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Effects of Land Use and Land Cover Change on Potential Ecosystem Service Value in Mathioya Watershed, Murang'a County, Kenya

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Abstract Wetlands in Mathioya watershed are declining due to continued alterations caused by human and natural factors. This study assessed the effects of spatiotemporal changes in Land Use and Land Cover (LULC), on potential ecosystem service value in Mathioya watershed, Murang'a County, Kenya. We considered the period between 1987 and 2020. Supervised classification using maximum likelihood classifier was performed in ERDAS imagine v.15. The values obtained from the analysis of LULC maps were then used together with the global data for habitats to approximate the ecosystem service value (ESV) change within the watershed. Six LULC classes namely, forestland, wetlands, agricultural land, water bodies, built-up areas and barren lands, were identified. Analysis of Landsat images revealed that between 1987 and 2020, human activity led to decrease in the area covered by wetlands, forestland, water bodies, and barren land. Area under these land cover classes decreased by 45%, 34%, 50% and 27%, respectively. During the study period, agricultural land and built-up areas increased by 43% and 85%, respectively. Changes in LULC resulted in decline of ESV from $368.5 million/ha/year in 1987 to $337.7 million/ha/year in 2020. With respect to individual ecosystem services, regulating services declined. Between 1987 and 2020, water regulation and climate regulation declined by 48% and 16%, respectively. However, provisioning services such as food production increased by 34%. Wetlands play a critical role in the provision of ecosystem services. The loss of wetlands translated to decline of critical ecosystem services such as water regulation. Eventually, this will lead to poor water quality within the watershed and the entire County, thus impacting negatively on the health of the locals. Hence, there is a need for urgent action to prevent the current trend of wetland loss within Mathioya watershed.

Keywords: GIS, human activity, LULC, ecosystem service value, wetlands

1. Introduction

Ecosystem services refer to the benefits that we get from the natural ecosystems [1]. The monetary value of the relative contribution of ecosystems towards the wellbeing of man is referred to as ecosystem service value (ESV) [1]. By quantifying the changes in ESV, the public can be made aware of the important role various ecosystems play. Also, analysis of ESV would stimulate conservation of critical ecosystems such as wetlands that provide vital services.

Wetlands provide a variety of environmental benefits, including, mitigation of climate change, habitat for wildlife, purification of water and flood control [2]. Further, wetlands play a significant role in sustaining agricultural production and reliability of the world's water resources. With respect to agricultural production, wetlands are rich in nutrients and remain productive throughout the year. In addition, wetlands act as a source of quality pasture during the dry seasons and their periphery supports growth of fast maturing crops such as vegetables [3].

Despite the critical roles wetlands play, they are subjected to severe pressure and rapid degradation. About 87% of wetlands have been lost globally since the pre-industrial era [4]. Harvesting of wetland products, grazing, clearing for agriculture and draining of the wetlands for irrigation are some of the human activities threatening the existence of wetlands. Increased human population, coupled with a rise in socio-economic activities is a recipe for changes in the land use and land cover. To be food secure, man has exploited fertile wetlands and converted them to farmlands [5]. Lack of policies or the existence of weak policies in developing countries like Kenya, also contribute to the continued disappearance of wetlands [5]. Loss of wetlands would mean loss of the ecosystem services provided by wetlands.

Various authors [1], [6], [7] have conducted studies on the ESV of natural resources. Their studies were driven by the growing concern about the benefits derived from different ecosystems and the potential impacts of anthropogenic activities on those ecosystems [6]. Land use and land cover change is a consequence of the interactions between human beings and the environment. LULC change have a direct impact on the provision of ecosystem services [8]. Further, LULC changes can either increase or decrease availability of ecosystem services [9]. A study conducted in West Africa reported a decline in ESV due to LULC change [10], while another study done in China reported an increase in ESV [11]. Thus, this shows that changes in ESVs are location specific and making general conclusion may not be accurate.

Murang'a county has undergone rapid changes over the past three decades due to the interactions between humans and the environment [12], [13]. Particularly, wetlands in Murang'a County are facing threats from human activities [12], [13]. Despite studies on LULC changes being carried out in Murang'a County, no study has been carried out to understand the impacts of such changes on the ESV. In order to formulate applicable natural resource management policies, studies on LULC change are essential. Similarly, determining the drivers of LULC change is challenging, necessitating more research [14]. Drivers of LULC change can be either location-specific or time-bound, or both [15]. Additionally, in order to predict future changes and mitigate these changes, it is crucial to carry out studies relating to patterns, extent and rates of change [16].

Mathioya watershed is endowed with many small wetlands which are critical in the provision of water to the locals and neighboring counties such as Nairobi, the capital city of Kenya. Despite the crucial roles these wetlands play, they are being converted to agricultural lands at an alarming rate. The consequences of such changes in LULC are not properly understood. Thus, the objective of the study was to evaluate the effect of LULC change on the potential ecosystem service value in Mathioya watershed, Murang'a County, Kenya, between 1987 and 2020.

2. Materials and Methods

2.1. Study Area

The study was conducted in Mathioya watershed, Murang'a county, Kenya. The watershed covers three Sub-counties namely; Kiharu, Mathioya and Kangema. The area is located between longitudes 36°50'0"E and 37°10'0"E and latitudes 0º45'0"S and 0º34'30"S with an area of 541 km^2 (Fig. 1).

The main tributaries of River Mathioya are River Mathioya South and River Mathioya North, which are in turn fed by many low order streams (Fig. 1). The study area extends from an altitude of 2500 m to 2900 m above sea level (ASL). The area is mostly used for small-scale tea production, as well as coffee, maize, potatoes, and agroforestry systems, including macadamia nut cultivation. In addition, the majority of households engage in subsistence farming, primarily maize, vegetables, and arrowroots, as well as animal rearing. The soils in the area are primarily nitisols and andisols, with pyroxenes, olivine, amphiboles, and feldspars as major constituents [17]. The rainfall pattern is bimodal, with long rains occurring between March and May and short rains occurring between October and December [17]. The annual average rainfall reaches a maximum of 2700 mm at 2500 m ASL and the maximum daily temperature ranges between 26ºC and 30ºC, while the daily minimum temperature ranges between 14 ºC and 18 ºC [17].

