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Impact of land use/land cover changes on ecosystem service values in the cherangany hills water tower, Kenya

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ABSTRACT

Land Use/Land Cover (LULC) changes alter the ecosystem structure and function, resulting in variations of the Ecosystem Service Values (ESVs). This study investigated the impacts of LULC changes on ESVs over 37 years in the Cherangany Hills Water Tower (CHWT) of Kenya. Landsat images from 1985 and 2022 were used to examine historical LULC changes in the CHWT. Supervised classification was carried out using the Random Forest (RF) classifier in R-Studio while ArcGIS desktop software was used for mapping to evaluate the LULC changes. Accuracy assessments were also conducted for each reference year. The estimation of ESVs was done using the Benefit Transfer Approach (BTA), employing modified local value coefficients. Six LULC types (Forest, Cropland, Grassland, Water bodies, Bareland, and Built-up area) were successfully classified, with overall accuracies of more than 92.5% and Kappa coefficients greater than 0.91. Our study findings showed an expansion in built-up areas (201.63%), cropland (36.78%), and water bodies (40.05%) whereas grassland, forest, and bareland experienced a reduction in their land areas by 28.26%, 13.38%, and 24.15% respectively between 1985 and 2022 in the CHWT. Consequently, there was an increase in the ESV of cropland while forest and grassland registered a decrease in their ESVs. Overall, the total ESV of the CHWT declined by 7.16% from 121.22 million United States Dollars (USD) in the year 1985 to 112.54 million USD in 2022. As for the individual ESVs, 15 out of the 17 individual Ecosystem Services (ES) registered negative changes in their ESVs. Food production and biological control were the two individual ES with positive ESV changes over the study period. There is a need to curb the current drivers of LULC changes within the water tower, especially the expansion of croplands, to stop further ecosystem degradation for optimum delivery of ES.

1. Introduction

Ecosystem Services (ES) refers to the aspects of ecosystems utilized either actively or passively for human well-being (Fisher and Turner, 2008; Millennium Ecosystem Assessment [MEA], 2005). These benefits can be categorized into direct benefits (regulating, provisioning, and cultural services), which affect the well-being of humans in the short term, and indirect benefits (supporting services), which are critical in sustaining the production of the other services; hence affects human well-being in the long run (Costanza et al., 1997; de Groot et al., 2012).

ES are crucial for sustaining life on earth and preserving the ecosystem's integrity (The Economics of Ecosystems and Biodiversity [TEEB], 2010). Despite their significance, ES are threatened by socio-economic and biophysical pressures such as expanding human settlements, expanding agriculture, population growth, urbanization, and accessibility to markets (Kindu et al., 2016; Li et al., 2007). Unprecedented Land Use/Land Cover (LULC) changes in different parts of the world due to human and natural activities have had adverse impacts on biological diversity and ecosystems, affecting their ability to provide ecosystem services (Costanza et al., 1997; Gashaw et al., 2018; Hernández-Blanco et al., 2020). As a result, such changes have been identified as one of the leading drivers of ES loss both globally and locally. LULC changes characterized by the conversion of natural habitats such as forests, grasslands, and wetlands into agricultural lands, and urban areas have led to increased food production and housing, but at the cost of ES, human well being, and biodiversity (Biratu et al., 2022; Gashaw et al., 2018; Hasan et al., 2020; Lawler et al., 2014; Polasky et al., 2011; Tolessa et al., 2021).

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Globally, research has been carried out to understand, value, model, and manage ES (Badamfirooz et al., 2021; Cabral et al., 2016; Costanza et al., 2014, 1997; De Groot et al., 2012; Gashaw et al., 2018; Hasan et al., 2020; Jha et al., 2020; Kindu et al., 2016; Marques et al., 2021; Niquisse et al., 2017; Sannigrahi et al., 2020; Sharma et al., 2019; Shiferaw et al., 2019; Talukdar et al., 2020; Tolessa et al., 2017). ES valuation entails estimating the marginal value of ES which determines the benefit of preserving or the cost of losing a given amount or quality of ES (Pearce, 1998). The valuation of ES, therefore, provides an essential tool for creating awareness and influencing policy and decision making. It provides an easily understandable measure of the true value of ES to prioritize the conservation of ecosystems and biodiversity (Qin et al., 2019; Thellmann et al., 2019). There are different valuation methods of ES which can be broadly divided into two categories: a) the primary valuation methods, which follow economic approaches involving market prices, production approaches, travel cost, opportunity cost, the hedonic method, conjoint analysis, and replacement cost; and b) the land use proxy-based method, which utilizes the Benefit Transfer Approach (BTA) by applying the existing Ecosystem Service Values (ESVs) data from one region to a new region which has little or no data (De Groot et al., 2012; Farber et al., 2006; Kindu et al., 2016; Richardson et al., 2015). Kenya has experienced LULC changes over time due to a combination of anthropogenic and natural factors. The Food and Agriculture Organization of the United Nations (FAO) reports a decrease in areas covered by forests (6.58%) and grasslands (2.07%) in Kenya, while areas under settlement, cropland, and wetlands increased by 150.88%, 11%, and 1.09%, respectively, between 1990 and 2015 (FAO, 2015). Several studies have been done to quantify and map historical LULC changes in different regions of Kenya (Campbell et al., 2005; Cheruto et al., 2016; Kogo et al., 2021; Muhati et al., 2018; Petersen et al., 2021) and estimate the economic values of ecosystems (Langat et al., 2021; Ministry of Environment and Forestry, 2019; Nature Kenya, 2019; Okumu and Muchapondwa, 2017), but studies linking the two are scarce.

The Cherangany Hills Water Tower (CHWT) is among the five major water towers (Mt. Kenya, Mt. Elgon, Cherangany Hills, The Aberdare range, and The Mau Forest complex) of the 18 gazetted water towers in Kenya. It makes a significant contribution to the national economy by providing numerous environmental, economic, social, and cultural benefits (Kenya Water Towers Agency, 2020). While efforts have been made towards studying the impact of LULC changes on ES globally, no such studies have been carried out in the CHWT of Kenya. The objectives of this study, therefore, are to 1). Analyze LULC changes in the CHWT from 1985-2022 using Remote Sensing (RS) and Geographical Information System (GIS) 2). To find out the total ESV change in response to the LULC changes in the CHWT and 3). To estimate the impact of LULC dynamics on individual ESVs in the CHWT. Our research findings will provide a better understanding of the status and dynamics of ES in the CHWT for future land use planning and natural resource management by the relevant stakeholders.

2. Materials and methods

2.1. Study area

The CHWT is geographically located between 35°.00′ to 35°.83′ E and 0°.50′ to 1°.50′ N spanning four administrative counties of Elgeyo-Marakwet, West Pokot, Trans-Nzoia, and Uasin Gishu (Fig.1). The water tower covers an area of 263,771ha (2,637.71km^2), which comprises 97,397ha of gazetted forest and 166,374ha of a 5 kilometers (km) buffer zone around the gazetted forest (Kenya Water Towers Agency, 2020). The gazetted forest is made up of 14 forest blocks, mainly comprised of indigenous forests with a few continuous forest plantations and grassland, while the buffer zone is dominated by agricultural land and human settlement (Kenya Forest Service, 2015; Kenya Water Towers Agency, 2020).

The water tower has an altitude range of 2,000m to 3,365m above sea level at Cheptoket peak. The area receives bimodal rainfall, with long rains occurring from April to June and short rains from July to October. The average yearly rainfall in the water tower ranges from 800 mm in the north to about 1,500 mm in the west, with cool and humid weather conditions. Temperatures range from 14 °C to 30 °C, with July being the coldest month and January the hottest (Kenya Forest Service, 2015). CHWT is a vital watershed area for lake Turkana and Victoria basins as it hosts critical headwaters for rivers Turkwel, Nzoia, and Kerio that drain into the two lakes (Kenya Forest Service, 2015). Cambisols form the major soil group in the water tower, characterized by good drainage, good structure, varied acidity, and high organic matter (OM) content (Kenya Water Towers Agency, 2020).

