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Integrating Remote Sensing and Total Economic Valuation: A Spatially Explicit, Degradation-Adjusted Assessment of Ecosystem Services in Kakamega Forest

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Abstract: Kakamega Forest in Western Kenya is a remnant of the Guineo-Congolian rainforest and a biodiversity hotspot. It supports one of the country's most populous and impoverished regions, yet its value as an economic asset remains underappreciated. This study integrates original spatiotemporal forest health analysis (Landsat 8, SAVI 2013–2023) with synthesized Total Economic Valuation from existing literature to provide a spatially explicit, degradation-informed valuation framework. Our synthesis estimates that the forest generates about KES 8.7–13.6 billion annually (approximately 65–102 million USD), with roughly 79% attributable to indirect regulating services. Applying the observed 24.36% net forest degradation to the indirect use value component (KES 6.8–10.9 billion) under a linear proportional assumption gives an estimated annual loss of KES 1.7–2.7 billion in ecosystem service flows. These estimates are derived from secondary data and benefit transfer. The estimated per-unit-area economic return of conserved forest exceeds that of the most common agricultural conversions, indicating that short-term opportunity-cost arguments for deforestation are not supported by the aggregate valuation. However, the observed resource-use intensity, combined with high local poverty rates, is consistent with a poverty-degradation feedback. Beyond its local relevance, this work provides a replicable methodological template for a spatially explicit, degradation-informed valuation framework in tropical forest contexts worldwide, showing how adaptive management is made possible in a time of fast land-use change by combining remote sensing with economic assessment.

Keywords: total economic value; natural capital accounting; remote sensing; Payment for Ecosystem Services (PES); forest degradation; Kakamega Forest

1. Introduction

The Kakamega Forest in Western Kenya is a remnant of the Guineo-Congolian rainforest and a recognised biodiversity hotspot. The forest's gazetted area is approximately 240 km^2 [1,2]. However, actual closed-canopy forest cover is smaller due to historical clearing, natural glades, and infrastructure. The spatiotemporal analysis presented in this study applies a vegetation-index-based forest mask, yielding a baseline canopy area of approximately 210 km^2 for the 2013–2023 study period. All degradation percentages and economic loss calculations are expressed relative to this canopy area. It is surrounded by one of Kenya's most densely populated regions [3], where over 90% of adjacent households depend on forest resources for fuelwood, water, and livelihoods [4]. Despite high local dependence, the forest has undergone degradation, and its full economic contribution has not been quantified. Previous studies focused on ecological fragmentation and species composition [1,2,5] or on household resource use and the poverty-degradation cycle [4]. An integrated valuation that links forest condition over time to economic values has been lacking.

This study addresses that gap by combining original spatiotemporal forest health analysis (Landsat 8 Soil-Adjusted Vegetation Index (SAVI), 2013–2023) with a synthesized Total Economic Value (TEV) of ecosystem services drawn from existing literature. We ask three questions: (1) What is the order-of-magnitude annual economic value generated by Kakamega Forest? (2) How does observed forest degradation translate into economic loss? and (3) What policy mechanisms can reconcile conservation incentives with local development needs? A key methodological contribution is addressing a central criticism of TEV research: that static results quickly become obsolete in dynamic environments. We address this by embedding TEV within a dynamic socio-ecological system framework, using it as a diagnostic tool rather than an end objective. By integrating repeatable remote sensing techniques (SAVI) with economic valuation, we make natural capital spatially and temporally explicit. This study therefore provides a spatially explicit framework that links remote sensing to economic valuation while accounting for degradation.

2. Theoretical Framework and Literature Review

2.1. Natural Capital and Total Economic Valuation

The theoretical construct of natural resources as 'natural capital' provides the foundation for this study. Natural capital is defined as 'a stock of natural assets which is capable of furnishing a flow of valuable commodities and services' [6]. Forests are a quintessential form of natural capital. The field of forest economics has accordingly shifted from a narrow focus on timber production to a broader understanding of forests as socio-ecological systems that deliver a diverse range of provisioning, regulating, cultural, and supporting services [7]. Within the TEV framework [8,9], these services generate four economic value types: Direct Use Value (consumptive and non-consumptive uses), Indirect Use Value (regulating services), Option Value (future potential uses), and Existence Value (intrinsic worth).

2.2. The Socio-Ecological Context of Kakamega Forest

Kakamega Forest, located in the Lake Victoria Basin, is a paleoecological remnant that has endured periods of aridification; thus, the region has served as a living laboratory for research in biogeography and evolution [1]. This background has endowed the region with a unique biodiversity, marked by high endemism of flora and fauna, including *Cercopithecus neglectus* (De Brazza's monkey), *Eremomela turneri* (Turner's Eremomela), and a wide range of butterflies and plant species [5]. The geographical coordinates of the region are 34°50′00″–35°0′00″ East and 0°25′30″–0°4′00″ North (Figure 1).

Earlier ecological-oriented studies identified its unique flora and fragmentation consequences [1,2]. Remote sensing studies have refined degradation monitoring across African tropical forests [10,11]. Concurrently, socioeconomic studies by [4] have comprehensively studied the dependence of nearby populations on the forest for fuelwood, herbal remedies, building materials, and food. Poorer households were more dependent, creating a poverty-degradation cycle. Forest management has shifted from a state-centric, exclusive model to a more participatory model with the Forest Conservation and Management Act (2016), which sets up Community Forest Associations (CFAs). However, challenges remain: elite capture, unequal benefit sharing, and illegal activities undermine both conservation and development [12].