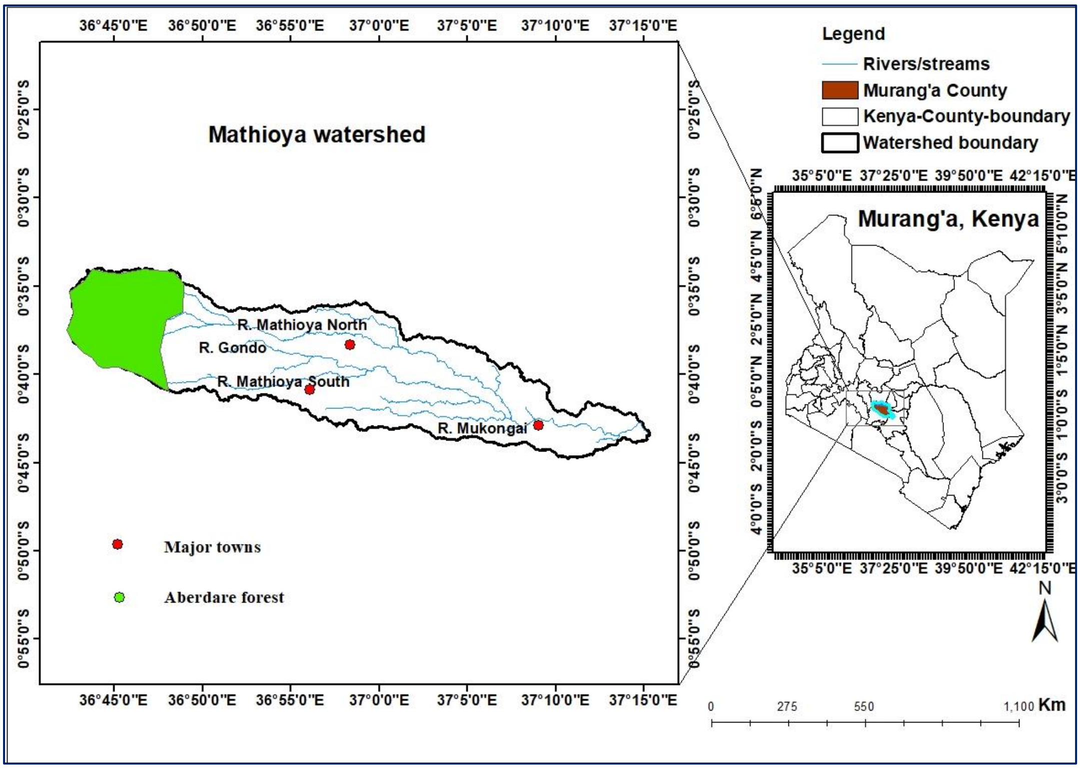

Fig. 1: Location of Mathioya Watershed, Murang'a County, Kenya

2.2. Data Acquisition and Image Processing

For LULC analysis, many types of satellite imagery are accessible. Landsat imagery, on the other hand, is recommended when conducting studies to monitor LULC changes because of its high temporal resolution and near and mid-infrared bands, which allow for a close examination of vegetation and landscape features [14]. Four cloud-free Landsat 5 (TM), Landsat 7 (ETM+), and Landsat 8 (OLI) satellite data sets were used in this study. The cloud cover on all four images was less than 10%. To help limit the impact of seasonal fluctuations on LULC analysis, the images used were taken throughout the same yearly season. The precise characteristics of the data used in this study are presented in Table 1.

ERDAS Imagine v. 2015 was used to preprocess the data. This involved atmospheric correction, layer stacking, geo-referencing and clipping of the image. The four images had the same projection parameters (UTM Zone 37, with WGS 84).

Table 1: Characteristics of the Landsat images used for the study

Satellite	**Sensor**	**Path/Row**	**Spatial resolution (m)**	**Spectral bands**	**Band range (μm)**	**Date**	**Source**
Landsat 5	TM	168/60	30	Band 4	0.76-0.90	1987-02-25	USGS
				Band 3	0.63-0.69		
				Band 2	0.52-0.60		
Landsat 5	TM	168/60	30	Band 4	0.76-0.90	1997-01-29	USGS
				Band 3	0.63-0.69		
				Band 2	0.52-0.60		
Landsat 7	ETM+	168/60	30	Band 5	1.55-1.75	2007-02-13	USGS
				Band 4	0.77-0.90		
				Band 3	0.63-0.69		
Landsat 8	OLI	168/60	30	Band 6	1.57-1.65	2020-02-20	USGS
				Band 5	0.85-0.88		
				Band 4	0.64-0.67		
				Band 3	0.53-0.59		

2.3. Image Classification

Maximum Likelihood Classifier was utilized to conduct supervised classification in ERDAS Imagine v. 2015. According to Kaul and Sopan [18], maximum likelihood classification algorithm (MLCA) is a preferred choice, because it is a straightforward and easy to implement approach. Furthermore, it is well-known and has been successfully applied to a wide range of remote sensing issues. Consequently, 75 training datasets were obtained for each LULC class with the help of Google Earth Pro [19]. The images were classified based on the researcher's local knowledge gathered during ground truthing. The identified classes were forestland, agricultural land, built-up area, wetlands, water bodies and barren land (Table 2).

Table 2: Description of different LULC categories

LULC Class	Description
Wetland	Permanent grasslands along the streams, marshy land and swamps [14]
Water body	Comprises of rivers, ponds, and dams [20]
Forest	Areas that are densely covered with trees or open forest [14]
Built-up	Settlements, industries, and roads [21]
Agricultural land	Both cultivated and uncultivated agricultural lands [14].
Barren land	Areas with no vegetation cover, exposed soils, quarry, and rocks [21].

2.4. Accuracy Assessment of the Classified Images

In LULC change analysis, assessing the accuracy of a classed image is a crucial step [22]. To guarantee that all six (6) LULC classes were appropriately represented based on their proportional area; an equalized random sample procedure was utilized to collect 98 reference data. The reference data was extracted using Google Earth images. The confusion (error) matrix was used to determine the accuracy evaluation, which included the Kappa coefficient, overall accuracy, producer's and user's accuracies [23]. The correlation between the classified map and the reference data is reported using the Kappa coefficient [14]. Producer's accuracy shows how well a given land cover type has been classified. The user's accuracy examines the reliability of classified LULC. The overall classification accuracy was calculated using equation (1). The error matrix was used to compute the overall accuracy of the six (6) land use classes both individually and collectively.

$$OA = \frac{C}{A} 100 \qquad (1)$$

Where: OA is the overall classification accuracy; C is the number of correct points; A is the total number of reference points.