The water tower is rich in biodiversity, with about 1,296 vascular plant species from 130 families and 608 genera spread across the forest blocks, including 17 endemic species. This flora represents 54.17%, 43.83%, and 18.50% of the Kenyan plant families, genera, and species, respectively (Mbuni et al., 2019). The water tower is home to many fauna, including buffaloes (*Syncerus caffer*), elephants (*Loxodonta africana*), leopards (*Panthera pardus*), black and white Colobus monkeys (*Colobus guereza*), the rare swamp-dwelling sitatunga antelope (*Tragelaphus spekii*), and the near-threatened mountain bongo antelope (*Tragelaphus eurycerus*) (Kenya Forest Service, 2015; Kenya Forestry Research Institute, 2017a). It has attractive recreation sites such as Kipkoboi caves, Kiptaberr mountain, Mtelo campsite, and Muyein waterfalls (Ministry of Environment and Forestry, 2019). Communities living within the water tower include the Cherang'any/Sengwer, Marakwet, Pokot, and Luhya, whose livelihoods are supported by economic activities like farming, wage labor, beekeeping, and small businesses (Mbuni et al., 2020; Rotich, 2019).

2.2. Data collection, image processing, and classification

Satellite imageries and ancillary data were used to examine the historical LULC changes in the study area over 37 years, from 1985 to 2022. The year 1985 was chosen as the baseline for the change detection analysis because it was the year with the best available quality satellite image data close to 1964, the year when Cherangany forest was gazetted as a forest reserve (Kenya Forest Service, 2015), and 2022 was the most recent year for comparison. A subset of Landsat satellite imageries was downloaded from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov/) using the Google Earth Engine (GEE) script. Inbuilt in the script were radiometric, geometric correction, cloud masking, and filling using available same season imagery using Landsat quality assessment band, image subsetting, and mosaicking of the images. For the best comparison of the acquired satellite data for the two time periods, images captured during the dry season were used, which fell on 0 to 90 Julian days (January to March). For 1985, Landsat 4-5 Thematic Mapper (TM) was selected while Landsat 8-9 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) was used for 2022, both at 30m spatial resolution. Images were sourced for path/row 169/059, covering the CHWT fully. To address the challenge of clouds on the imageries, this study used the clouds score algorithm in GEE to mask pixels that had high cloud cover based on Landsat quality image files. The algorithm scores clouds on an image in the value range of 0 to 100, and for this study, a threshold value of 20 was used to mask the cloudy pixels. The masked clouds were replaced with pixels of images in the Landsat archive acquired within the defined 0-90 day Julian period.

Pixel-based supervised classification was executed using the Random Forest (RF) classifier in R-Studio using the packages; snow, maptools, sf, randomforest, raster, rgdal and lwgeom. The advantage of using RF over maximum likelihood is the ability to limit overfitting without substantially increasing error due to bias. Running RF in R-Studio is faster, easier to integrate validation data, and generates a confusion matrix within the model (Shelestov et al., 2017). Visual interpretation of high resolution (<1.5m) Google Earth images, as well as the use of secondary data,

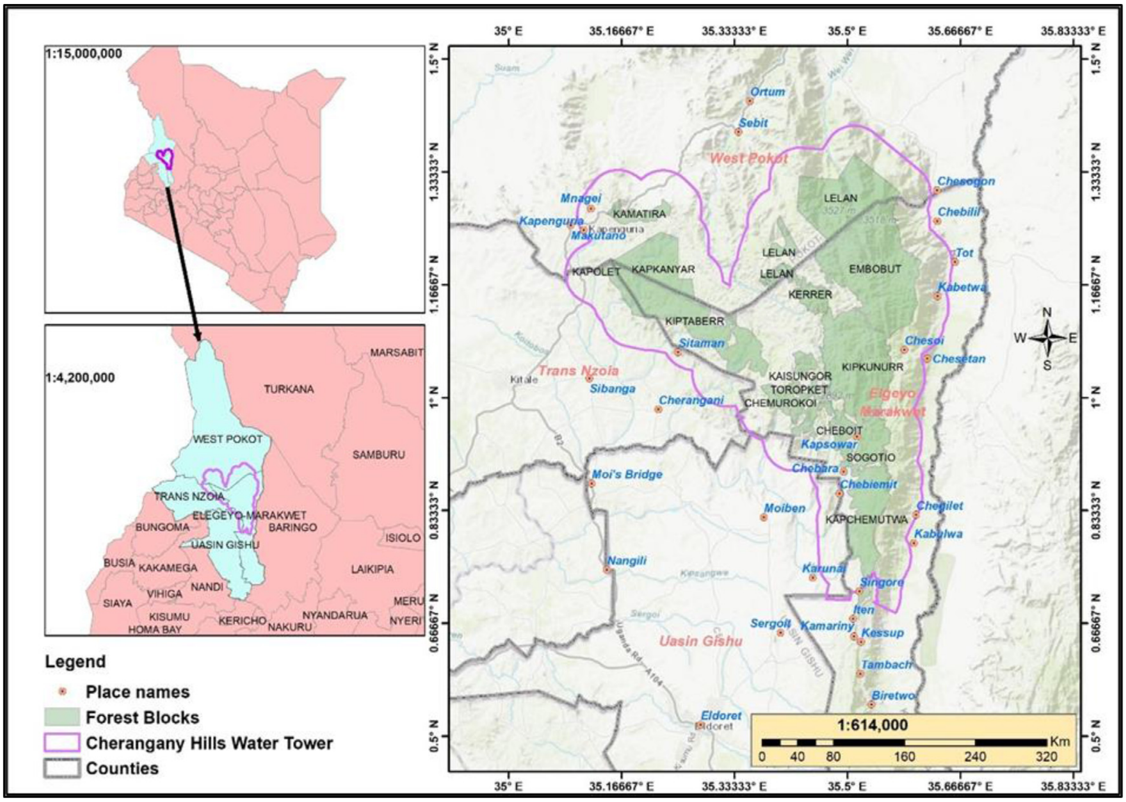

Fig. 1. Map of Cherangany Hills Water Tower, Kenya.

Table 1
The number of training samples used for LULC classification.

LULC types	1985 Polygons	Training Pixels	2022 Polygons	Training Pixels
Forest	16	400	22	400
Cropland	19	400	43	400
Grassland	31	200	34	200
Water bodies	4	200	3	400
Bareland	5	200	22	200
Built-up area	2	100	5	100
Total	**77**	**1500**	**129**	**1700**

guided digitization of polygons used as training sites for the LULC classes defined using the national classification scheme, modified from the Intergovernmental Panel on Climate Change (IPCC) classification scheme as shown in Table 2 (Intergovernmental Panel on Climate Change, 2003; Kenya Forest Service, 2021) . In total, 1500 pixels were collected for 1985 and 1700 pixels for 2022 as training samples. The training samples were determined using a user-defined number of pixels based on the proportion of the polygons per landcover class as provided in Table 1. The samples were then used to train the classifier using the stratified random sampling method. The validation samples were interpreted visually on the composite Landsat images and Google Earth high-resolution images.

To determine the accuracy of the landcover classification, a random stratified sample of an equal number of pixels (as provided for the training pixels in Table 1) was applied in each stratum (landcover class) and a confusion matrix was generated. The metrics used to assess the accuracy were the Kappa coefficient, user and producer error matrices. Six LULC types were identified and classified based on Kenya's national level LULC classification approach domesticated from the IPCC classification guidelines of 2003 (Intergovernmental Panel on Climate Change, 2003; Kenya Forest Service, 2021). The classes comprised cropland, forest, grassland, bareland, built-up area, and water bodies as described in Table 2.

In order to determine LULC changes between 1985 and 2022, change detection was carried out by converting the classified land cover images to polygons for each year and overlay analysis carried out in the GIS environment. The output was a change matrix with land cover transitions. The area in hectares for each land cover conversion was then computed and a LULC transition map generated.

The data processing workflow is shown in Fig. 2.

2.3. Ecosystem services value estimation

This study used the BTA to estimate the study area's ESVs due to the lack of local-level data (Costanza et al., 1997; Hu et al., 2008; Richardson et al., 2015). Numerous studies have used a similar approach through the benefit transfer method, which refers to the process of utilizing existing values from an original research to estimate the ESVs of other similar locations in the absence of site-specific valuation data (Gashaw et al., 2018; Kindu et al., 2016; Munthali et al., 2022; Rai et al., 2018; Sharma et al., 2019; Talukdar et al., 2020; Temesgen et al., 2018; Tolessa et al., 2017). Modified conservative local value coefficients developed for 9 biomes by Kindu et al. (2016) were adopted for this study to determine ESVs due to the unavailability of historical data for our study area and the high cost of ground data

Table 2
Land use and land cover types in the CHWT as per the national LULC classification scheme (Kenya Forest Service, 2021).