Since the foundational works of [4,13], the ecosystem services valuation literature in African tropical forests has expanded considerably. Recent studies have refined benefit-transfer protocols [14], integrated remote sensing with conservation assessment in the Congo Basin, and applied natural capital accounting to protected areas in Madagascar [15]. In East Africa, choice experiments in the Mau Forest have quantified willingness-to-pay for watershed protection [16].

A synthesis linking the forest's ecosystem services to macroeconomic development in Western Kenya has been absent from the literature. Most studies examine specific components of these services without fully integrating them into a coherent narrative of forest function as economic infrastructure within the region. This study addresses that gap by applying the TEV framework to synthesize economic values for Kakamega Forest.

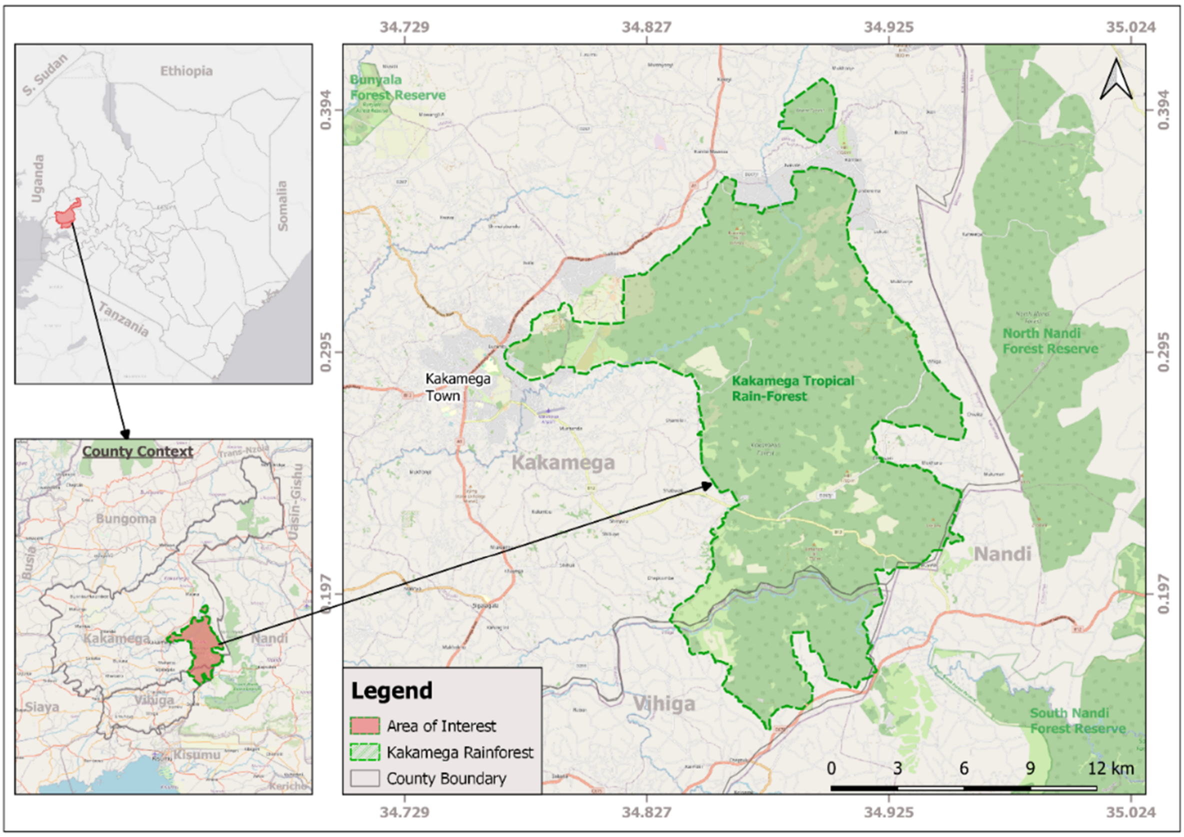

Figure 1. Geographic Location of Kakamega Tropical Rainforest in Western Kenya.

3. Methodology

We employ a descriptive case study design [17]. Primary Landsat 8 analysis quantifies forest degradation, while secondary data are synthesized within a TEV framework. The systematic review protocol is described next.

3.1. Data Collection and Sources

This study combines secondary data synthesis with original geospatial analysis. This allows integration of existing economic valuations with independently derived degradation trajectories. We conducted a literature search of Scopus, Web of Science and Google Scholar. The search used Boolean combinations of the terms "Kakamega Forest", "ecosystem service", "economic valuation", "non-timber forest products" and "ecotourism" The review followed a systematic protocol adapted from the PRISMA guidelines [18]. Results were limited to publications between 2000 and 2024. After removing duplicates, 289 unique records were screened by title and abstract. Of these, 112 were assessed for eligibility through full-text review. Inclusion criteria were: (i) peer-reviewed articles, institutional reports or postgraduate theses; (ii) studies that provided quantitative or qualitative data on the economic value of ecosystem services; (iii) studies conducted in Kakamega Forest or in East African tropical forests where suitable for benefit transfer. Exclusion criteria were: conference abstracts, opinion pieces, and studies that did not report primary or synthesized valuation data.

Following full-text review, 24 studies met the inclusion criteria and were retained for data extraction. A risk-of-bias assessment was performed for each retained study, considering sample representativeness, valuation-method appropriateness and transparency of assumptions; no study was excluded solely on this basis, but limitations were noted and used in the sensitivity discussion. An additional 12 sources, grey-literature reports (e.g., [3,19]), national statistics, remote-sensing method papers and foundational valuation handbooks (e.g., [8,20,21]) were incorporated outside the database search to supply demographic data, benefit-transfer coefficients and methodological context.