The Kappa coefficient (Khat) was also determined for each LULC and used to compare the classification accuracy (Table 3). The Kappa coefficient is a measurement of how well classification and real values agree. A Kappa value of 1 indicates complete agreement, whereas a value of 0 indicates no agreement [24]. Equation (2) shows how to calculate the Kappa coefficient:

$$k = \frac{N\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n}(G_i C_i)}{N^2 - \sum_{i=1}^{n}(G_i C_i)} \qquad (2)$$

Where i is the class number; N is the total number of classified values compared to truth-values; $m_{i,i}$ is the number of values belonging to the truth class i that have been classified as class i (values found along the diagonal of the confusion matrix); C_i is the total number of predicted values belonging to class i; G_i is the total number of truth-values belonging to class i.

The results of the Kappa coefficient for the periods (1987–2020) LULC were analyzed and interpreted (Table 3) [24].

Table 3: Level of Kappa coefficient of agreement

Kappa coefficient (K_{hat})	Level of agreement/ accuracy
>0.80	Strong
0.40-0.80	Medium
<0.40	Poor

2.5. Land Use Land Cover Change Detection

2.5.1. Land Use and Land Cover Change

After supervised classification was performed, initial LULC map was edited using Google earth history function to verify the LULC classes. Following the verification, certain classes were recoded into their original classes. Change detection was determined by calculating the difference in area between the initial and final study periods in the area in square kilometer (km^2) for the 1987–1997, 1997-2007, 2007-2020 and 1987-2020 using equation (3) and (4).

$$C = (\Delta f - \Delta i) \quad (3)$$

$$C\% = \frac{(\Delta f - \Delta i)}{\Delta i} \times 100 \quad (4)$$

Where C is the total change in a given LULC type in (km^2); C (%) is the LULC change in percentage; Δf is the total area coverage of LULC in final year; Δi is the total area coverage of LULC in initial year.

2.5.2. Determination of Annual Rate of LULC Change

Net change in a LULC is the difference between gain and loss between images of different periods. The annual rate of LULC change for the four periods (1987–1997, 1997-2007, 2007-2020 and 1987-2020) was calculated using equation (5).

$$\mathrm{R} = \frac{Q_2 - Q_1}{t} \quad (5)$$

Where R refers to the rate of LULC change; Q_1 is the area (km^2) of LULC class of an earlier land cover image; Q_2 is the area (km^2) of LULC class of a later land cover image and t is the time interval between Q1 and Q2 in years.

2.6. Estimation of Ecosystem Service Values

The results of the LULC change analysis were combined with the ecosystem service value coefficients produced by Costanza et al. [1] to estimate the ESVs. The ecosystem service value coefficients can be employed in a wider range of climatic zones, particularly in data-scarce regions of the world [6]. Each LULC class was represented by the most representative biome (Table 4).

Table 4: LULC classes and their corresponding equivalent biome.

LULC class	Equivalent biome
Agricultural land	Crop land
Forest land	Tropical forest
Built-up area	Urban
Wetlands	Swamps/floodplains
Water body	Lakes/rivers
Barren land	Desert

Data obtained from [1].

Author [1] developed ecosystem service values for 17 ecosystem services (Table S5). The individual ecosystem services were then grouped into four categories including regulating, cultural, provisioning and supporting services. The value of each ESV category is the sum of the individual ecosystem service values. The values are used to assess changes in the service values over time and space [25]. The aggregate ESV in the study area for 1987, 1997, 2007 and 2020 was obtained using equation 10 [6].

$$ESV = \sum(A_k * VC_k) \quad (10)$$

Where: ESV is the estimated ecosystem service value; A_k is the area (ha), and VC_k is the value coefficient (US\$ ha^{-1} yr^{-1}) for LULC class k. Change in ESV was estimated by calculating the differences between the estimated values for each LULC class in 1987, 1997, 2007 and 2020. The percentage changes in ESV between each year were calculated using equation 11:

$$\%\ change\ in\ ESV = \frac{ESV_{t2} - ESV_{t1}}{ESV_{t1}} 100 \quad (11)$$

Where: ESV_{t2} (US\$ ha^{-1} yr^{-1}) is the ecosystem service value in the recent year, and ESV_{t1} (US\$ ha−1 yr−1) is the ecosystem service value in the previous year.

Further, the effects of LULC change on the individual ecosystem services were calculated using Equation 12 [6].

$$ESV_i = \sum(A_k * VC_{ik}) \quad (12)$$

Where: ESV_i is the estimated ecosystem service value of function i, A_k is the area (ha) and VC_{ik} the value coefficient of function i (US\$ ha^{-1} yr^{-1}) for LULC category k.

Sensitivity analysis was carried out to establish the dependence of the changes in ESV on the applied valuation coefficients [6]. The value coefficient of a given LULC class was adjusted by ±50 % keeping the value coefficient constant for the other LULC classes [25]. Coefficient of sensitivity (CS) was calculated using the standard economic concept of elasticity as shown in Equation (13) [7], [25].

$$CS = \frac{(ESV_j - ESV_i)/ESV_i}{(VC_{jk} - VC_{ik})/VC_{ik}} \quad (13)$$

Where: ESV is the estimated ecosystem service value, VC is the value coefficient, '*i*' and '*j*' represent the initial and adjusted values, respectively, and 'k' represents the land use category.

3. Results and Discussion

3.1. Land Use and Land Cover Change in Mathioya Watershed

During the study period (1987–2020), forestland and agricultural land were the predominant LULC classes in the watershed (Fig. 2). In 1987, agricultural land, forest land, wetlands, water bodies, built-up areas and barren land covered 42%, 44%, 5%, 5%, 2.4% and 2%, respectively (Table 6). There was a decrease in the area covered by forest land (34%), wetlands (45%) and water bodies (50%) between 1987 and 2020. On the other hand, built-up area and agricultural area increased by 85% and 43%, respectively in the same period. The overall classification accuracies were 87%, 92%, 85% and 88%, in 1986, 1997, 2007 and 2020, respectively, with Kappa indexes of 0.8454, 0.8632, 0.9058 and 0.8519, respectively. A Kappa index greater than 0.8 shows a strong level of agreement (Table 3) between the classified maps and what is on the ground.