LULC type	Description
Forest	Land area more than 0.5ha dominated by trees greater than 2m in height, with a crown cover greater than 15%
Cropland	Tilled land and land under cultivation of crops
Grassland	Areas with temporary or permanent grass cover
Water bodies	Watercourses including rivers, streams, wetlands, and dams
Bareland	Areas without vegetation covered by rocks, rough roads, or degraded lands
Built-up area	Land dominated by houses, huts, paved roads, and industrial facilities

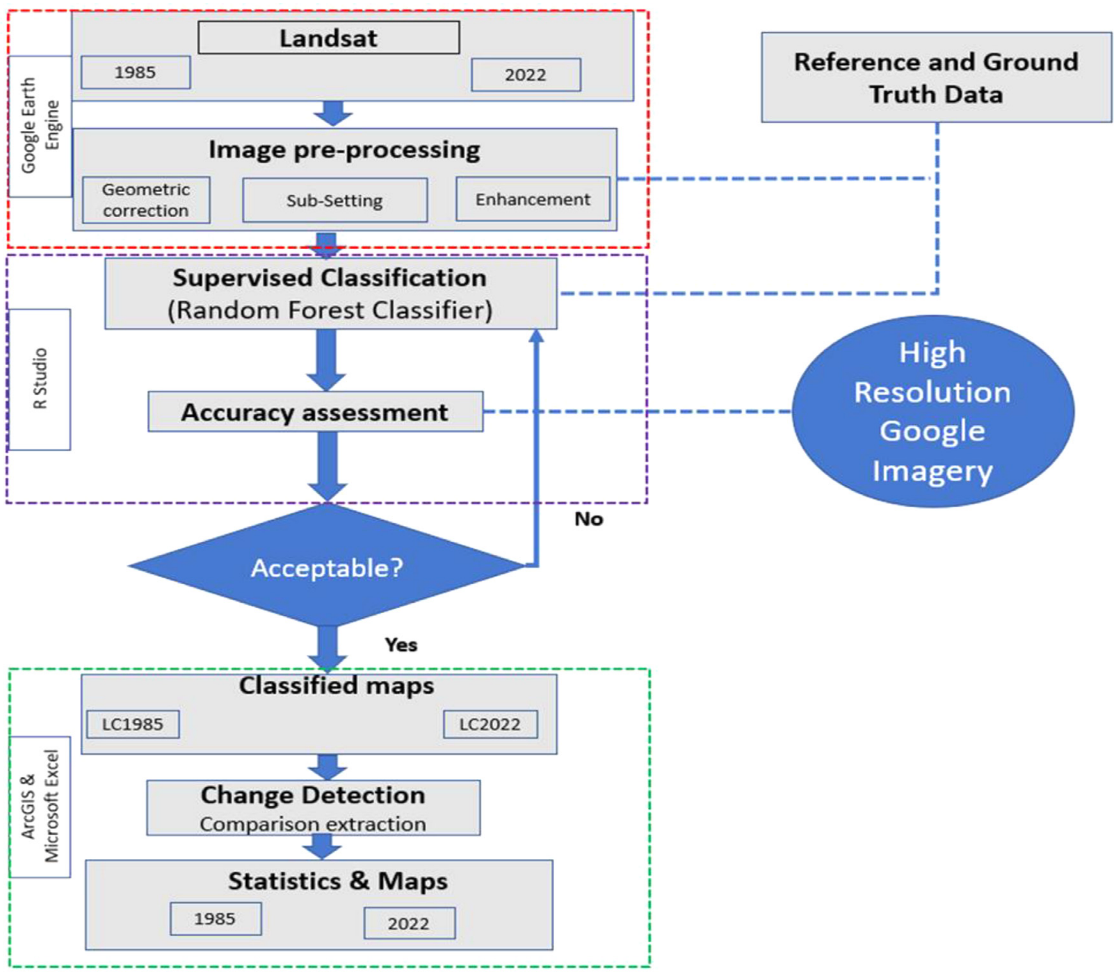

Fig. 2. Data processing workflow.

collection. These more locally valid coefficients (Kindu et al., 2016) were preferred to the often used global coefficients (Costanza et al., 1997) since our study area is within the same geographic location (East African Great Rift Valley), with similar market values, climatic conditions (mean annual rainfall of 1500mm, with a bimodal pattern), and topographic conditions (montane forested highland peaking at 3365m asl) (Kenya Forest Service, 2015; Kenya Water Towers Agency, 2020; Kindu et al., 2016, 2013). Additionally, Costanza et al's. (1997) unit values for a particular good were derived based on an assumption that the average unit value throughout all locations of that good was homogeneous, which may not be the case in reality (Kindu et al., 2016). Comparably, the coefficients developed by Kindu et al. (2016) has been widely utilized by other researchers to estimate ESVs and compute ESV changes following LULC changes in data scarce African countries including Ethiopia (Alebachew et al., 2022; Gashaw et al., 2018; Shiferaw et al., 2021), Tanzania (Msofe et al., 2020), and Malawi (Munthali et al., 2022). Kindu et al. (2016) modified the coefficients from those employed by Costanza et al. (1997) through a benefit transfer method using expert knowledge of the study landscape conditions and other studies, mainly from TEEB valuation database which comprised more than 1300 original values compiled mainly based on local studies across the globe (Van der Ploeg et al., 2010) and (Knoke et al., 2011). To ensure the applicability of the data from TEEB valuation database, Kindu et al. (2016) considered only values from tropical areas of similar LULC types to their landscape. The value coefficients were then adjusted using the consumer and producer price indices to check the effect of time development in the coefficients on the overall estimation of ESV changes (Kindu et al., 2016). The global coefficient values (Costanza et al., 1997) on the other hand were estimated from the then economic value of 17 ecosystem services for 16 biomes, based on a few original calculations and published studies hence the descrepancies in the coefficient values between the two pioneering studies (Costanza et al., 1997).

The modified coefficients by Kindu et al. (2016) notably have lower coefficient values for forest biomes and water bodies and higher coeffi-

Table 3
Six LULC types in the study area, their equivalent biomes, and ecosystem service coefficients based on the modified estimates (Kindu et al., 2016) and global coefficient values (Costanza et al., 1997).

LULC type	Equivalent biome Kindu et al., 2016	Costanza et al., 1997	Ecosystem serviceCoefficient (USDha^{-1} year^{-1}) Kindu et al., 2016	Costanza et al., 1997
Forest	Tropical Forest	Tropical Forest	986.69	2007
Cropland	Cropland	Cropland	225.56	92
Grassland	Grassland	Grass/rangelands	293.25	232
Water bodies	Water	Lakes/rivers	8103.5	8498
Bareland	Bareland	Desert	0	0
Built-up area	Urban	Urban	0	0

Table 4
Ecosystem service functions and their adopted modified value coefficients (USD ha^{-1} year^{-1}) for each of the six LULC types (Kindu et al., 2016).

Ecosystem services	Biome Tropical Forest	Cropland	Grassland	Water	Bareland	Urban
Provisioning services						
Water supply	8			2117		
Food production	32	187.56	117.45	41		
Raw material	51.24					
Genetic resources	41					
Regulating services						
Water regulation	6		3	5445		
Water treatment	136		87	431.5		
Erosion control	245		29			
Climate regulation	223					
Biological control		24	23			
Gas regulation	13.68		7			
Disturbance regulation	5					
Supporting services						
Nutrient cycling	184.4					
Pollination	7.27	14	25			
Soil formation	10		1			
Habitat/refugia	17.3					
Cultural services						
Recreation	4.8		0.8	69		
Cultural	2					
Total	**986.69**	**225.56**	**293.25**	**8103.5**	**0**	**0**

cient values for cropland and grassland in comparison to Costanza et al's. (1997) global coefficient values (Table 3). Six LULC classes from our study were identified then compared with their corresponding equivalent biomes (Table 3), where the most representative biomes were used as a proxy for each LULC type, including 1) Tropical Forest for Forest, 2) Cropland for Cropland, 3) Grassland for Grassland, 4) Urban for Built-up area, 5) Water for Water bodies and 6) Bareland for Bareland.

