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ORIGINAL RESEARCH ARTICLE

Land-use/land-cover change in the Ngerengere River Catchment, Tanzania: Insights from 2004 to 2034

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Abstract: Land use and land cover (LULC) surrounding the Ngerengere River, Tanzania, which is a crucial water source, has led to a rapid decline in vegetated areas. Understanding these changes is vital for informed decision-making and sustainable river catchment management. This study assessed historical LULC trends from 2004 to 2024, projected the current trend of change to 2034, and analyzed the human activities driving the trends using Landsat TM imagery. The study utilized both spatial and non-spatial datasets from primary sources (Landsat imagery via Google Earth Engine and field surveys) and secondary sources (literature and government reports). Landsat 5 (2004) and Landsat 8 (2014, 2024) images were processed using Arc-GIS and QGIS to minimize cloud interference. Land cover classification combined unsupervised and supervised methods, validated with ground reference points collected through GPS. A rule-based classification system used spectral indices to identify land cover types. Classified maps were visualized and exported for further analysis. Furthermore, systematic field visits were conducted along the catchment to assess human land use activities, *that is*, agriculture, settlements, and deforestation. Results revealed a 17.6% decline in sparse vegetation between 2004 and 2014, and a further 27.01% decrease from 2014 to 2024. Bare land increased by 8.58% over the two decades. Built-up areas rose from 0.67% in 2004 to 5.44% in 2014, then dropped to 2.1% in 2024. In contrast, dense vegetation increased from 0.04% in 2004 to 7.13% in 2024. Overall, the land cover projection for 2034 indicates continued ecological transformation within the Ngerengere River catchment. These shifts, primarily driven by agricultural expansion and deforestation, underscore the urgent need for sustainable land management. The significant vegetation cover decline in the catchment is largely due to agricultural encroachment into forested areas.

Keywords: Anthropogenic activities; Biodiversity; Climate change; Deforestation; Ecosystem; Forest; River catchment; Water

1. Introduction

Vegetation cover, particularly forests, plays a crucial role in maintaining river catchments, protecting watersheds from erosion and sedimentation, and supporting biodiversity.[1-3] In addition, they act as important carbon sinks, absorbing and storing large quantities of carbon dioxide, thereby mitigating the impacts of climate change.[4-6] Beyond these ecological services, forests also support livelihoods, especially in rural areas, by providing timber, non-timber forest products, and ecosystem functions that are crucial for agriculture, clean water supply, and disaster risk reduction.[7,8] However, land use and land cover (LULC) changes (LULCCs), driven by deforestation, forest degradation, and the expansion of human activities – such as agriculture, infrastructure development, and fuelwood extraction – have historically led to widespread land cover loss on both local and global scales.[6,8-10] According to global assessments, the Earth lost approximately 4.4% of its forest cover between 1990 and 2020 – an area equivalent to about 178 million hectares – primarily as a result of anthropogenic pressures.[9]

For instance, in Africa, remote sensing data and field assessments from 2000 to 2020 show a continued decline in vegetation cover across many countries, with tropical and subtropical forest zones being the most affected.[11,12] This trend is largely fueled by the conversion of forests into farmland, logging for timber and charcoal, and infrastructure projects aimed at improving connectivity and economic growth.[12-14] While these developments contribute to short-term gains, they often come at the expense of long–term environmental sustainability.[15,16] The loss of forested land in Africa has led to the degradation of river catchments, disruption of hydrological cycles, reduced rainfall infiltration, increased surface runoff, and the siltation of rivers and reservoirs – ultimately compromising water availability and quality.[7,17-19] In West Africa, extensive vegetation decline has been documented between 2000 and 2020, particularly in tropical forest zones converted to cropland, logged for timber or charcoal, or cleared for infrastructure – activities that often yield short–term economic gains at the expense of long-term ecological stability.[20-22] This trend is especially pronounced in countries, such as Nigeria, Ghana, Côte d'Ivoire, and Burkina Faso, where deforestation and land conversion have intensified over the past two decades.[20-23] Studies highlight alarming rates of forest loss, notably in the Guinean Forest Zone – one of the region's most biodiverse ecosystems. For instance, in Nigeria, satellite data reveal significant forest reduction due to agricultural expansion, urban sprawl, and logging.[22] In Ghana and Côte d'Ivoire, cocoa cultivation and illegal timber harvesting have degraded vital watersheds such as the Pra, Ankobra, and Bandama basins.[20,23] Specifically, Ghana's Bonsa catchment lost over 0.3% of its forest annually between 1986 and 2011, driven by mining and settlement expansion.[20] In the Black Volta basin, urbanization increased surface runoff by ~27% and reduced groundwater recharge by ~6% between 2000 and 2013.[21] Similarly, Côte d'Ivoire's N'ZI watershed has experienced substantial forest and savanna loss due to agricultural encroachment.[23] These land use changes have disrupted hydrological cycles, reduced infiltration, intensified sedimentation, and compromised river water quality, posing risks to ecosystem services and rural livelihoods.[22] Understanding these dynamics is crucial for integrated land and water resource management across West African catchments.