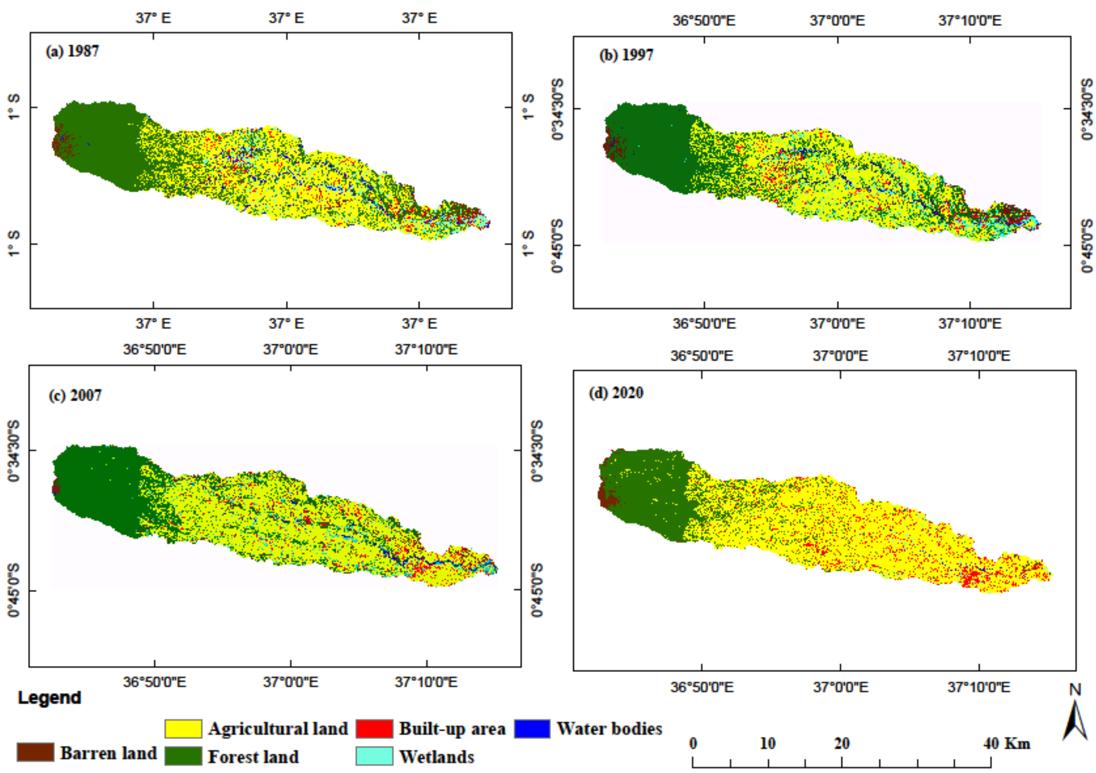

Fig. 2: Land Use and Land Cover Maps in Mathioya Watershed (1987-2020)

Table 6: LULC Change Trend in Mathioya Watershed

LULC class	**Area (Km^2)**				**% change in LULC**
	1987	**1997**	**2007**	**2020**	**(1987-2020)**
FL	236	223	188	157	-34
AL	226	238	279	323	43
WL	29	26	22	16	-45
WB	26	23	18	13	-50
BL	11	15	16	8	-27
BA	13	16	18	24	85
Total	**541**	**541**	**541**	**541**	

FL-Forest land, AL-Agricultural land, WL-Wetland, WB-Water bodies, BL- Barren land, BA-Build-up area

The results of the change detection analysis show that LULC change occurred across the 33-year study period (1987 - 2020). Agriculture was the most common land use in the Mathioya watershed. Ground truthing confirmed that agricultural land was expanding at the expense of forests and wetlands. In Kenya, agricultural policy is mainly focused on increasing production and income for the smallholder famers. Little attention is paid to the environmental consequences of unsustainable agricultural practices. For instance, the Kenyan government introduced the *Shamba* system to support the growth of monoculture seedlings [26]. The system involved smallholder farmers growing perennial crops in state-owned forests. Even though the system benefited the farmers, it resulted to massive loss of forestland, particularly in Central Kenya [26]. Indeed, agriculture was the major contributor to the net change in forest land (Fig. 3) A study [14] reported that forestland and wetlands were being converted into agricultural lands. Similarly, [15] found that in the period between 1990 and 2000, wetlands decreased by an area of 1012.96 ha, whereas agricultural land increased by an area of 338.94 ha.

Built-up area increased along the major roads and in towns, mainly Murang'a town, Kangema and Gitugi. Increase can be linked to the rise in population in the region. In 2009, the population in the watershed was 197, 465 (365 persons/ km^2) and it increased to 226, 679 (419 persons/ km^2) in 2019. This has led to clearing of forests for settlement, increased demand for timber and agricultural produce. In addition, the area has benefited from increased tarmac roads in 2020 compared to 1987 where most roads were not tarmacked. From a related study [15], built-up area increased from 52.46 ha in 1990 to 581.18 ha in 2017. This change was attributed to an increase in population in the region. Substantial increase in the area covered by built-up area (from 761.67 ha in 1991 to 7,999.56 ha in 2015) was reported in a related study [14].