While this protocol provides transparency and replicability, the review is not exhaustive. The search was limited to English-language sources, and grey literature beyond major institutional repositories may not have been fully captured. A residual risk of selection bias is therefore acknowledged. No systematic review was required for the geospatial analysis; all satellite datasets were obtained directly from the USGS EarthExplorer archive and processed by the authors.

Demographic, macroeconomic, and regulatory data were obtained from the Kenya National Bureau of Statistics (KNBS), Kenya Forest Service (KFS), Kenya Tea Development Agency (KTDA), Kakamega County Water and Sanitation Company (KACWASCO), and Kenya Wildlife Service (KWS). Additional context came from publications of the Millennium Ecosystem Assessment (MEA) and World Resources Institute (WRI). Additionally, all monetary values reported in this study are expressed in constant 2023 Kenyan Shillings (KES). Where original studies reported values in earlier years, we adjusted them to 2023 price levels using the KNBS Consumer Price Index (CPI) series. For values originally reported in foreign currency, we applied the 2023 average exchange rate of KES 139.85 per US Dollar (Central Bank of Kenya). These adjustments ensure comparability across disparate study periods and provide a current estimate of economic flows.

3.2. Environment-Economic Data Analysis

We grouped ecosystem services according to TEV categories: Direct Use (provisioning, tourism), Indirect Use (regulating), and Option/Non-Use values. The synthesis examined interdependencies and trade-offs between economic activities and sustainability.

Combining economic valuation with time-series remote sensing enables simultaneous monitoring of ecosystem service values and natural capital condition. Linking SAVI-derived degradation classes to changes in service flows allows iterative updating as new satellite images become available. This combination of valuation and monitoring is a notable gap in the ecosystem services literature, where the two are often treated separately.

All economic valuation figures (Direct Use Values, Indirect Use Values, and the aggregated TEV summary) are synthesized from peer-reviewed literature and institutional reports; no primary economic data collection was undertaken. In contrast, the spatiotemporal forest degradation analysis (Landsat 8, SAVI, Jenks natural breaks classification, and accuracy assessment) constitutes original empirical work conducted by the authors. The novel contribution of this paper is the integration of these two streams: superimposing the original degradation trajectories onto the synthesized economic values to produce the degradation-adjusted annual loss estimate.

3.3. Calculation of Degradation-Adjusted Ecosystem Service Loss

To estimate the annual economic loss attributable to forest degradation, we applied the proportion of net degraded forest area to the indirect use value component of TEV. We focus on indirect use value because these regulating services (watershed protection, carbon sequestration, pollination, soil and climate regulation) are most directly dependent on the biophysical condition of the forest canopy and ecosystem structure, as measured by SAVI. Direct use values (e.g., Non-Timber Forest Products (NTFPs), tourism) may not scale linearly with canopy degradation and are therefore excluded from this degradation-loss calculation. This exclusion likely results in an underestimation of total economic losses because some direct use values (e.g., fuelwood availability, tourism attractiveness) also decline with forest degradation. However, the magnitude and functional form of those declines are not established in the literature for Kakamega Forest, and applying a proportional loss to direct use values would be speculative. Hence, the reported loss estimate is a conservative lower bound. The degradation-induced loss is calculated as:

$$\text{Loss} = (\text{Proportion of degraded area}) \times (\text{Indirect Use Value})$$

The calculation assumes a linear proportional relationship between the proportion of degraded forest area and the loss of indirect ecosystem service flows. This is a standard simplifying assumption in benefit-transfer and natural capital accounting studies when primary production functions linking vegetation condition to service delivery are unavailable [8,20].

The proportion of degraded forest area was derived from the SAVI classification in Section 4.1. Degraded pixels were defined as those falling below the ‘Moderate’ SAVI threshold (≤0.6880), corresponding to visibly reduced canopy cover validated by accuracy assessment (overall accuracy >85%). The loss estimate incorporates an additional buffer for the ±2.6 km^2 confidence interval in the degraded area estimate (approximately ±5% relative error). The final reported range therefore reflects both the TEV uncertainty interval and the geospatial confidence interval.

We acknowledge that a linear assumption may over- or under-estimate actual losses if ecosystem services respond non-linearly to degradation.

For the aggregate bundle of indirect use services, a linear approximation is justified on two grounds. First, degradation is spatially dispersed (Figure 2), so service losses are averaged across multiple patches. Second, although individual services (e.g., carbon sequestration, pollination) may respond non-linearly [22], aggregating multiple services with different response curves reduces overall non-linearity [23]. In the absence of site-specific dose-response functions, this approach provides a transparent and replicable first approximation [8,20].

3.4. Geospatial Analysis of Status of Forest Degradation

To quantify and show spatiotemporal patterns of forest degradation, remote sensing and GIS analysis were used. Landsat 8 OLI satellite imagery (30m resolution) from 2013, 2018, and 2023 was downloaded from the USGS EarthExplorer archive. The images were obtained and analyzed using the Google Earth Engine platform [24]. Prior to analyses, image preprocessing was conducted for geometric correction and cloud masking. Clouds and cloud shadows were screened from every image using the Landsat 8 pixel quality assessment (QA) band; only clear-sky pixels were retained for the analysis, ensuring that interannual variation is driven by vegetation change and not by atmospheric artefacts. The study area's boundary was drawn using official shapefiles from the Kenya Forest Service. The SAVI, which identifies low plant cover associated with deforestation, was used to assess forest health. The index was computed across the study areas using the Equation (1) defined below:

