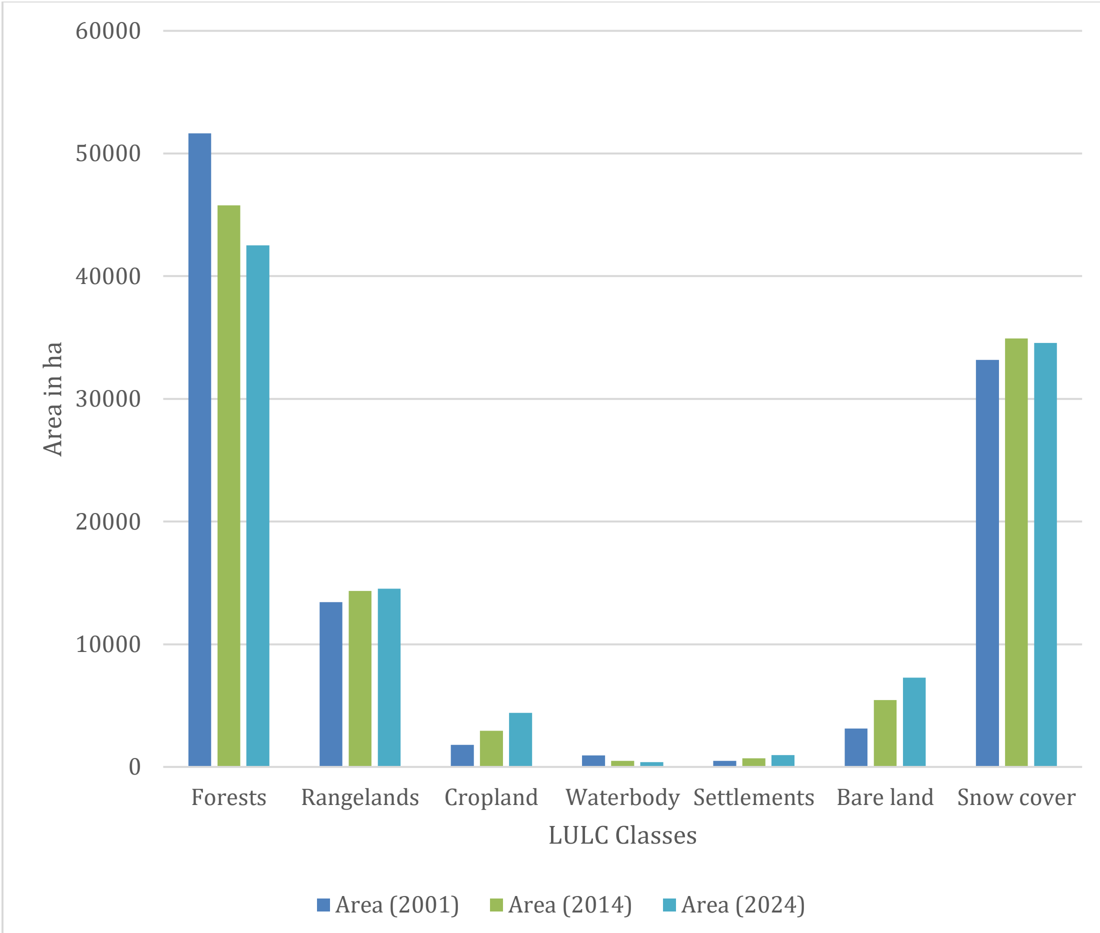


Fig. 4 LULC year-wise area proportion (in ha)

Table 4 LULC Change matrix from 2001 to 2014 (in ha)

LULC Classes	Area (2001)	Area (2014)	Area change dynamics (2001-2014)	
			Difference in ha	% difference
Forests	51640.11	45779.49	-5860.62	-11.35
Rangelands	13438.89	14352.3	913.41	6.80
Cropland	1805.76	2948.4	1142.64	63.28
Waterbody	944.28	488.52	-455.76	-48.27
Settlements	506.34	706.32	199.98	39.5
Bare land	3133.89	5453.28	2319.39	74.01
Snow cover	33176.61	34917.57	1740.96	5.25