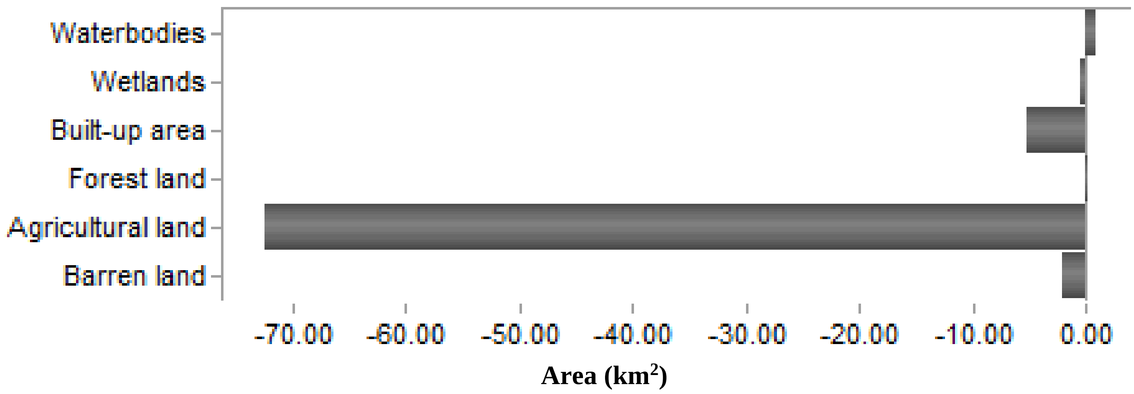

Fig. 3: Contribution to Net Change in Forest land

The decrease in water bodies over the years was likely due to increased pressure from agriculture [27] and construction activities. Additionally, most of the small streams within the watershed had dried up. Barren land increased between 1987 and 2007. This could be attributed to deforestation within the watershed and increase in quarrying activities. However, the area under barren land decreased between 2007 and 2020. This was caused by the conversion of barren land to built-up areas and agricultural lands (Fig. 4). Additionally, some of the quarries were rehabilitated by planting of trees and grasses. Similarly, a study [20] found that the area under bare soil increased from 780.84 ha in 1978 to 2734.56 in 1999, then between 1999 to 2017, the area under bare soil decreased to 591.28 ha.

In 1987, wetlands covered 29 km^2 of the watershed. However, in 2020, wetlands only covered 16 km^2. The loss of wetlands is likely associated to their rapid conversion into agricultural land and other land use classes (Fig. 5). Agriculture and built-up area were the major contributors to wetland loss (Fig. 6). More than 60% of wetland area was converted to agricultural lands between 1987 and 2020. In addition, 29% and 3% of the wetland area was lost to built-up area and forest land, respectively. Because wetlands are moist for the majority of the year and have higher soil fertility than adjacent areas, they have a lot of potential for agricultural growth and intensification [28]. In addition, most of the wetlands in Mathioya watershed occur in private land. This makes it difficult for the relevant authorities to conserve the wetlands [12].

Loss of wetlands will result to a decline in the quality and quantity of water available in the study area. Consequently, the livelihood of communities living adjacent to the wetlands will be affected. The observed trend is consistent with the findings of [29], who determined that land use changes in Malawi's Likangala River basin were caused by farming along river banks, deforestation, and over-exploitation of natural resources. People are motivated to farm in marginal terrain such as hill slopes, riverbanks, and wetlands due to poverty and rising need for agricultural products [30]. Land clearance and drainage as a result of urbanization [31], agricultural expansion [32], and industrial development have resulted in wetlands decreasing globally in recent years.

There are several laws seeking to protect wetlands and riparian lands in Kenya. The Water Act of 2002, the Water Resource Management Act of 2007, and the Environment Management and Regulations Act of 2006 are among them. The laws, however, are in conflict with one another. The Water Act, for example, calls for a minimum riparian distance of 6 meters, whereas the Agriculture Act calls for a minimum of 2 meters. The Environmental Management and Regulation Act, on the other hand, recommend a riparian buffer of 30 meters. The survey Act of 1989 recommends a riparian buffer of 10 meters. The Kenyan government, through the National Assembly, identified the need for a national policy framework after noting the inconsistencies in the wetland legislation. In 2014, the National Wetland Policy was developed as a result of this. However, the policy is yet to have an impact on small wetlands, which continue to be destroyed by human activities [15]

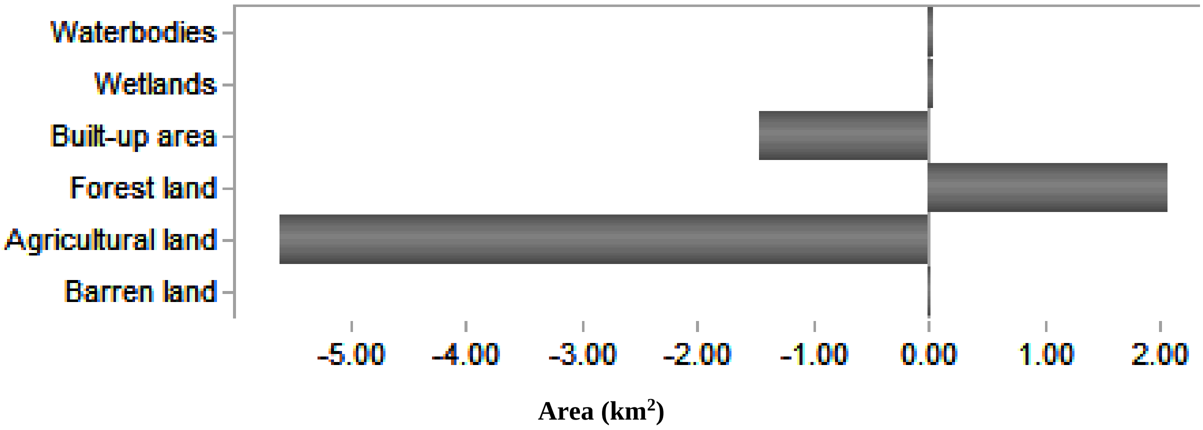

Fig. 4: Contribution to Net Change in Barren land

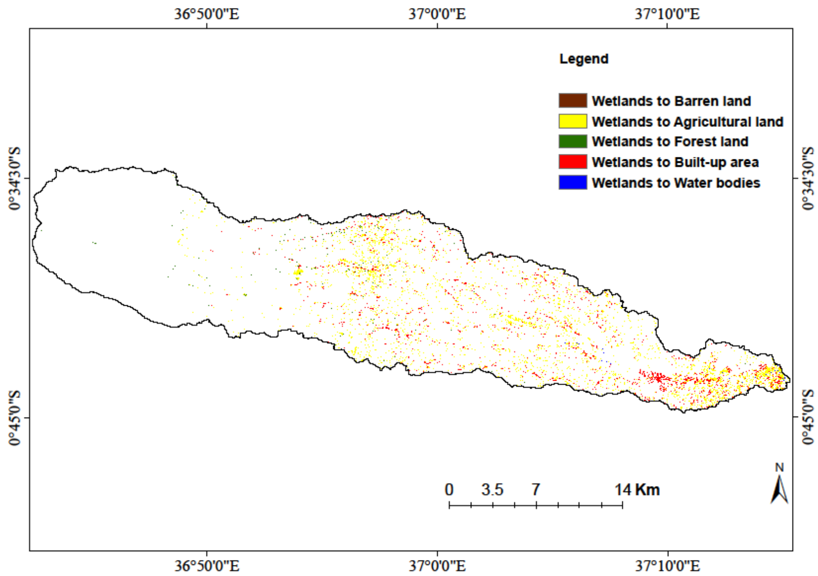

Fig. 5: Transition of Wetlands to Other Land Use and Land Cover Classes (1987-2020)