Similarly, modified conservative annual value coefficients for the ecosystem service functions of each LULC type by Kindu et al. (2016) were used for this study (Table 4).

The LULC data for each reference year was prepared, and their corresponding area in hectares was calculated in a GIS environment. The value coefficients were then assigned to each LULC type based on the values of the modified coefficients Table 3). We calculated ESVs and changes using equations (Equations 1-(3) derived from the model proposed by Costanza et al. (1997) and further modified by Kreuter et al. (2001), Hu et al. (2008), Gashaw et al. (2018) and Kindu et al. (2016). The total ESV for each LULC type was obtained by multiplying the area of each LULC type with its corresponding value coefficient. The values for the LULC types for each year were then summed up to estimate the total ESV of the water tower for each year, as shown in equation 1 (Hu et al., 2008; Kindu et al., 2016; Kreuter et al., 2001).

$$\mathrm{ESV} = \sum \left(\mathrm{A}_k \times \mathrm{VC}_k\right) \qquad \text{(Equation 1)}$$

where ESV = total estimated ecosystem service value, A_k = the area (ha) and VC_k = the value coefficient (USD ha^{-1} year^{-1}) for LULC type 'k'.

The values of services provided by individual ecosystem functions within the study area were also estimated using equation 2 (Gashaw et al., 2018; Kindu et al., 2016; Tolessa et al., 2017).

$$\mathrm{ESVf} = \sum \left(\mathrm{A}_k \times \mathrm{VC}_{fk}\right) \qquad \text{(Equation 2)}$$

Where ESV_f = calculated ecosystem service value of function 'f', A_k =the area (ha) and VC_{fk} = value coefficient of function 'f' (USDha^{-1} year^{-1}) for LULC type 'k'.

The changes of ESVs over time were calculated in USD and percentages from the difference between the estimated values in each reference year and presented in a table (Table 8). The percentage changes in ESVs were calculated by comparing the values of the last and first years, as shown in equation 3 (Gashaw et al., 2018; Kindu et al., 2016; Li et al., 2019).

$$Percentage\ ESV\ change = \left(\frac{ESV\ final\ year - ESV\ initial\ year}{ESV\ initial\ year}\right) \times 100 \qquad \text{(Equation 3)}$$

3. Results

3.1. LULC classification accuracy

The overall classification accuracy, Kappa coefficient, user and producer error matrices for different LULC classes for 1985 and 2022 were calculated and presented in Tables 5a and 5b, respectively. The LULC map from 1985 had an overall classification accuracy of 97.6% with a corresponding Kappa coefficient of 0.97, whereas the LULC map for the year 2022 had an overall accuracy of 92.5% with a Kappa coefficient of

Table 5a
Accuracy assessment for the year 1985.

Reference data ClassifiedData	Forest	Cropland	Grassland	Waterbodies	Bareland	Built-upareas	Total	User accuracy
Forest	**394**	4	1	1	0	0	400	0.99
Cropland	3	**386**	7	0	4	0	400	0.97
Grassland	1	8	**188**	0	2	1	200	0.94
Water bodies	0	0	1	**199**	0	0	200	1.00
Bareland	0	0	3	0	**197**	0	200	0.99
Built-up areas	0	0	0	0	0	**100**	100	1.00
Total	398	398	200	200	203	101	**1500**	
Producer accuracy (%)	0.99	0.97	0.94	1.00	0.97	0.84		

Overall accuracy = 97.6%, Kappa Coefficient = 0.97.

Table 5b
Accuracy assessment for the year 2022.

Reference data ClassifiedData	Forest	Cropland	Grassland	Waterbodies	Bareland	Built-upareas	Total	User accuracy
Forest	**384**	4	11	1	0	0	400	0.96
Cropland	7	**353**	24	0	16	0	400	0.88
Grassland	19	25	**153**	0	2	1	200	0.77
Water bodies	0	0	0	**400**	0	0	400	1.00
Bareland	0	10	0	0	**190**	0	200	0.95
Built-up areas	0	4	0	0	4	**92**	100	0.92
Total	410	396	188	401	212	93	**1700**	
Producer accuracy (%)	0.94	0.89	0.81	1.00	0.90	0.84		

Overall accuracy = 92.5%, Kappa Coefficient = 0.91.

Table 6
LULC classification results and area changes from 1985 and 2022 in the CHWT.

	1985		**2022**		**Area change (1985-2022)**		
LULC type	Area (ha)	(%)	Area (ha)	(%)	Ha	%	Annual change rate (ha)
Forest	77400.4	29.34	67047	25.42	-10353.4	-13.38	-279.82
Cropland	95392	36.16	130473.9	49.46	35081.9	36.78	948.16
Grassland	78488.8	29.76	56307.5	21.35	-22181.3	-28.26	-599.49
Water bodies	39.2	0.01	54.9	0.02	15.7	40.05	0.42
Bareland	12254.3	4.65	9295.4	3.52	-2958.9	-24.15	-79.97
Built-up area	196.4	0.08	592.4	0.22	396	201.63	10.70
Total	**263771.1**	**100**	**263771.1**	**100**			

0.91. These results are within the acceptable range, hence we proceeded and used the classification output for the estimation of the ESVs of the different LULC classes (Kindu et al., 2013; Landis and Koch, 1977).

3.2. LULC spatial distribution patterns

The six LULC types in CHWT from 1985 and 2022 were mapped, and their spatial distribution patterns displayed (Fig. 3). In 1985, cropland represented the dominant LULC type, covering about 36.16% of the total land area in the water tower. The areas under grassland and forest were equally significant, as they covered 29.76% and 29.34% of the study area, respectively. In contrast, the remaining LULC types (built-up areas, water bodies, and bareland) made up only 4.74% of the total land area of the water tower (Table 6). By the year 2022, there were variations in the spatial distribution patterns as the proportion of cropland had increased to 49.46%. Forest and grassland covered lesser areas (25.42%) and (21.35%), respectively, while the combined area covered by water bodies, built-up, and bareland was a meagre (3.76%).

3.3. Land use land cover changes

Between 1985 and 2022, areas under cropland, water bodies, and built-up zones increased, whereas forest, grassland, and bareland areas diminished. Croplands expanded the most by 35,081.9ha, while grassland (-22,181.3ha) and forest (-10,353.4ha) experienced a significant reduction in their total land area (Table 6). Built-up areas showed the highest expansion percentage (202%). However, this high percentage increase of the built-up class does not mean houses and roads covered a large land area, but it is instead the relative proportion of increment of the LULC type observed over the 37 years. As for the mean annual area gains and losses rates, cropland areas had the highest average yearly expansion at approximately 948.16 ha/year, while grassland reduced the most annually by around 600 ha/year. Water bodies exhibited the least positive mean annual change rate at 0.42 ha/year, while bareland decreased the least annually by 79.97ha/year.

3.4. LULC transitions

Over the 37 years, there were several conversions from one LULC type to another in CHWT. The respective LULC transitions in the study area are presented in Table 7.

A considerable chunk of the forestland was converted to grassland (11,793.4ha) and cropland (9,539ha), respectively. Around 53% (41,836.3ha) of the grassland and 56% (6,837.5ha) of the bareland were also converted to cropland in the CHWT over the study period. Therefore, it is evident that the highest share of conversions within the grassland, bareland, and forest classes in the water tower was towards croplands. Overall, in the 37 years of this study, approximately 13% of the total landmass in the CHWT was converted to cropland. This shows that key transitions in the CHWT are mainly attributed to agricultural activities.