Source: Author's own calculations

Table 5 LULC Change matrix from 2014 to 2024 (in ha)

LULC Classes	Area (2014)	Area (2024)	Area change dynamics (2014-2024)	
			Difference in ha	% difference
Forests	45779.49	42511.14	-3268.35	-7.14
Rangelands	14352.3	14531.4	179.1	1.25
Cropland	2948.4	4407.03	1458.63	49.47
Waterbody	488.52	391.77	-96.75	-19.8
Settlements	706.32	976.41	270.09	38.24
Bare land	5453.28	7267.77	1814.49	33.27
Snow cover	34917.57	34567.56	-350.01	-1.01

Source: Author's own calculations

Fig. 5 demonstrates percentage difference in LULC classes from 2001 to 2024. In the figure, green line indicates percentage change from 2001 to 2014 and blue line indicate percentage change from 2014 to 2024. The most fluctuating LULC classes during 2001 to 2014 are bare land, cropland, waterbody and settlement. Among them bare land has the highest positive percentage difference (74.01%), followed by cropland (63.28%) and settlements (39.5), while waterbody has shown drastic negative percentage difference of -48.27. Time span 2014 to 2024 has shown high positive fluctuation in cropland (49.47%) followed by settlements (38.24%) and bare land (33.27%). Least change has been observed in rangelands and snow cover while the most dominant land use class forests has witnessed moderate change. Fig. 6 displays spatial transition map of KWLS in LULC classes during 2001 to 2024. It reflects the conversion of highly occupied land cover i.e., forests, rangelands, and snow cover into other land use classes such as forests have converted into rangelands, cropland, bare land and snow cover. Rangelands have converted into forests, cropland, bare land and snow cover while the snow cover has majorly transformed into bare land.