$$SAVI = \frac{(NIR - RED) * (1 + L)}{(NIR + RED + L)} \tag{1}$$

where *RED* and *NIR* are the surface reflectance values of the spectral bands of Red and near-infrared (*NIR*) in the Landsat 8 OLI images while $(1 + L)$ is the multiplication factor added so that the index can conform to the maximum and minimum Normalized Difference Vegetation Index (NDVI) range. For most purposes and in this study, the value of L is 0.5, corresponding to intermediate vegetation canopy cover. SAVI values range from +1 to −1. High value implies non-degraded vegetation, whereas low value indicates degraded vegetation. Using the Jenks natural breaks method in QGIS 3.28, pixels were classified into five degradation classes: Class 1 (Very Low), ≤0.6459; Class 2 (Low), 0.6459–0.6880; Class 3 (Moderate), 0.6880–0.7300; Class 4 (High), 0.7300–0.7720; and Class 5 (Very High), >0.7720. Change detection analysis was conducted using the Post-Classification Comparison method, calculating area changes and transition matrices between time periods. Accuracy assessment was performed using 150 randomly stratified reference points, with overall accuracy exceeding 85% for all classified images and the Overall Accuracy (*OA*) and Kappa (*K*) statistic metrics computed using Equations (2) and (3) below respectively.

$$OA = \frac{(\sum MDP)}{TP} * 100\% \tag{2}$$

$$K = \frac{((\sum MDP * TP) - \sum(CRT * CCT))}{TP^2 - (\sum(CRT * CCT)} \tag{3}$$

where *OA* = Overall Accuracy, *MDP* = Main Diagonal Pixels, *TP* = Total classified pixels, *K* = Kappa Statistic, *CRT* = Class Row Total, *CCT* = Class Column Total in the confusion matrix table.

3.5. Study Limitations

One of the major limitations of the study is that the economic valuation component relies on secondary data synthesis, owing to the vastness of the topic and the integrative nature of the study. Additionally, although the literature search followed a systematic protocol, the review was not exhaustive; unpublished grey literature and non-English sources were not systematically included, and the reliance on secondary data introduces a risk of selection bias that should be considered when interpreting the TEV ranges. The spatiotemporal degradation analysis, however, constitutes original primary analysis conducted by the authors. There are gaps in the data, and sometimes it has been necessary to make estimates for the regions based on local studies, as a primary economic valuation of the Kakamega Forest Basin has not been conducted. Non-use values (option and existence) are not quantified due to a lack of primary willingness-to-pay studies; they are recognised conceptually but excluded from the aggregated TEV. The case study approach has limitations, but the findings may be relevant to other tropical forests in developing countries.

4. Results

The results are presented in two streams. First, original spatiotemporal degradation analysis (Section 4.1) is presented as the study's independent empirical contribution. Second, economic values synthesized from existing literature (Sections 4.2 and 4.3) are reported. The integration of both streams yields the degradation-adjusted loss estimate reported in Section 4.3. All monetary values reported in this section are synthesized from existing secondary literature and, where necessary, benefit transfer from ecologically similar sites. Given the limitations of the source data and the assumptions inherent in benefit transfer, these figures should be interpreted as order-of-magnitude estimates rather than precise valuations.

4.1. Spatiotemporal Analysis of Forest Degradation

4.1.1. Accuracy Assessment Results

Across all the analyzed images, the Overall Accuracy (OA) and Kappa (K) statistic results exceeded 85% and 0.83 respectively (Table 1), hence providing sufficient reliability to draw conclusions from the results.

Table 1. Overall Accuracy (OA) and Kappa (K) statistic results.

Degradation Assessment Year	2013	2018	2023
Kappa (K)	0.848	0.841	0.858
Overall Accuracy (OA as a %)	88.0	87.3	88.7

Accuracy was assessed for 2013, 2018, and 2023. Validation data for 2019 were unavailable due to the absence of cloud-free, high-resolution reference imagery; the 2019 accuracy is therefore inferred from the nearest assessed years. The economic-loss calculation (Section 3.5) uses the net cumulative degraded area at the end of the study period (2023), which was directly validated with an overall accuracy of 88.7%. Consequently, the absence of 2019 reference data does not affect the robustness of the loss estimate. The interannual disturbance pattern, while informative for interpreting degradation dynamics, is not used quantitatively in the valuation. The consistently high accuracy across the three validated years (2013, 2018, 2023) indicates that the SAVI-based classification is stable over time; therefore, the annual trajectory and the derived net degradation are well supported.

The confusion matrices for the 2013, 2018, and 2023 classifications are presented in Table 2, including user's accuracy (UA), producer's accuracy (PA), and overall accuracy (OA) for each SAVI-derived degradation class.

Table 2. Confusion Matrices Computations.

		Reference Data						
	SAVI Classes	**Very Low (≤0.6459)**	**Low (0.6459–0.6880)**	**Moderate (0.6880–0.7300)**	**High (0.7300–0.7720)**	**Very High (>0.7720)**	**Total**	**UA**
CIY-2013	Very Low (≤0.6459)	19	0	0	1	0	20	0.950
	Low (0.6459–0.6880)	0	19	2	0	1	22	0.864
	Moderate (0.6880–0.7300)	2	0	34	0	0	36	0.944
	High (0.7300–0.7720)	3	2	1	31	2	39	0.795
	Very High (>0.7720)	0	1	2	1	29	33	0.879
	Total	24	22	39	33	32	150	
	PA	0.792	0.864	0.872	0.939	0.906		0.880
CIY-2018	Very Low (≤0.6459)	25	0	1	2	0	28	0.893
	Low (0.6459–0.6880)	0	21	2	0	0	23	0.913
	Moderate (0.6880–0.7300)	2	0	29	0	0	31	0.935
	High (0.7300–0.7720)	0	4	1	31	2	38	0.816
	Very High (>0.7720)	1	1	2	1	25	30	0.833
	Total	28	26	35	34	27	150	
	PA	0.893	0.808	0.829	0.912	0.926		0.873
CIY-2023	Very Low (≤0.6459)	26	0	1	1	0	28	0.929
	Low (0.6459–0.6880)	1	24	1	0	1	27	0.889
	Moderate (0.6880–0.7300)	2	0	32	0	0	34	0.941
	High (0.7300–0.7720)	0	2	1	28	2	33	0.848
	Very High (>0.7720)	1	1	2	1	23	28	0.821
	Total	30	27	37	30	26	150	
	PA	0.867	0.889	0.865	0.933	0.885		0.887

Where CIY = Classified Image Year.