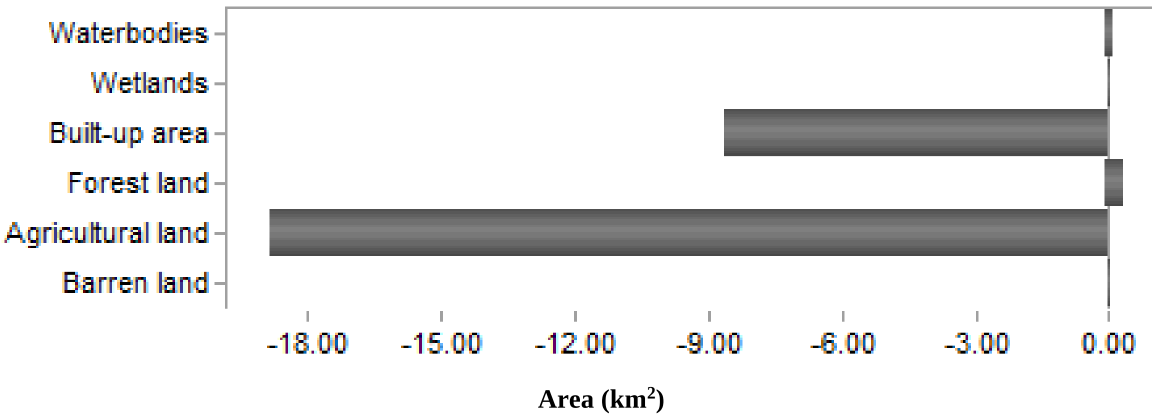

Fig. 6: Contribution to Net Change in Wetlands

Further, the analysis reveals a spatial trend in the LULC changes in Mathioya watershed between 1987 and 2020. Changes in the area covered by wetlands were mainly concentrated in the southeastern part of the watershed. Particularly, loss of wetlands to agriculture (Fig. 7) and built-up area (Fig. 8) took place in the southeast of the watershed. The southeastern part of Mathioya watershed is fairly flat compared to the other parts, which are mainly hilly. Hence, the section is more suitable for buildings and agricultural practices. The spatial trend of changes in the forest land to built-up area was also concentrated in the southeastern part of the watershed (Fig. 9). However, loss of forestland to agricultural land was more concentrated at the middle part of the watershed (Fig. 10). This can be attributed to the clearing of forest land to create space for the tea farms. It is important that in our quest to achieve economic and social stability, we also need to ensure that the environment is conserved. Hence, economic development should be carried out sustainably, in harmony with environmental and social development.