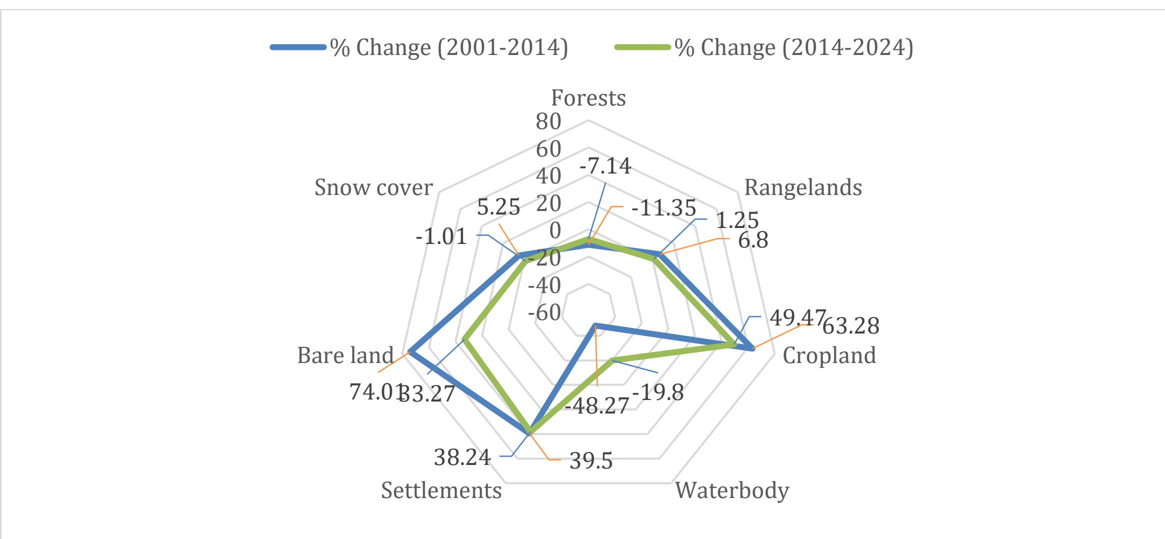


Fig. 5 Percentage change in LULC classes from 2001 to 2024

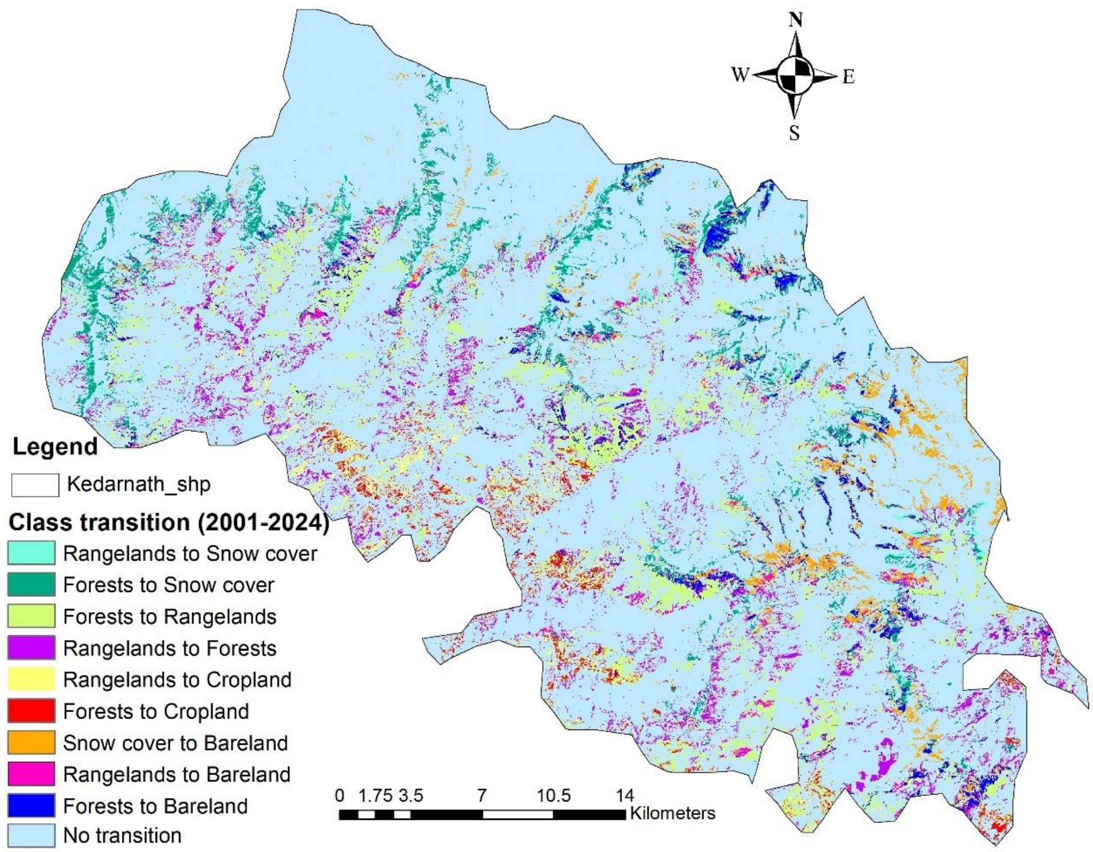


Fig. 6 Spatial transition map of major LULC classes from 2001 to 2024

3.2 Estimation of ecosystem service value over time from the year 2001 to 2024

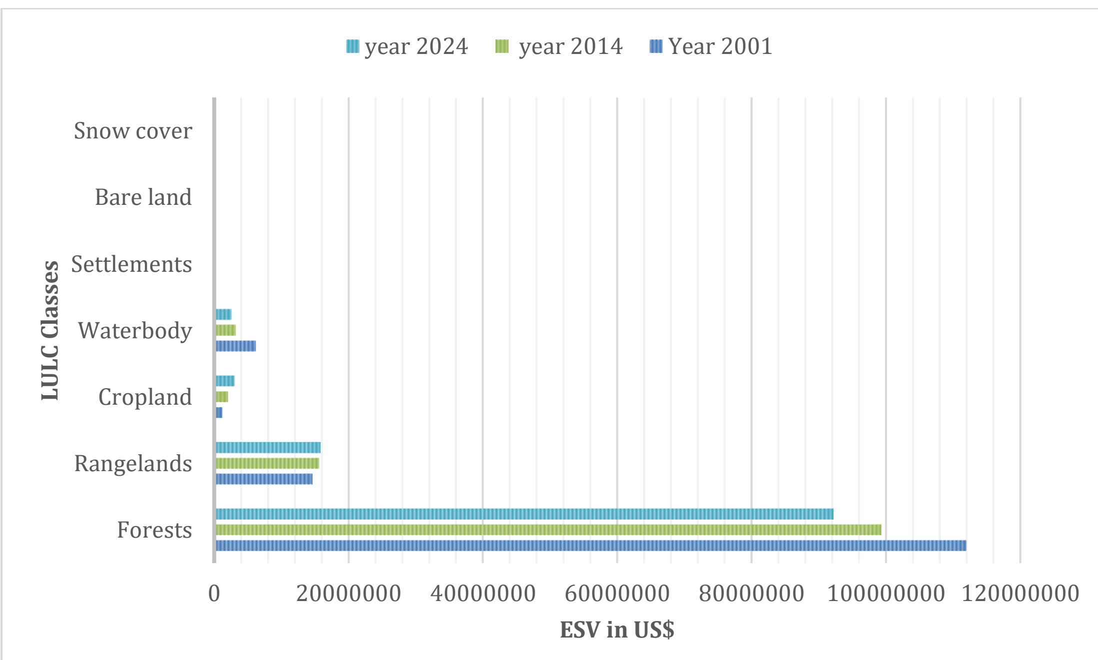
In the present study, the benefit transfer method (BTM) was employed to quantify the ESVs in monetary terms as a response to the spatio-temporal changes in diverse LULC classes for the periods 2001, 2014, and 2024. Based on ecosystem services, quantified by (Xie et al., 2003) (Table 3), current study has adopted and calculated the ESV between 2001 and 2024 in the Kedarnath wildlife sanctuary (KWLS). The classified LULC map of KWLS was utilised to assess the variations in the value of ecological services over time.

Table 6 and Fig.7 depicts economic quantification of ESVs all land use types, and Fig.7 provides the graphical representation of the total ESV for each reference study period. ESV for all LULC classes was computed by multiplying the land cover (in ha) of land use types to their corresponding adopted coefficient factor. In this study, land use classes forests, rangelands, cropland, and waterbody were assigned their respective coefficient value however no coefficient were assigned to settlements, bare land, and snow cover classes since these classes lack in vegetation (Muche et al., 2023). In the year 2001, forests land cover class indicate the highest value of ecosystem service (~112.00 million dollars), followed by rangelands (~14.64 million dollars), waterbody (~6.19 million dollars), and cropland (~1.26 million dollars). Reference year 2014 again shows the similar trends of LULC class contribution in ESV as the year 2001, however the ESV of forests (~99.29 million dollars) and waterbody (~3.20 million dollars) has decreased and ESV of rangelands (~15.63 million dollars) and cropland (~2.06 million dollars) has increased. The year 2024 has demonstrated change in ESV dynamics due to the changes in land coverage of LULC classes. In 2024, cropland (~3.08 million dollars) has surpassed the contribution of waterbody (~2.57 million dollars) in ESV while forests class still has the highest contribution (~92.20 million dollars) followed by rangelands (~15.83 million dollars). From the Fig. 6, it is apparent that total ESV of forests and waterbody has decreasing trend while rangelands and cropland are showing increasing trend during 2001 to 2024.