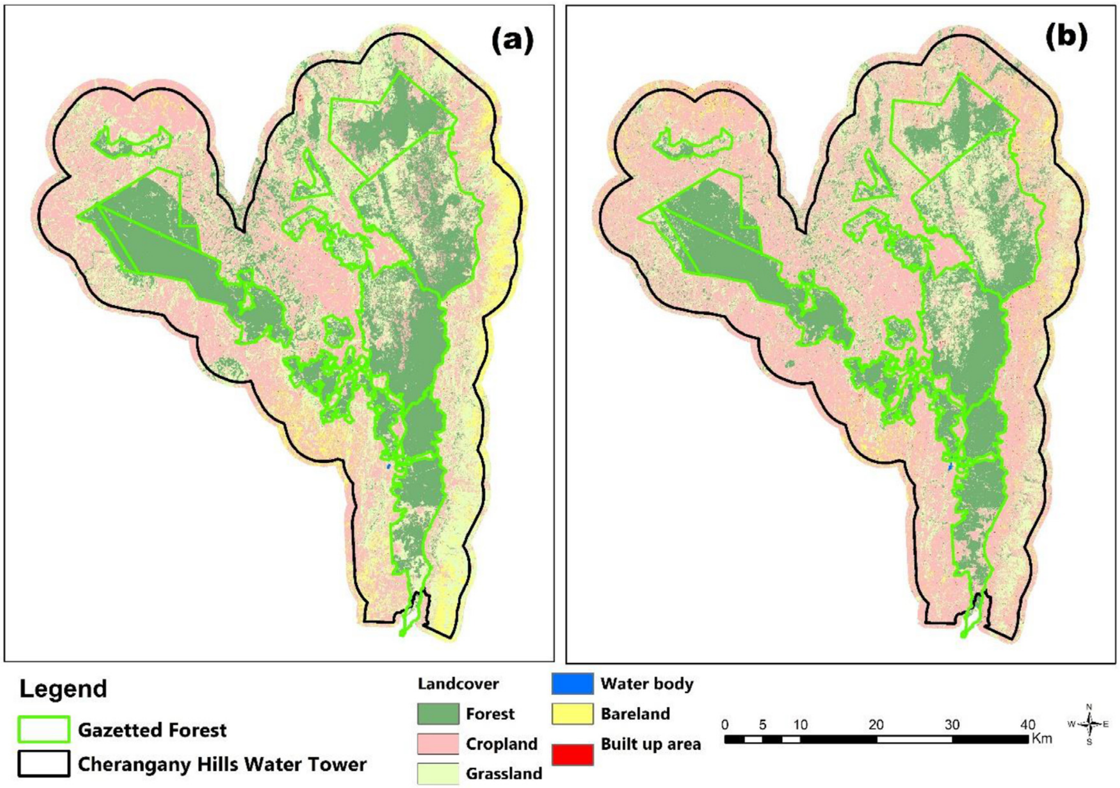

Fig. 3. LULC maps of the CHWT from 1985 (a) and 2022 (b).

Table 7
Transition matrix showing LULC changes (ha) in the water tower between 1985 and 2022.

	LULC type	**2022** Forest	Cropland	Grassland	Waterbodies	Bareland	Built-up areas	**Grand Total**
1985	Forest	**55944.1**	9539.0	11793.4	10.8	100.8	12.3	**77400.4**
	Cropland	3469.6	**72135**	13557.5	2.6	5872.2	355.1	**95392**
	Grassland	7593.9	41836.3	**27713.7**	13.9	1177	154	**78488.8**
	Water bodies	9.9	1.1	0.7	**27.5**	0	0	**39.2**
	Bareland	29.1	6837.5	3221.1	0.1	**2104.3**	62.2	**12254.3**
	Built-up areas	0.4	125.0	21.1	0	41.1	**8.8**	**196.4**
	Grand Total	**67047**	**130473.9**	**56307.5**	**54.9**	**9295.4**	**592.4**	**263771.1**

A detailed scrutiny of the spatial distribution of these transitions (Fig. 4) shows that forestland in the southern mid-high slopes of Chebiemit, Kaptum, and Kendur locations exhibited vast conversions to croplands. A similar observation was made in forested areas on low to mid slopes around Yemit and Kabtabuk locations and in the western regions bordering the Kapolet and Kamatira forest blocks. The eastern forest blocks of Lelan, Embobut, and Kipkunurr also exhibited conversion of forestland to grassland.

3.5. Estimation of ecosystem services values, distribution, and changes

The estimated ESVs and percentages from 1985 and 2022 for each LULC type were calculated and summarized in Table 8. Negative values depict a decrease in ESV while positive values indicate an increase in ESV (Li et al., 2007; Ligate et al., 2018).

The total ESV of the water tower was estimated at 121.22 million USD for 1985 and 112.54 million USD for 2022. This signifies an overall decline in the total ESV by 8.68 million USD (-7.16%). As for the individual LULC types, the forest had the greatest contribution to the total ESV in 1985 at 63% (76.37 million USD), followed by grassland, which made up 18.99% of the total ESV (23.01 million USD), cropland made 17.75% of the total ESV (21.52 million USD), and water bodies had the least contribution of 0.26% (0.32 million USD). In 2022, forest accounted for 58.78% of total ESV (66.15 million USD), cropland 26.15% (29.43 million USD), and grassland 14.67% (16.51 million USD), with water bodies accounting for the smallest percentage of the total ESV at 0.40% (0.45 million USD). According to Costanza et al. (1997), built-up area and bare land do not provide any ES hence the nil valuation for these biomes for our study area.

The spatial distribution of ESVs for the years 1985 and 2022 in the CHWT is shown in Fig. 5. From ESV maps, it is evident that the ESV distribution in 1985 was high in the sections of the study area within the gazzeted forest blocks due to the presence of forest and water bodies. The eastern border of the study area (Tot, Kabetwa and Chesoi) had low ESV as a result of the barelands. In 2022, there is a visible reduction of ESV in the northern and central parts of the water tower comprising the Lelan, Embobut, and Kipkunurr forest blocks, mostly due to encroachment and conversion of forestland to grassland. The 5km buffer zones (Mnagei, Sitaman, and Chebara) also exhibited a slight increase in ESV in 2022 due to the expansion of cropland areas over the study period.

Over the 37 years, there were notable changes in the areas of individual LULC types, which contributed to changes in their ESVs and an

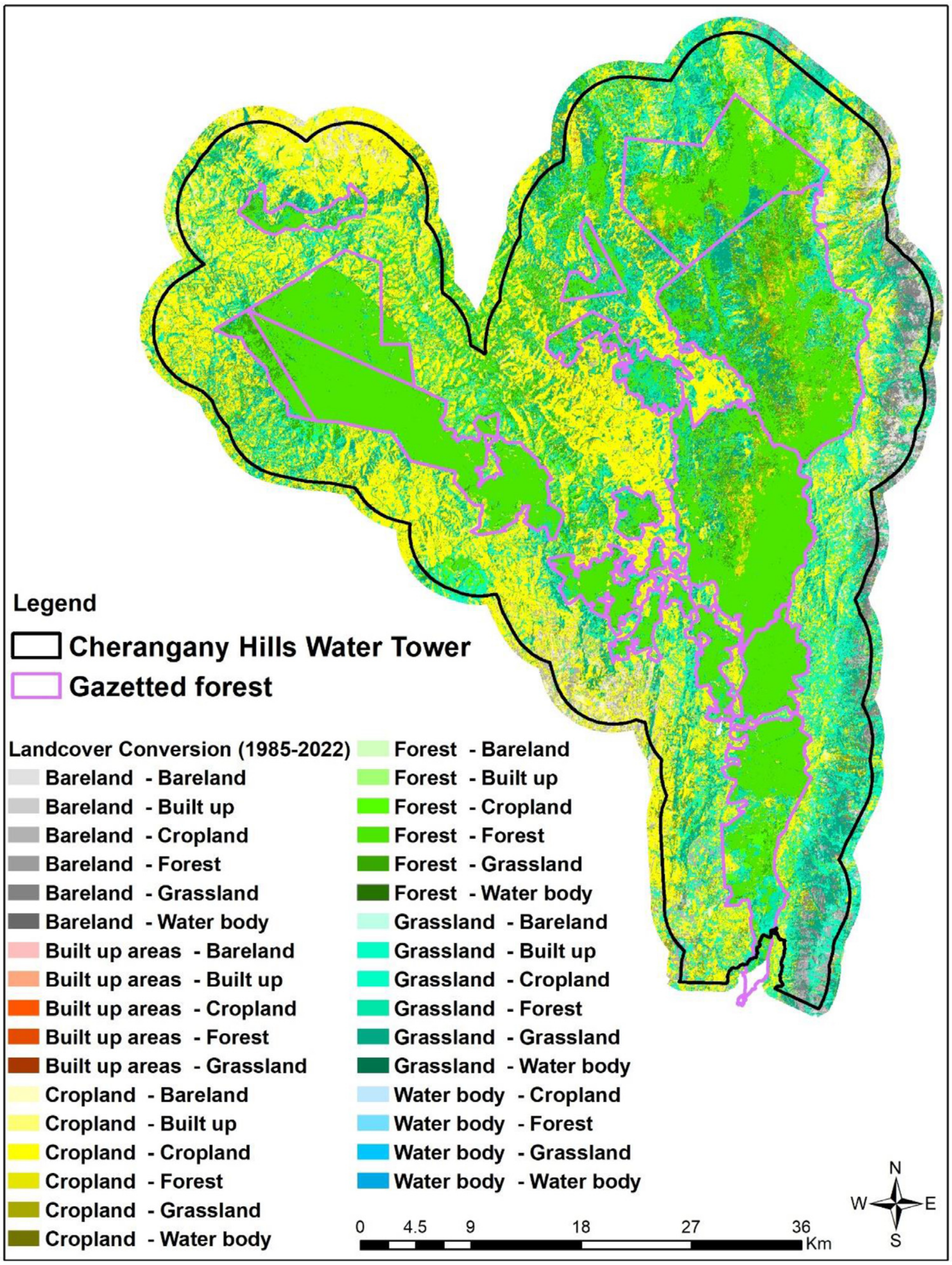

Fig.4. LULC transition map of the CHWT (1985-2022).