4.1.2. Forest Degradation Level

The mean SAVI values computed annually from Landsat 8 data between 2013 and 2023 exhibit moderate fluctuations around an overall stable baseline (Figure 2), with the mean values ranging from 0.6039 to 0.8190. It was classified into five categories: Very Low (≤0.6459), Low (0.6459–0.6880), Moderate (0.6880–0.7300), High (0.7300–0.7720) and Very High (>0.7720). The moderate SAVI values were noticed for regions that remained undisturbed across the entire study period (2013–2023). High to Very High values (0.7300–0.8190) were given higher ranks and represent high canopy vegetation, indicating non-degraded forest. These areas mainly occurred in the interior of the forest implying least human disturbance due to remoteness.

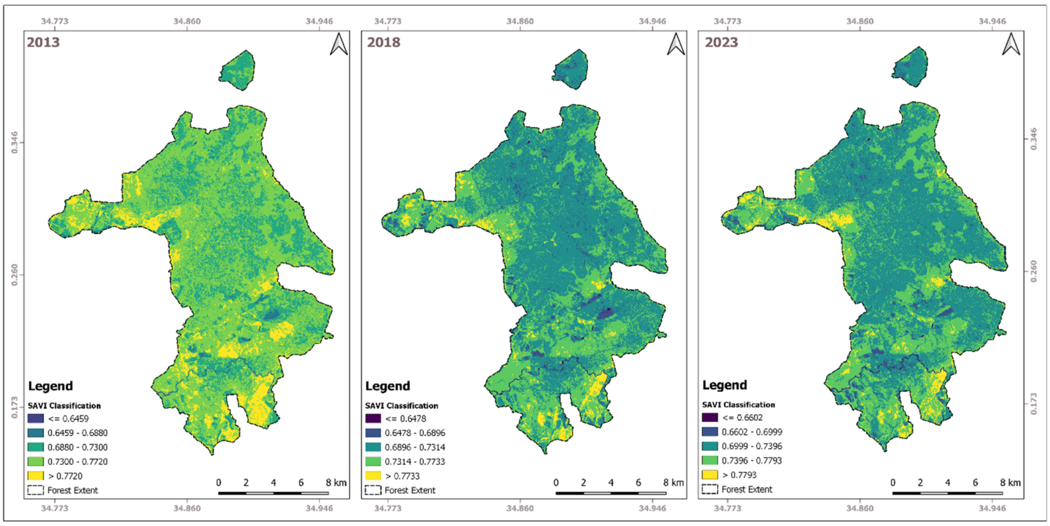

Figure 2. Spatiotemporal Forest Degradation (2013–2023).

The annual area of newly degraded forest (Figure 3) shows a pronounced spike in 2018–2019, reaching 121.2 km^2. This value represents the sum of pixel-level disturbance detections in the period from 2018 to 2019, not the net cumulative degraded area. The Global Forest Watch program, which uses 30-m resolution satellite imagery for fire monitoring, identified fire incidents in the region during this period [25]. However, no primary fire records or independent high-resolution validation for 2019 were available; therefore, the magnitude of the spike is uncertain and the value is presented only as an observed anomaly, not used in subsequent economic calculations. The annual disturbance values represent the sum of pixel-level degradation detections in each interval, including pixels that may have been disturbed multiple times or that recovered partially in subsequent years. The net cumulative degraded area (51.3 km^2) accounts only for pixels that remained below the moderate SAVI threshold at the end of the study period, thereby excluding regrowth areas. The large difference between annual disturbance and net degradation indicates that approximately 70 km^2 of disturbed area experienced some regrowth between 2019 and 2023.

The net cumulative degraded area (unique pixels remaining below the 'Moderate' SAVI threshold at the end of the study period, regardless of annual fluctuations) is 51.3 km^2 ± 2.6 km^2, representing 24.36% of the baseline canopy area of approximately 210 km^2. All degradation percentages and economic loss calculations are expressed relative to the canopy area, not the gazetted area. The relationship between annual disturbance and net degradation is non-linear because of recovery, regrowth, and repeated disturbances. To avoid misinterpretation, we report the net figure as the basis for the economic loss calculation (Section 3.5).