Table 6 Calculated ecosystem services value (ESV) in USD/ ha/year

LULC Classes	2001	2014	2024
Forests	111999136.2	99288389.09	92199860.88
Rangelands	14637504.6	15632381.64	15827455.57
Cropland	1262894.371	2062022.508	3082144.571
Waterbody	6187838.512	3201256.904	2567257.057
Settlements	0	0	
Bare land	0	0	
Snow cover	0	0	

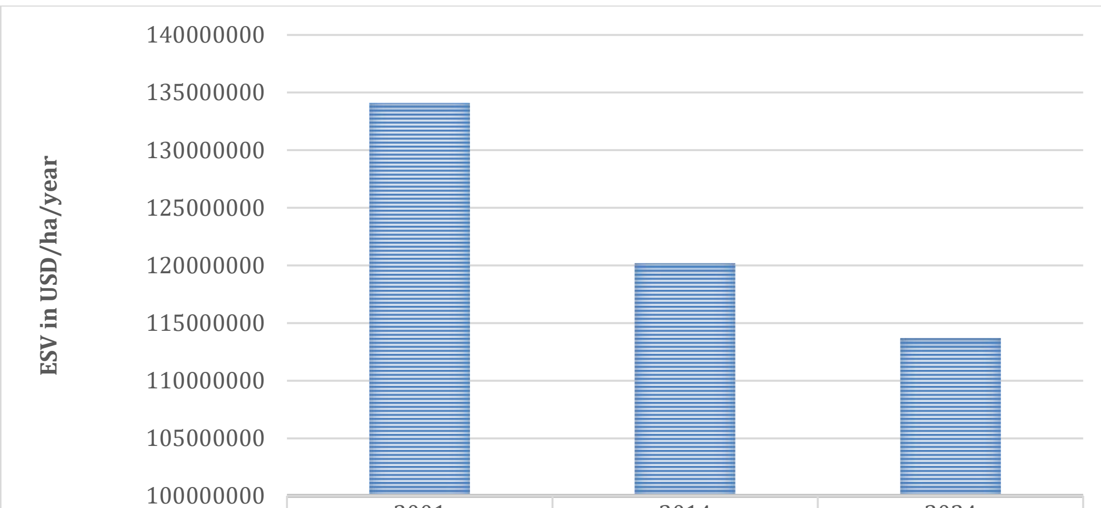
Source: Author's own calculations



Source: Author's own creation

Fig. 7 Ecosystem service value of each LULC classes in the year 2001, 2014, and 2024

The total ESV (ESV_t) for the Kedarnath sanctuary was computed by adding the calculated ESVs from all the LULC classes. ESV_t for the year 2001, 2014, and 2024 is presented in Fig. 8. From the figure, a declining trend of ESVs has been observed for the study periods as indicated by: ESV_{2001} = ~134.09 million dollars, ESV_{2014} = ~120.08 million dollars, and ESV_{2024} = 113.68 million dollars. The ESV was estimated by the areas of seven LULC classes based on equivalent proxy coefficients; that is why, the spatial changes and distribution of each LULC class and total ESVs for the selected reference years are similar to that of the LULCs. Decline in total ESV has occurred due to the unprecedented transformation in the structure of terrain cover in the last few decades. The sanctuary has experienced significant LULC transitions occurred due to human interference such as agricultural area expansion and urbanization. Forests land use class caused substantial impact to the reduction in ESVs, and its ESV has constantly been declining following the drastic reduction in area coverage over time.