overall change in the total ESV of the water tower. Forest and grassland registered losses in their ESVs by 10.22 million USD (-13.38%) and 6.50 million USD (-28.26%), respectively. On the other hand, there were gains in the ESV for cropland by 7.91 million USD (36.78%) and 0.13 million USD (40.05%) for water bodies. Fig. 6 visualizes the percentage and monetary ESV changes for the different LULC types between 1985 and 2022 in the CHWT.

The annual individual ES for the two reference years and their respective changes were also estimated, and their values summarized (Table 9).

Regulating services were the dominant ES offered by the water tower, followed by provisioning services, supporting services, and cultural services in that order for both years (Fig. 7). The top three contributors to the total ESV of the 17 individual ES in the study area for the year 1985 included food production (29.59 million USD/year), erosion control (21.24 million USD/year), and water treatment (17.37 million USD/year). In 2022, food production (33.23 million USD/year) was the top-ranking individual ES from the water tower, followed by erosion control (18.06 million USD/year) and climate regulation (14.95 million USD/year). Regarding individual ES changes, 15 of the 17 ES registered negative changes in their ESVs between the two years, with water treatment (-3.33 million USD/year) and erosion control (-3.18 million USD/year) diminishing the most. The two ES with positive changes in their ESVs included food production (3.64 million USD/year) and biological control (0.34 million USD/year). Generally, there were losses in regulating services (-14.12%), supporting services (-11.56%), and cultural services (-15.25%), while provisioning services increased by 7.05% between 1985 and 2022 (Table 9).

4. Discussion

4.1. Land use land cover changes

The CHWT underwent several LULC changes over the study period, with a notable increase in areas under cropland, built-up areas, and wa-

Table 8
Ecosystem Service Values (Million USD) and percentages for each LULC type in 1985 and 2022 in the CHWT.

LULC type	1985 ESV	%	2022 ESV	%	1985-2022 ESV change	% Change
Forest	76.37	63.00	66.15	58.78	-10.22	-13.38
Cropland	21.52	17.75	29.43	26.15	7.91	36.78
Grassland	23.01	18.99	16.51	14.67	-6.50	-28.26
Water bodies	0.32	0.26	0.45	0.40	0.13	40.05
Bareland	0	0	0	0	0	0
Built-up area	0	0	0	0	0	0
Total	**121.22**	**100**	**112.54**	**100**	**-8.68**	**-7.16**

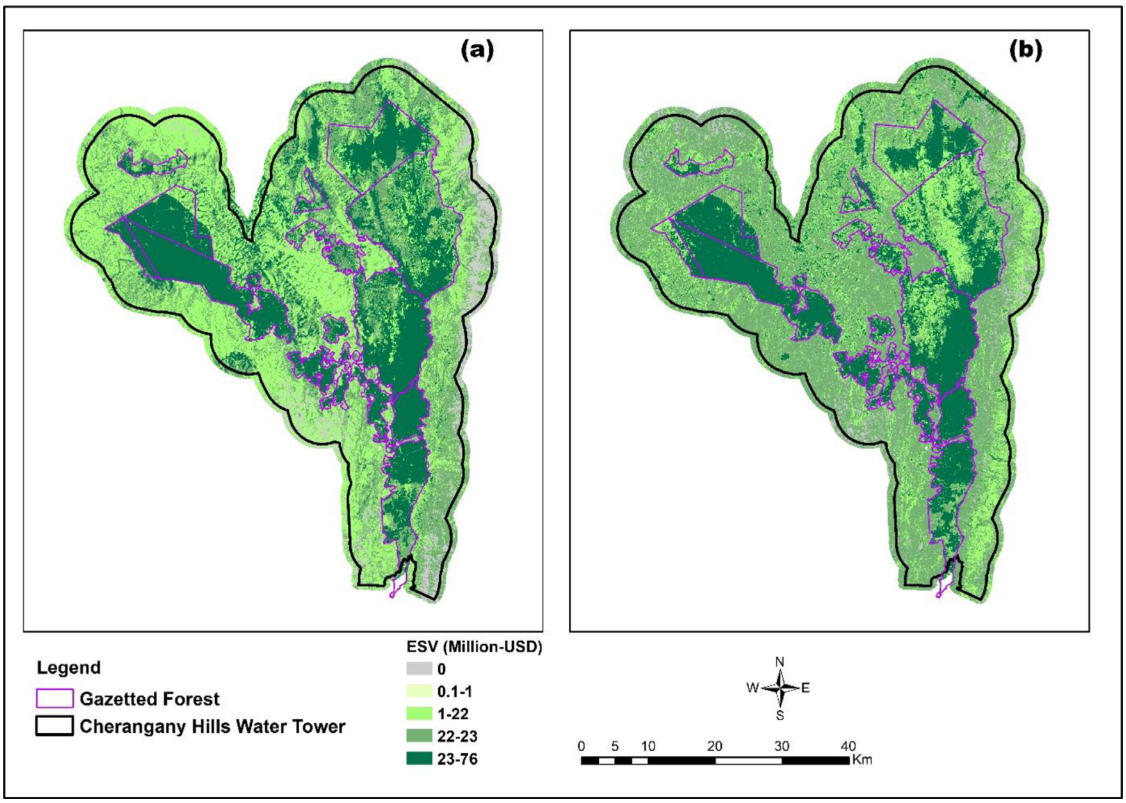

Fig. 5. Spatial distribution of ESVs in the CHWT for 1985 (a) and 2022 (b).

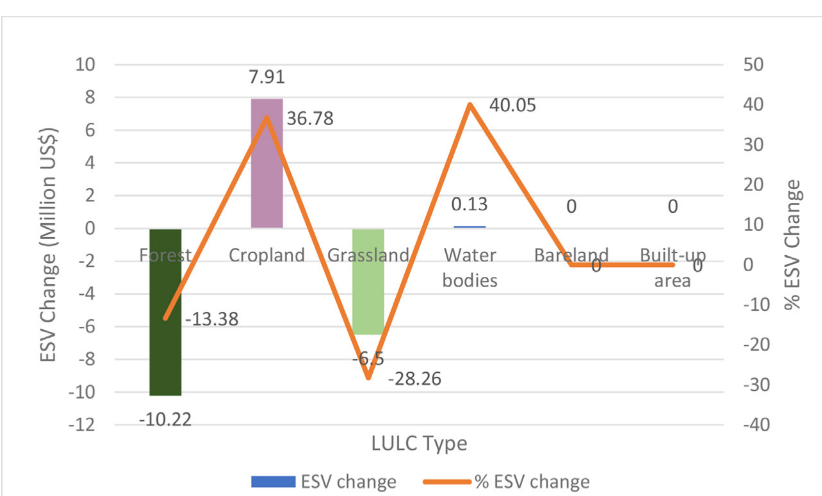

Fig. 6. Changes in ESVs (% and Million USD) for each LULC type between 1985 and 2022.