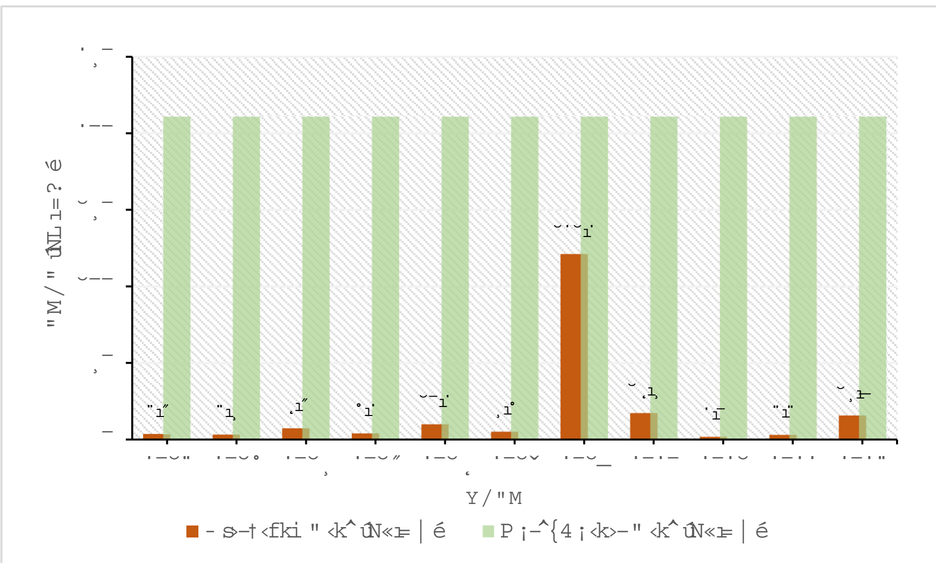

Figure 3. Annual area of forest degradation (km^2) from 2013 to 2023.

4.2. Direct Use Values

Fuelwood and charcoal are the most important NTFPs; over 90% of households depend on the forest for energy and income [26]. The forest provides savings on commercial energy and cash income from NTFP sales [4] (see Table 3 for quantified estimates). Traditional healers use forest plants (e.g., *Warburgia ugandensis*, *Zanthoxylum gilletii*) for medicinal treatments. The associated economic value derives from avoided pharmaceutical costs and workforce health maintenance. Wild foods and fodder also contribute to household diets and livestock feed, particularly during seasonal shortages. KFS regulates timber production from exotic plantations (Cypress, Pine), providing jobs, government revenue, and raw materials for furniture industries in Kakamega and Webuye. However, illegal logging and charcoal production undermine this legitimate activity, threatening both economic returns and forest sustainability. Kakamega Forest supplies water to Western Kenya by regulating hydrological flows and feeding permanent rivers (Yala, Isiukhu, Nzoia) that are tributaries of Lake Victoria. These rivers provide clean water for domestic, agricultural, and industrial use, substantially reducing treatment costs.

Table 3 shows the breakdown of the TEV. Kakamega Forest generates an economic value of KES 8.7 to 13.6 billion annually (approximately 65 to 102 million USD). Notably 21% of the economic value of the forest comes from the direct provision of services such as water supply. The remaining 79%, however, comes from the provision of indirect services. All values in Table 3 represent annual flows of ecosystem services (KES year^{-1}), not the capitalized stock value of the forest as a natural asset. For instance, the carbon value reflects the annual sequestration rate rather than the total standing carbon stock. This flow-based accounting aligns the economic valuation with the spatiotemporal degradation analysis presented in Section 4.1.

Table 3. Total Economic Valuation Summary.

Valuation Category (Key Services or Products)	Estimated Annual Value (KES Million) (% of TEV)	Primary Beneficiaries	Valuation Method	Key Sources and Technical Justification
Direct Use Value	1850–2720 (21%)			
NTFPs (Fuelwood, medicine, food, construction)	800–1170 (9%)	Households, healers, traders	Market Price; Substitute Price; Opportunity Cost of Time	Market prices (e.g., for fuelwood in local markets [27]) and opportunity cost of collection time [4] were used. Value per household = (Quantity collected × market price) + (Collection hours × shadow wage rate). Shadow wage rate = 50% of rural agricultural wage (KES 250/day). Annual per-household NTFP value: KES 20,000–23,400. Dependent households: 40,000–50,000 (from >200,000 people, household size 4–5).
Regulated Timber (Cypress, Pine plantations)	100–150 (1%)	KFS, formal sector	Market Price	KFS revenue records for timber sales (Cypress, Pine). Annual harvest volumes: 6100–7500 m^3 (Cypress), 3000–4500 m^3 (Pine); stumpage fees: KES 11,000–12,500/m^3.
Tourism (Entry fees, guiding, accommodation)	140–205 (2%)	KWS, local businesses	Travel Cost Method	Visitor expenditure data (entry fees, transport, accommodation, guiding) were aggregated following [28]. Annual visitors: 17,000–20,000; average expenditure per visitor: KES 8200–10,250.
Water Provision (Domestic, agricultural, industrial)	800–1200 (9%)	Water utilities, farmers	Market Price (water tariffs); Benefit Transfer	Prevailing water tariffs in Kakamega County [29] were applied to estimated volumetric flows. Annual water yield from forest catchments: 60–90 million m^3, of which an estimated 30–50% is abstracted for direct human use. Based on local abstraction records [29], annual domestic abstraction is 25–30 million m^3. Applying the domestic tariff (KES 32–40/m^3) gives KES 800–1200 million. Industrial abstraction is excluded to avoid double-counting with watershed protection (replacement cost of water treatment).
Indirect Use Value	6800–10,900 (79%)			