	2001	2014	2024
Total Estimated ESV	134087373.7	120184050.1	113676718.1

Source: Author's own creation

Fig. 8 Year-wise total estimated ESV in USD/ha/year

Due to the conversion of most vegetated surface i.e. forests and rangelands into cropland, snow cover and bare land which produce less ecosystem service, the green service across the region has massively deteriorated. Therefore, it is imperative to preserve the integrity and extent of natural environments within the study area since it is essential for the sustenance of diverse ecosystem services and benefits, and to ensure their long term provision at the research location.

4. Discussion and conclusion

Assigning a monetary value to ecosystem services is an effective method for increasing public consciousness about the limited availability of natural resources and the advantages they offer, many of which are not commercially traded. The present study has conducted an assessment of the effects of changes in land use patterns on the value of environmental services within the Kedarnath wildlife sanctuary (KWLS) using Landsat images for the year 2001, 2014 and 2024. Benefit transfer method (BTM) was used to calculate the monetary value of ecosystem services using the GIS and remote sensing technique which is cost-effective, and less time taken method to study the data scarce region. Random forest (RF) classifier was employed in Google Earth Engine (GEE) to prepare the LULC map which further was utilized to estimate the ESV of each LULC class. The result reveals a massive decline in Total ESV during (2001-2024) resulting from reduction in natural vegetation and rise in artificial landscape.

The wildlife sanctuary, in spite of being a protected area (PA), witnessing rapid transitions in land use resulting into the deterioration of the whole landscape. A considerable amount of reduction in forests and waterbody LULC classes have been observed across the study region from 2001 to 2024. Forests offer a wide array of ecosystem benefits, including carbon sequestration, climate regulation, provision of food, fuel, animal feed, and wood. They are instrumental in sustaining the water cycle, safeguarding and preserving land-based biodiversity, and aiding in the prevention of land deterioration and salinization (Verma & Ghosh, 2022). The aquatic ecosystems such as rivers and lakes also provide many crucial ecosystem services, i.e., water provisioning and recreation, water retention, water purification and climate regulation (Grizzetti et al., 2016). These two land use types hold high ESV factor in the study region that is 2168.84 for forests and 6552.97 for waterbody but from them forests have the highest contribution in total estimated ESV which are continuously being reduced. There are a collection of studies experiencing the loss of forest cover with same pattern over time (Muche et al., 2023; Munthali et al., 2023; Sannigrahi et al., 2018). The main reason of declination might be attributed to changes in government policies, human interference and variations in climatic conditions. Cropland, settlements and bare land are swiftly encroaching on landscape cover, replacing natural forests as well as rangelands. Number of studies i.e., (Admasu et al., 2023; Baidoo & Obeng, 2023) report the same findings that degradation of natural vegetation and increment in less-vegetation land cover such as settlements and bare land are causing reduction in total environmental services.

The conversions in landscape cover are characterized by their dynamism and non-linearity. This implies that the transition from one type of land use to another doesn't adhere to a consistent pattern. This variability can be attributed to both natural and human-induced factors such as changes in policy, fluctuations in population, and a decline in land productivity. In contrast to the findings of present study, several studies revealed improvement in total ecosystem services resulting from increased open forests, cultivated land and grassland over the time (1985-2016) (Solomon et al., 2018) and increase in total ESV resulting from the growth of natural vegetation, forests, farmland, and urban cover during (1992-2015) (Kusi et al., 2023). This improvement was possible due to the intervention of several environmental protection, natural ecosystem management, soil and water conservation as well as participation of local communities in the protection of natural resources. Many incentives can be taken from such studies applying environment and land use policy implications to save the integrity and long-term resilience of Himalayan protected areas. Integrating LULC and ecological service quantification data can assist in recognising regions that are most susceptible to variations in ecosystem services at a landscape scale and offer an initial foundation for potential future land management strategies. Hence, this current research lays the groundwork for future studies into forecasting LULC dynamics in relation to Ecosystem Service Valuation (ESV) using remote sensing data, land suitability modelling, as well as developing a more precise and reliable value coefficients.

Declarations

Conflict of interest: The authors declare no conflict of interest.

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