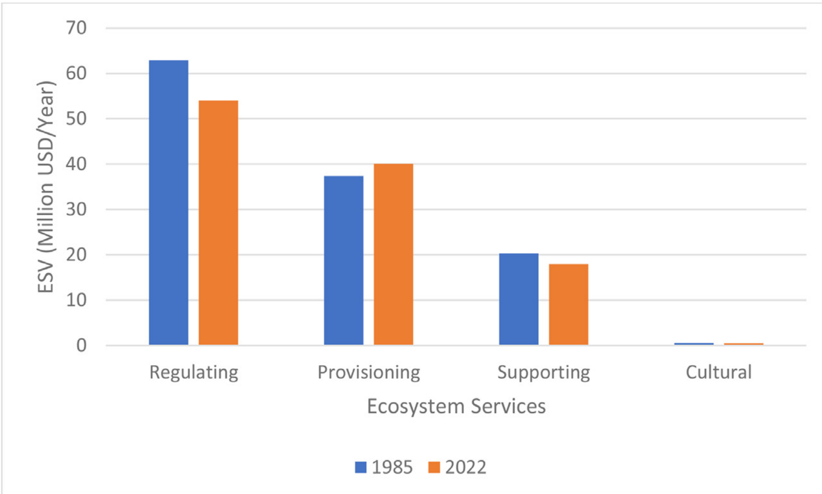

Fig. 7. Bar chart showing the four categories of individual ecosystem services (1985 and 2022).

Table 9
The estimated annual value and changes of individual ecosystem services (ESV in million USD per year).

	Ecosystem services	ESV 1985	ESV 2022	Change	% Change
1	**Provisioning services**				
	Water supply	0.70	0.65	-0.05	-7.14
	Food production	29.59	33.23	3.64	12.30
	Raw material	3.97	3.44	-0.53	-13.35
	Genetic resources	3.17	2.75	-0.42	-13.25
	Sub total$_1$	***37.43***	***40.07***	***2.64***	***7.05***
2	**Regulating services**				
	Water regulation	0.91	0.87	-0.04	-4.40
	Water treatment	17.37	14.04	-3.33	-19.17
	Erosion control	21.24	18.06	-3.18	-14.97
	Climate regulation	17.26	14.95	-2.31	-13.38
	Biological control	4.09	4.43	0.34	8.31
	Gas regulation	1.61	1.31	-0.30	-18.63
	Disturbance regulation	0.39	0.34	-0.05	-12.82
	Sub total$_2$	***62.88***	***54.00***	***-8.88***	***-14.12***
3	**Supporting services**				
	Nutrient cycling	14.27	12.36	-1.91	-13.38
	Pollination	3.86	3.72	-0.14	-3.63
	Soil formation	0.85	0.73	-0.12	-14.12
	Habitat/refugia	1.34	1.16	-0.18	-13.43
	Sub total$_3$	***20.32***	***17.97***	***-2.35***	***-11.56***
4	**Cultural services**				
	Recreation	0.44	0.37	-0.07	-15.91
	Cultural	0.15	0.13	-0.02	-13.33
	Sub total$_4$	***0.59***	***0.5***	***-0.09***	***-15.25***
	Total	**121.22**	**112.54**	**-8.68**	

ter bodies while forest, grassland, and bareland classes decreased. Our findings are in tandem with that of the Kenya Water Towers Agency. (2020), which showed a contraction of forest and grassland and a subsequent increase in cropland over 29 years from 1990 to 2019 in the study area. The loss of forest cover and grassland in the CHWT is triggered by a number of direct and indirect drivers. The direct drivers comprise encroachment into the forestland by the surrounding communities for farming, overgrazing, illegal logging of timber, charcoal production, unsustainable harvesting of firewood and building poles, forest excisions for settlement and farming, forest fires, and climate change (Kenya Water Towers Agency, 2020; Ministry of Forestry and Wildlife, 2013; Rotich and Ojwang, 2021). Indirect drivers of forest and grassland losses in the study area include population growth, which increases the demand for agricultural land for food production, poor implementation of existing forest and land use policies, limited institutional capacity for effective forest management and monitoring, and integrity issues among some officials in charge of forest management (Kogo et al., 2019; Ministry of Environment and Forestry, 2020; Rotich and Ojwang, 2021).

Similar forest cover loss trends have also been observed in the other prominent water towers of Kenya, including the Mau forest complex (Jebiwott et al., 2021; Ongong and Sweta, 2014), Mount Elgon (Masayi et al., 2021; Mugagga et al., 2012), Mount Kenya (Willkomm et al., 2016) and Aberdare ranges (Akotsi et al., 2006). According to Brink and Eva. (2009), the Sub-Saharan African region lost 16% of its forests and 5% of its open woodlands and bushlands between 1975 and 2000, while agricultural land increased by 55%. Most of the grassland areas within the water tower were also converted to cropland at an alarming average annual rate of about 600 ha/year. The grasslands mostly occupy the buffer zones around the forest; thus, their proximity to the forest and the fertile nature of the soils within the grasslands make them prone to conversion to cropland for food production (Kenya Forestry Research Institute, 2017b). The vast and rapid (948.16ha/year) expansion of cropland can be linked to population growth in the water tower, which leads to a demand for more land for food production to meet the population's needs. Rotich and Ojwang. (2021) report a 78.4% rise in the human population in the study area in just three decades from 1989 to 2019. This is affirmed by the upsurge in built-up areas (201.63%) observed in the water tower over the 37 years (Table 6). These findings corroborate with that by Odawa and Seo. (2019) in the Mau water tower in Kenya, over a 29-year study period (1986-2015). They found out that population growth resulted in massive LULC changes in the water tower, as farmers living around the 5 km forest buffer zone expanded their agricultural lands through their dynamic and extensive agricultural activities.

A historical LULC change analysis in East Africa from 1998 to 2017 also showed a 34.8% increase in the area under cropland at the expense of natural habitats (open forests, open grasslands, and wooded grasslands), resulting in a large-scale reduction of the woody vegetation classes (Bullock et al., 2021). A study in the Northeast China by Wang et al. (2015), further revealed an expansion of croplands at the expense of grassland and marginal forests. This expansion was linked to population growth and accompanying food requirements, which caused land degradation and the decline of ecosystem services. All the above studies underline the adverse impacts of cropland expansion on natural habitats.

Land use conversions in CHWT have resulted in the loss of grassland and forest, which play a critical role in carbon sequestration. If the trend continues, it could further exacerbate climate change and its associated impacts in the study area. Mwangi et al. (2020) report a rise in temperature by 0.3°C to 0.5°C per decade in the water tower from the years 1981 to 2010, with a projected rise of between 3.0°C to 3.5°C by the year 2050. This might have detrimental implications on the vast flora and fauna found within the CHWT and the capacity of the water tower to provide ES. Our analysis revealed that conversions of grassland and bareland to cropland mainly occurred in the mid slopes on the eastern and southwestern parts of the water tower. This information is helpful to the authorities as it can help guide conservation and restoration initiatives and mitigate further unsustainable LULC changes in CHWT in the future.

The increase in water bodies in the CHWT can be ascribed to the construction of a dam (Chebara dam) within the water tower in the year 1997 to supply water to Eldoret town. The dam supplies about 24,000 cubic meters (m^3) of water daily to Eldoret town (Kenya Water Towers Agency, 2020).

4.2. Changes in the total ecosystem service value

LULC change has been recognized as a key driver in altering ecosystems and their services (Kindu et al., 2016; Lin et al., 2018; Muleta et al., 2021). Different development priorities and management options can substantially impact the LULC and ES (Hernández-Blanco et al., 2020). Significant LULC changes in the CHWT were the decrease in forest and grassland, with a consequent increase in cropland. Overall, there was a 7.16% reduction in the total ESV in the water tower from an estimated value of 121.22 million USD in 1985 to 112.54 million USD in 2022. This loss can be attributed to the substantial decrease in the ESVs of forest and grassland proportionate to their respective LULC losses over the study period. The coefficients of the ecological value of forest are relatively high (986.69 USDha^{-1} year^{-1}) compared to the other land classes (Table 3), only second to water bodies; thus, the reduction in the forest cover over the 37 years negatively impacted the total ESV.