Table 3. *Cont.*

Valuation Category (Key Services or Products)	Estimated Annual Value (KES Million) (% of TEV)	Primary Beneficiaries	Valuation Method	Key Sources and Technical Justification
Watershed Protection (Flood control, siltation prevention)	3500–5000 (38%)	Agriculture, hydropower	Replacement Cost; Damage Cost Avoided; Benefit Transfer	Replacement cost for artificial flood control and water treatment to replace lost forest hydrological functions: KES 2000–3000 million. Avoided siltation costs for irrigation and hydropower [13]: KES 1500–2000 million. Benefit transfer from comparable East African montane catchments [8].
Carbon Sequestration (Carbon storage (potential REDD+))	800–1500 (10%)	National climate finance	Market Price (carbon credits); Benefit Transfer	Kakamega forest has an estimated annual carbon sequestration rate of 1.2 $MtCO_2e$/yr [30,31]). Valued at 2019–2023 voluntary carbon market prices ($5–8/$tCO_2e$) gives KES 800–1500 million. Exchange rate: KES 139.85/USD.
Pollination & Pest Control (Crop yield enhancement)	300–600 (4%)	Farmers	Production Function; Factor of Production Method	Pollinator-dependent crop area: 2000–3500 ha. Yield enhancement due to forest-proximal pollinators [32,33]: 15–25%. Baseline yields: passion fruit 10,000–15,000 kg/ha/yr, beans 800–1200 kg/ha/yr. Farm-gate prices: passion fruit KES 50–90/kg, beans KES 50–100/kg. Marginal value = Area × Yield increase × Baseline yield × Price.
Soil & Climate Regulation (Fertility, micro-climate)	2200–3800 (27%)	Regional agriculture	Replacement Cost; Benefit Transfer	Replacement cost of artificial fertilisers to substitute lost nutrient cycling [4]: KES 1200–2000 million, based on NPK prices and estimated nutrient loss from deforested areas (50–80 kg/ha/yr). Benefit transfer for microclimate regulation [8]: KES 1000–1800 million.
Option/Existence Value (Biodiversity, cultural heritage)	Not quantified (—)	Global & local community	Contingent Valuation (theoretical)	Not monetised in this study due to absence of primary willingness to pay studies specific to Kakamega Forest.
TEV	8650–13,620 (100%)			

The reported ranges reflect the combined uncertainty from primary data variability, benefit transfer assumptions, and methodological limitations. Given the absence of site-specific primary valuation for some services (e.g., non-use values), we adopted a conservative approach: we excluded option and existence values entirely and report a range rather than a point estimate for each service category. A qualitative sensitivity analysis (see Discussion) indicates that the overall TEV is most sensitive to watershed protection values; a ±50% variation in the watershed-protection component (the largest single indirect-use category) changes the total TEV by approximately ±19%, illustrating the sensitivity of the aggregate to this service category. Consequently, the figures should be interpreted as indicative approximations rather than precise financial accounts. To minimise double counting, services were mapped conceptually and validated with an explicit service interaction matrix (Table 4).

Following standard practice in data-scarce contexts [8,9], the TEV reported here aggregates only direct and indirect use values. Option and existence values are not monetized due to the absence of primary willingness-to-pay studies; therefore, the reported TEV represents a conservative lower bound of the forest's total economic value. The matrix in Table 4 below confirms that the TEV aggregation does not double-count any service flow. The two potential interaction zones (1) water provision/watershed protection and (2) watershed protection/soil regulation are managed by using distinct valuation bases: off-take and replacement costs for the former, and off-site damage versus on-site replacement for the latter. The remaining service pairs have no plausible conceptual overlap. This framework provides a transparent and auditable approach to TEV aggregation.

Table 4. Anti double counting service interaction matrix.

	Water Provision	Watershed Protection	Carbon Sequestration	Pollination & Pest Control	Soil & Climate Regulation
Water provision	—	Distinct	No overlap	No overlap	No overlap
Watershed protection	Distinct	—	No overlap	No overlap	Overlap managed
Carbon sequestration	No overlap	No overlap	—	No overlap	No overlap
Pollination & pest control	No overlap	No overlap	No overlap	—	No overlap
Soil & climate regulation	No overlap	Overlap managed	No overlap	No overlap	—

4.3. Indirect Use Values

The observed 24.36% net degradation is associated with an estimated annual loss of KES 1.7–2.7 billion in indirect ecosystem service flows. These regulating services (flood control, water purification, erosion prevention, microclimate moderation) support regional agriculture, hydropower, and water supply. The estimates are derived from replacement cost and damage cost avoided methods.

Estimated carbon stocks (Table 3) could generate revenue through REDD+ if verified and financed, but market access and verification are not yet in place. The forest regulates the microclimate, benefiting rain-fed agriculture, and supports wild pollinators that boost yields of passion fruit and beans [33].

Kakamega Forest supports ecotourism based on birding and scenery. Revenue from entry fees, accommodation, and guiding services is lower than in some comparable protected areas but depends directly on forest health.

For the Luhya people, the forest holds cultural and spiritual significance, with sacred sites and trees. These non-use values, while unquantified, contribute to social cohesion and intrinsic motivation for conservation.

5. Discussion

Three findings emerge from the integration of SAVI time-series with TEV. First, the resulting spatially explicit, degradation-informed framework can complement national natural capital accounting. Second, the trade-off matrix (Table 5) provides a replicable tool for data-scarce regions. Third, the observed poverty-degradation cycle demonstrates a mechanism of natural capital depletion.

The data indicate a reinforcing feedback between forest dependency and degradation. Agricultural encroachment continues, with short-term returns from land conversion that can appear to outweigh the long-term value of the intact ecosystem (Table 5). However, as Table 5 shows, conserved forest yields higher economic returns per km^2 than conversion to agriculture or charcoal. The per-unit return (KES 36–57 million/km^2) is the total TEV divided by the gazetted area (240 km^2). Note that the degradation percentage (24.36%) is expressed relative to the baseline canopy area (210 km^2) because that represents the biophysically meaningful unit for vegetation change, whereas the per-unit economic returns in Table 5 are conservatively calculated using the gazetted area (240 km^2) to capture the entire forest landscape to which the Total Economic Value is attributed. This intentional difference in denominators does not alter the comparative magnitude of the trade-off analysis.

Table 5. Economic Trade-off Analysis: Conservation vs. Conversion.