Fig. 7: Spatial Trend of LULC Change from Wetlands to Agricultural land

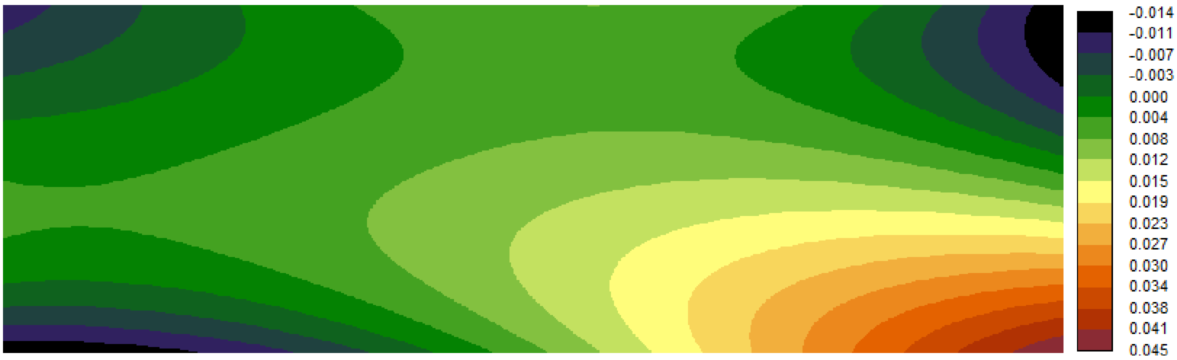

Fig. 8: Spatial Trend of LULC Change from Wetlands to Built-up area

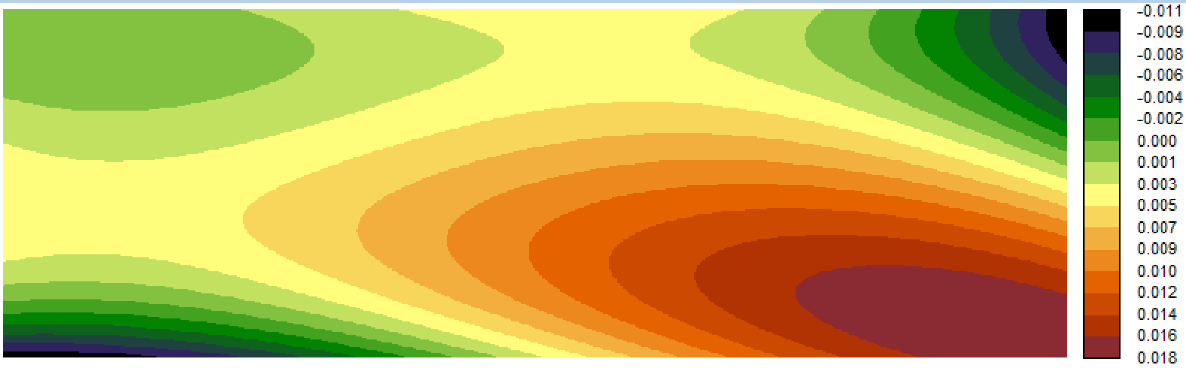

Fig. 9: Spatial Trend of LULC Change from Forest land to Built-up area

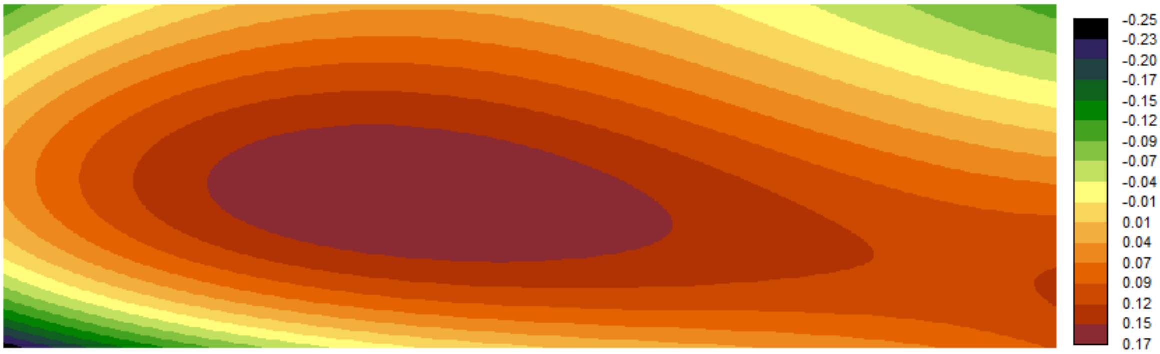

Fig. 10: Spatial Trend of LULC change from Forest land to Agricultural land

3.2. Ecosystem Service Value Change in Mathioya Watershed

The ESV declined within the study area, for each study period. LULC changes reduced the ESV by 2.6%, 3.1%, 2.8% and 8.5%, between 1987-1997, 1997-2007, 2007-2020 and 1987-2020, respectively. Forestland recorded the highest decrease in ESV between 1987 and 2020. This was closely followed by wetlands. The least decrease in ESV was recorded for the waterbodies. On the other hand, agricultural land registered the highest increase in ESV followed by built-up area which had a slight increase in the ESV (Table 7).

Forestland and wetlands showed the highest loss due to the high ESV attached to them, alongside their continued exploitation by human beings. Specifically, wetlands play a significant role to the surrounding ecosystem. This includes, flood mitigation, increase groundwater recharge, improving of the water quality by capturing sediments and filtering pollutants. However, despite the critical roles wetlands play, they still registered the highest loss in ESV after forestland. Also, even though wetlands cover a small area within the Mathioya watershed, the total amount of ESV lost indicates the critical roles they play in providing ecosystem services. Thus, it is critical that the protection and possible restoration of degraded wetlands be given priority in Mathioya watershed, where availability of water for drinking and farming is becoming an issue.

Table 7: Total ecosystem service values estimated for each land use and land cover class, and changes between 1987 and 2020

LULC Class	ESV (US million ha^{-1} year^{-1})				ESV change between periods			
	1987	1997	2007	2020	1987-1997	1997-2007	2007-2020	1987-2020
FL	127.0	120.0	101.2	84.5	-7(-6)	-18.8(-16)	-16.7(-17)	-42.5(-34)
AL	125.8	132.5	155.3	179.8	6.7(5)	22.8(17)	24.5(16)	54(43)
WL	74.5	66.8	56.5	41.1	-7.7(-10)	-10.3(-15)	-15.4(-27)	-33.4(-45)
WB	32.5	28.8	22.5	16.3	-3.7(-11)	-6.3(-22)	-6.2(-28)	-16.2(50)
BL	0	0	0	0	0	0	0	0
BA	8.7	10.7	12.0	16.0	2(23)	1.3(12)	4(33)	7.3(84)
Total	368.5	358.8	347.5	337.7	-9.7(-2.6)	-11.3(-3.1)	-9.8(-2.8)	-30.8(-8.5)

FL-Forest land, AL-Agricultural land, WL-Wetland, WB-Water bodies, BL- Barren land, BA-Build-up area
NB: The values in parenthesis () shows the percentage change in ESV between periods.

Provisioning services increased whereas supporting, cultural and regulatory services decreased between 1987 and 2020 in the study area (Table 8). For instance, food production increased by 34%, whereas, water regulation and climate regulation declined by 48% and 16%, respectively. The decrease of the mentioned services can be attributed to the loss of natural ecosystems such as forests and wetlands. Whereas, the increase in provisioning services is attributed to the expansion in agricultural area. However, the provisioning service depends on both regulating and supporting services [7] and hence it would be affected in the long run, due to the continued decline in the regulatory and supporting services. Generally, the total ESV decreased in the study area within the 33 year study period.

In a similar study done in Ethiopia, a total of $ 43.7 million/ha/year ESV was lost between 1973 and 2017 due to land use and land cover changes [6]. Similarly, a study [8] reported that the reduction of ESV was due to the modification of natural ecosystems such as wetlands and forestlands into agricultural lands and built-up areas. The loss of the natural ecosystems would translate to loss of critical ecosystem services which may affect human wellbeing [33] especially in the developing countries that are experiencing exponential economic growth. Particularly, growing of crops in the wetlands during the dry seasons affects wetland functions in the Mathioya watershed and the Murang'a County in general. This will eventually result to poor water quality within the watershed and the entire County, thus impacting negatively on the health of the locals.