Our results are in line with the findings of other researchers from different parts of the world, including Ethiopia (Alebachew et al., 2022; Gashaw et al., 2018; Kindu et al., 2016; Muleta et al., 2021; Shiferaw et al., 2021), China (Hu et al., 2008; Wang et al., 2015), Bangladesh (Rahman and Szabó, 2021), Tanzania (Msofe et al., 2020), Nepal (Sharma et al., 2019) and a transboundary landscape in Asia (Gu et al., 2021), who report a significant negative contribution of forest losses to the total ESV. On the other hand, an increase in forest area over time positively contributes to the total ESV and enhances ES supply (Hou et al., 2021; Paudyal et al., 2019; Wang et al., 2014; Yuan et al., 2019; Zhao et al., 2022). Our findings, therefore, underscore the crucial role of forests in determining the total ESV of a given ecosystem.

Despite the vast expansion of cropland (36.78%) in the study area between the two years, its low coefficient equivalent value per unit area meant its ESV could not offset the deficit created due to forest and grassland ESV losses. The small area covered by water bodies in comparison to the other LULC types also meant that its contribution to the total ESV was marginal despite its enormous coefficient equivalent value. Table 10 summarises the findings of select studies across the globe and further highlights the impacts of individual LULC type changes on the total ESVs.

4.3. Changes in individual ecosystem services values

Regulating services were the dominant ES in the water tower, followed by provisioning services, supporting services, and cultural services, respectively, for both study years (Fig.7). These findings are comparable to a similar study conducted in the water tower in terms of the relative contributions of the four categories to the total ESV (Langat, et al., 2021). Regulating services had the most outstanding contribution to the total ESV at 73%, provisioning services contributed 23%, supporting services 3%, while cultural services made up 1% of the total ESVs (Langat, et al., 2021). Three out of the four main categories of the individual ecosystem services (regulating services, supporting services, and cultural services) experienced a reduction in their ESVs while provisioning services ESV increased between 1985 and 2022. The gain in the provisioning services ESV was primarily contributed to by increased food production due to cropland expansion. Other researchers have reported similar positive contribution of increased cropland on provisioning services (Mengist et al., 2022; Tolessa et al., 2021). Tolessa et al. (2021) lament that a continued increase in provisioning services at the expense of regulating and supporting services is unsustainable as it hampers the future flow of these two essential ES; therefore, protection of regulating and supporting services is necessary in such cases.

For the individual ES, 15 out of the 17 ES registered negative changes in their ESVs between 1985 and 2022. The positive changes in the ESV for food production and biological control were due to the increase in the area under cropland in the study area over the two reference years. Likewise, a study conducted in central Ethiopia reported a historical and predicted increase in biological control and food production ESVs while the remaining 15 ESVs decreased throughout the study periods (Biratu et al., 2022). The regulating ESVs of the water tower were the most diminished after the LULC changes, specifically water treatment, erosion control, and climate regulation. This can be primarily attributed to the loss of forest and grassland cover in the water tower, chiefly from conversions to cropland. These two land cover types are vital for offering the aforementioned regulating services. These results are validated by the findings of a study conducted by Nadir et al. (2019) to assess the status of water quality in rivers originating from the water tower. High pollution levels were discovered in the rivers, notably high levels of iron, nitrates, chromium, Total Suspended Solids (TSS), copper, Chemical Oxygen Demand (COD), and Biological Oxygen Demand (BOD) exceeding the accepted limits in the environment (Nadir et al., 2019). The Ministry of Environment and Forestry. (2020) further reports that poor farming practices within the study area have led to increased soil erosion, thus impacting the state of the soil and rivers.

Pollination was the least affected individual ESV by the LULC changes (-3.63%), thereby indicating the capacity of the water tower to offer pollination services, which is a critical ecological survival function. The forest acts as a habitat for natural and insect pollinators, which are instrumental for crop production in the water tower.

4.4. Limitations of the study

Our study employed the benefit transfer method, which works on the assumption that values are constant across the types of ecosystems in comparison. In reality, however, most ecosystems are diverse, with variations in the service beneficiary populations (Sharma et al., 2019). Tolessa et al. (2017), however, note that the estimation of ESVs using LULC and established ESV coefficients is useful in regions where there is a scarcity of data on historical land uses and ground data collection is expensive as it provides robust information and alternatives for landscape-level decision making.

Secondly, we did not use the Coefficient of Sensitivity (CS) analysis method to account for the uncertainty of the represented biomes, as employed in many other similar studies (Akber et al., 2018; Kindu et al., 2016; Muleta et al., 2021; Tolessa et al., 2017). This is due to the inability of the CS method to address the reliability of the ESV estimation (Aschonitis et al., 2016). A simplistic calculus used in CS analysis returns CS values that are always between 0 and 1, leading to the conclusion that the applied coefficients by the users are always robust. Moreover, the CS values of ecosystem services are always independent of the percentage change of the ES coefficient defined by the user (Aschonitis et al., 2016). Several studies have also been conducted to estimate ESVs changes in response to LULC changes without incorporating the CS analysis (Biratu et al., 2022; Gashaw et al., 2018; Msofe et al., 2020; Munthali et al., 2022; Sharma et al., 2019). Therefore, there is a need to come up with a more reliable method that takes into account the uncertainty of the model and the biomes it represents.

Table 10
Summary of select studies globally showing the impacts of LULC changes on the total ESVs.

Study area	Study period	Change in LULC Type (%) Forest	Cropland	Grassland	Water	Urban	Change in Total ESV(%)	Reference
Munessa–Shashemene landscape (Ethiopia)	1973-2012	-11.8	35.5	-18.1	-0.1	1.1	**-14.8**	(Kindu et al., 2016)
Jibat forest landscape (Ethiopia)	1973-2015	- 47.38	42.88	15.75	-	349.75	**-39.1**	(Muleta et al., 2021)
Nenjiang River Basin (China)	1980-2005	-3.24	13.46	-11.32	-6.72	-	**-2.43**	(Wang et al., 2015)
Andassa watershed (Ethiopia)	1985-2015	-1.6	14.1	-2.7	-	1	**-21.73**	(Gashaw et al., 2018)
Menglun Township (China)	1988-2006	-21.16	33.53	-12.68	0.09	0.43	**-27.73**	(Hu et al., 2008)
Kilombero Valley Floodplain (Tanzania)	1990-2016	-10.3	11.3	13.3	-0.7	0.1	**-26.6**	(Msofe et al., 2020)
Dhaka, (Bangladesh)	1990-2020	-2.05	-2.06	-	-1.98	188.35	**-59.55**	(Rahman and Szabó, 2021)
Terai Arc Landscape (Nepal)	2001-2016	-0.7	-3	-	-5	127	**-0.86**	(Sharma et al., 2019)
Ningxia (China)	2000-2010	0.51	-0.08	-0.64	0.16	0.79	**22.76**	(Wang et al., 2014)
Shangzhou district (China)	2000-2015	3.35	-7.46	0.21	10.47	67.56	**89.2**	(Yuan et al., 2019)
Three Gorges Reservoir (China)	2000-2018	1.49	-1.34	-2.81	0.56	2.12	**3.46**	(Zhao et al., 2022)

5. Conclusion

This study used Landsat images and conservative ES valuation data from Kindu et al. (2016), from a similar geographical setting rather than relying on the global values from Costanza et al. (1997), which could otherwise overestimate the economic values of the ecosystem services in the CHWT. Between 1985 and 2022, areas under cropland, water bodies, and built-up zones increased, whereas forest, grassland, and bareland areas diminished in the water tower. Within the same period, there was a resultant negative change (-8.68 million USD) in the total ESV of the water tower from 121.22 million USD to 112.54 million USD. Out of the 17 individual ES in the water tower, 15 registered losses in their ESVs, with only two (food production and biological control) recording gains in their ESVs.

Our findings provide evidence that expansion of agriculture and subsequent losses in forest and grassland cover can drive LULC changes and associated losses of ESVs elsewhere globally, with similar socio-economic and environmental conditions as our study area. There is a need to curb the current drivers of LULC changes within the water tower to stop further degradation of the ecosystem and its corresponding values for optimum delivery of ecosystem services. Advocating for active community participation in the management of forest resources and enforcement of relevant agrarian and land laws and policies can help check further anthropogenic intrusions into the water tower. Restoration efforts for the degraded areas should also be scaled up. Our findings, therefore, pave the way for future research efforts and the advancement of robust value coefficients for better estimation of ecosystem values of the natural resources within the study area and in other regions of Kenya.

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Declaration of Competing Interests

The authors declare that they have no competing interests.

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