Land Use Scenario	Annual Economic Return (KES Million/km^2)	Key Economic Outputs	Sustainability	Source
Conserved Forest	36–57	Water regulation, carbon, NTFPs, tourism, biodiversity	Sustainable (perpetual)	Derived from TEV synthesis (Table 3), divided by forest area (240 km^2); see text
Sugarcane Plantation	2.5–4.0	Sugar, molasses, bagasse	10–15 year cycles, soil depletion	Farmer surveys in Kakamega [34]
Tea Estate	3.0–5.0	Tea leaves	Long-term but high input	Market prices [19,35]
Maize Subsistence	0.8–1.5	Food crop	Seasonal, rain-dependent	Market prices [3,35]
Charcoal Production	1.0–2.0 (one-time)	Charcoal	Unsustainable (resource depletion)	Local market surveys [4,35]

Conserved forest returns are calculated by dividing the total annual TEV of direct and indirect use values (KES 8,650–13,620 million from Table 3) by the forest area (240 km^2). Agricultural and charcoal returns are based on regional average yields, market prices, and production costs, drawn from [3,19], and peer-reviewed studies [34]). Charcoal returns represent one-time revenue before resource depletion.

Watershed services (KES 3.5–5.0 billion) are of sufficient magnitude to potentially support Payment for Watershed Services (PWS). However, unsustainable logging, charcoal production, and governance failures continue to degrade the forest and erode community support [12], perpetuating a poverty-degradation cycle.

One interpretation of these dynamics is that reducing degradation may depend on a transition from extraction-oriented use to natural capital management, with TEV integration into regional planning potentially facilitating that shift. Potential mechanisms include Payments for Ecosystem Services (PES), where downstream beneficiaries compensate upstream stewards, and REDD+ carbon financing. However, empirical studies from comparable East African contexts caution that benefits can be captured by local elites unless transparent governance and equitable benefit-sharing rules are in place [12,36]. For example, Kenya's PES scheme in the Mau Forest was undermined by land-tenure disputes, elite capture, and inconsistent monitoring [37,38], while Tanzania's REDD+ pilots faced overestimated carbon revenues, inequitable benefit-sharing, and deforestation leakage [39]. Both cases revealed weak governance, high transaction costs, and poor post-pilot community engagement. These lessons do not preclude PES or REDD+ in Kakamega, but they emphasise that success hinges on transparent institutions, secure land rights, and adaptive monitoring that links payments to verified outcomes. These conditions are not yet fully established in the study area, given the documented governance challenges [12] and persistent poverty-degradation feedback (Section 4.2).

The TEV estimates are subject to uncertainty from benefit-transfer assumptions and the exclusion of non-use values. A univariate sensitivity analysis shows that the TEV is most sensitive to the watershed protection component (≈38% of TEV); varying this component by ±50% changes the total TEV by approximately ±19% (from the midpoint of KES 11.1 billion to KES 9.0–13.2 billion). Primary valuation studies are needed to refine these estimates.

Recent work by [40] valued Kakamega's tangible services at USD 283,362, complementing our broader synthesis. A systematic review [41] confirms increasing use of both participatory and non-participatory valuation methods, consistent with our hybrid approach. Our TEV estimate is conservative compared to the global TEEB benchmark of USD 5264 ha^{-1} yr^{-1} [21] and specific valuations such as rainfall generation in the Amazon [42], highlighting the need to incorporate non-use values. Available evidence from choice experiments in the Mau Forest [16] suggests that including non-use values would likely increase the TEV further, though application to Kakamega requires site-specific verification.

6. Conclusions

This study provides a synthesized Total Economic Valuation of Kakamega Forest, integrating economic estimates from existing literature with original spatiotemporal analysis of forest degradation (Landsat 8 SAVI, 2013–2023). The findings indicate that the forest generates ecosystem service flows valued on the order of KES 8.7–13.6 billion annually (approximately USD 65–102 million), with indirect regulating services accounting for roughly 79% of this total. The observed 24.36% net forest degradation, measured relative to the baseline canopy area, corresponds to an estimated annual economic loss of KES 1.7–2.7 billion under a linear proportional assumption. This loss is derived from the indirect regulating services portion of TEV only, consistent with the methodology. These estimates should be interpreted as order-of-magnitude approximations, subject to uncertainties from benefit-transfer assumptions, data gaps in primary valuation studies, and the exclusion of non-use values. The per-unit-area comparison (conserved forest: KES 36–57 million km^{-2} yr^{-1}; agricultural conversion: KES 0.8–5.0 million km^{-2} yr^{-1}) suggests an aggregate economic advantage for forest cover, but this finding is not a causal econometric estimate.

The spatially explicit, degradation-informed valuation framework presented in this study is transferable to other tropical forests. By linking changes in forest condition to estimated service flows, this approach enables ongoing monitoring of natural capital depreciation. Future research should prioritize primary valuation studies to quantify non-use values for Kakamega Forest, econometric analysis of the causal relationship between conservation investments and regional economic outcomes, and development of site-specific dose-response functions linking vegetation indices to individual ecosystem service flows.

The findings indicate that conservation of Kakamega Forest could support sustainable development objectives in Western Kenya, depending on implementation of mechanisms such as PES, community-based natural resource management, and livelihood diversification. The aggregate TEV suggests that conserved forest yields higher annual returns per square kilometre than the dominant agricultural alternatives. Whether this potential is realised depends on governance, equity, and poverty-related factors.

Author Contributions

M.M.: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Resources; Software; Supervision; Validation; Visualization; Writing—original draft; and Writing—review & editing. I.W.: Data curation; Formal analysis; Methodology; Software; Validation; Visualization; and Writing—original draft. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work the authors used https://scispace.com/ in order to generate a compelling graphical abstract. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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