The current trend of LULC change in Mathioya watershed indicates a continued loss of wetlands. This shows that the ecosystem services provided by wetlands will continue to be lost, and the cost of restoring the degraded wetlands is likely to be much higher compared to the benefits being derived from their current unwise use [6]. Additionally, lack of appropriate mechanism in payment for ecosystem services due to limited knowledge on ecosystem services of wetlands, further hampers their protection [25]. Therefore, there is an urgent need to make informed decision on the protection of the remaining wetlands to prevent further decline in the ESV [8]. In a related study conducted in India, a net loss of ESV ($ 1.2 trillion/year) was reported between 1995 and 2015 [33]. The loss of ESV was attributed to the decline of forestland and wetlands. The study also reported an increase in ESV for both cropland and urban coverage, whereas, a decline in ESV was recorded for forestland and wetlands. A similar study conducted in India found that the ESV would decline by 29.7% between 2020 and 2030, particularly due to the loss of wetlands [19]

.**Table 8:** Estimated Annual Value of Ecosystem Services (ESV in US$ million per year)

Ecosystem service	ESV_{1987}	ESV_{1997}	ESV_{2007}	ESV_{2020}	$ESV_{1987-2020}$
Climate regulation	60.1	58.1	52.6	50.7	-9.4(-16)
Water supply	15.6	15.3	15.8	16.4	0.8(5)
Water regulation	36	32.1	26.1	18.9	-17.1(-48)
Soil formation	12.9	13	15.1	17.4	4.5(35)
Erosion control	17.9	16.8	15.1	12.9	-5(-28)
Pollination	1.2	1.2	1.2	1.2	0(0)
Food production	59.3	61.6	70.1	79.3	20(34)
Erosion control	17.9	16.8	15.1	12.9	-5(-28)
Nutrient cycling	7.7	4.5	3.9	2.8	-4.9(-64)
Disruption regulation	10.2	9.3	7.8	5.8	-4.4(-43)
Gas regulation	0.3	0.3	0.3	0.2	-0.1(-33)
Biological control	3.8	3.5	3.2	2.8	-1(-26)
Waste treatment	22.9	22.1	21.6	20.7	-2.2(-10)
Habitat	8.1	7.3	6.2	4.6	-3.5(-43)
Raw material	8.5	8.5	8.9	9.3	0.8(9)
Genetic resource	59.2	58.5	57.3	57.1	-2.1(-4)
Recreation	41.8	41.2	37.7	36.4	-5.4(-13)
Cultural	5.9	5.3	4.5	3.3	-2.6(-44)

NB: The values in parenthesis () shows the percentage change in ESV between periods.

All the LULC classes recorded a coefficient of sensitivity (CS) that is less than one in each year (Table 9). When the ratio of the percentage change in the estimated total ecosystem service value (ESV) to the percentage change in the adjusted valuation coefficient (VC) is more than one, the estimated ecosystem value is said to be elastic. If the ratio is smaller than one, the estimated ESV is considered inelastic [6]. The high value of CS recorded for agricultural land is an indication of the large area occupied by this land use within the watershed. Further, adjustment of the ESV of agricultural land by ±50% resulted to an increase in the ESV by 27% in 2020. On the other hand, a decrease in the ESV of forestland and wetlands by ±50% resulted to a decrease in ESV by 13% and 6%, respectively in 2020. CS values being less than one implies that the estimated ESVs were inelastic to the ESV coefficients proposed by [1]. Additionally, the results show that the proxies adopted for the different LULC classes are reliable [6]. Other similar studies also recorded a CS value of less than one [8], [6], [7], [25].

Table 9: Change in Total Estimated Ecosystem Services and Coefficient Sensitivity (CS) after Adjusting Ecosystem Services Valuation Coefficient (VC) in Mathioya Watershed

***Change in valuation coefficient**	**1987**		**1997**		**2007**		**2020**	
	Percent	**CS**	**Percent**	**CS**	**Percent**	**CS**	**Percent**	**CS**
Forestland	±17	0.34	±17	0.33	±15	0.29	±13	0.25
Agricultural land	±17	0.34	±19	0.37	±22	0.45	±27	0.53
Wetlands	±10	0.20	±9	0.19	±8	0.16	±6	0.12
Water bodies	±4	0.09	±4	0.08	±3	0.06	±2	0.05
Built-up area	±4	0.07	±2	0.03	±2	0.03	±2	0.05

*All the LULC classes were adjusted with a value coefficient (VC) of ±50%

4. Conclusion

The study has revealed that land use and land cover changes

have an effect on the availability of ecosystem service value. Further, the findings show that the ecosystem service value is declining within the watershed, an indication of environmental degradation within the watershed. Loss of ecosystem service values will have detrimental impact on the health and livelihood of communities living within the watershed and entire Murang'a County. Changes in land use and land cover were observed within the 33 year period (1987-2020) in Mathioya watershed. Agricultural land, built-up area increased whereas, forestland, wetlands, waterbodies and barren lands decreased in size between 1987 and 2020.

Wetlands decreased considerably within the watershed. This was mainly due to conversion of wetlands into agricultural lands especially during the dry season. Additionally, some parts of the wetlands were reclaimed for purposes of construction of roads and residential buildings. The loss of wetlands resulted to a decline in the overall ecosystem service value as well as a decrease in the supporting and regulating services. Provisioning services increased owing to the increase in agricultural land, but these are likely to be hampered in the long run owing to its dependence on the regulating and supporting services. There is a need to protect the natural ecosystems which are on a steady decline within the watershed. Continued loss of the natural ecosystems such as wetlands will result to a further loss of the ESV within Mathioya watershed. Thus, urgent measures need to be taken to curb the current trend and ensure the already degraded ecosystems have been restored.

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Conflicts of Interest

The authors declare no conflict of interest.

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Table S5: Categories of ecosystem services, LULC types and ESV coefficients (million USD $ /ha/yr)

Ecosystem services		Agricultural land	Forest land	Built-up area	Wetlands	Water body	Barren land
Categories	**Individuals**						
Provisioning	Water supply	400	27		408	1808	0
	Food production	2323	200		614	106	0
	Raw material	219	84		539		0
	Genetic resources	1042	1517		99		0
	Sub-Total	**3984**	**1828**		**1660**	**1914**	**0**
Regulating	Gas regulation		12				0
	Climate regulation	411	2044	905	488		0
	Disturbance regulation		66		2986		0
	Water regulation		8	16	5606	7514	0
	Erosion control	107	337		2607		0
	Waste treatment	397	120		3015	918	0
	Biological control	33	11		948		0
	Sub-Total	**948**	**2598**	**921**	**15650**	**8432**	**0**
Supporting	Soil formation	532	14				0
	Nutrient cycling		3		1713		0
	Pollination	22	30				0
	Habitat		39		2455		0
	Sub-Total	**554**	**86**		**4168**		**0**
Cultural	Recreation	82	867	5740	2211	2166	0
	Cultural		2		1992		0
	Sub-Total	**82**	**869**	**5740**	**4203**	**2166**	**0**
	TOTAL	**5,568**	**5,381**	**6,661**	**25,681**	**12,512**	**0**

Source: [1]