Globally, LULCCs are increasingly recognized as a critical environmental challenge with far-reaching implications for climate change, food security, water scarcity, and socioeconomic development.[9,11,24] These changes significantly disrupt ecological processes, particularly in sensitive areas such as river catchments, where alterations in vegetation cover can degrade watershed functions, affect hydrological cycles, and reduce water availability downstream.[14] The impacts are not confined to the environment alone – and can directly affect millions of people who rely on forests and natural ecosystems for clean water, agriculture, energy, and livelihoods.[2,7] As river catchments degrade, the resilience of both ecosystems and communities weakens, further exacerbating poverty, vulnerability to climate extremes, and the loss of biodiversity. Addressing LULCC in the context of protecting river catchments is therefore essential for promoting sustainable development and safeguarding human and ecological well-being.[19,25,26]

In Tanzania, LULCC has emerged as a critical environmental issue, especially within the Ngerengere River catchment located in the Wami–Ruvu Basin of the Morogoro region. Over recent years, this area has experienced notable transformations in land cover, driven by deforestation, agricultural encroachment, urban development, and shifts in climate patterns.[14,27] These changes present serious threats to water availability, biodiversity, and the sustainability of land-use practices.[28] The Ngerengere River catchment is an ecologically important zone, home to a wide variety of plant and animal species, and serves as a vital source of natural resources for surrounding communities.[2,27,29] However, escalating human activities in and around the catchment – particularly along riverbanks – have led to severe forest degradation, increased soil erosion, and declining water quality. The conversion of forested areas into agricultural land has been a major contributor to this degradation.[14,30] Furthermore, rapid urbanization in the Morogoro region has amplified the pressure on land and natural resources, accelerating deforestation and ecosystem decline.[13,31] Overall, one of the primary factors driving vegetation cover change in the

Ngerengere River catchment is LULCC. The impacts of LULCC on watershed ecosystems have raised growing concerns due to their wide-ranging social, economic, political, and environmental implications at local, regional, and national levels.[29,32,33] As a result, detecting and analyzing LULCC has become essential for gaining deeper insights into land–use dynamics, tracking environmental change, and guiding effective river ecosystem management. In river catchments, alterations in vegetation cover can significantly disrupt hydrological functions, reducing the land's capacity to retain water, increasing surface runoff, and elevating the risk of droughts and floods.[14,29]

Despite advances in remote sensing and Earth observation technologies, a global knowledge gap remains in integrating field-based observations with satellite data to assess LULCC, especially at the catchment scale. Remote sensing offers broad landscape monitoring, but without ground-truthing, classification accuracy is limited and can misrepresent human–environment interactions.[34] Many global studies rely on either remote or field data alone, failing to consider key socio-ecological drivers of LULCC.[35] In East Africa – particularly Kenya, Uganda, Rwanda, and Tanzania – this gap is pronounced. Activities like small-scale farming, informal settlements, and charcoal production often escape detection without local input. For example, in Tanzania and Kenya's Tana Basin, forest loss and urban expansion are detected remotely but lack contextual attribution.[36] Integrating ground data with remote sensing is essential for accurate LULCC analysis and for designing effective, catchment-specific management interventions.[37] Therefore, a comprehensive understanding of LULCC in the Ngerengere River sub-catchment is crucial for supporting evidence-based land-use planning, enhancing biodiversity conservation efforts, and informing strategies for climate change adaptation. In general, this study aimed to: (i) assess the historical trends of LULCCs from 2004 to 2024 along the Ngerengere River catchment, (ii) predict the LULCCs for 2034 along the Ngerengere River catchment, and (iii) evaluate human activities performed along the Ngerengere River catchment.

2. Materials and methods

2.1. Study area

The study was conducted in the Morogoro region (06°49′27″S, 37°39′48″E), Tanzania, with a specific focus on the Ngerengere River sub-catchment (Figure 1). The Ngerengere River (7°03′S 38°31′E), covering an area of 2,780 km^2, is part of the Wami–Ruvu basin. It originates as fast–flowing streams in the Uluguru mountains and plays a critical role in supplying water to urban areas of Morogoro municipality before draining into the Mindu reservoir.[14,38] The river spans a significant portion of the Morogoro region, including Morogoro urban district and parts of Morogoro rural district.

The Ngerengere River catchment is characterized by a bimodal rainfall pattern (Figure 2a). The short rains typically occur from November to January, followed by a brief dry period in February. The long rainy season extends from March to May and is followed by a prolonged dry spell from June to October. Annual rainfall across most of the catchment ranges between 800 mm and 1,000 mm, but in the upstream areas near the Uluguru Mountains, it exceeds 2,000 mm. Temperatures throughout the year are relatively stable.[27] July is usually the coolest month, averaging around 16°C, while October tends to be the hottest, with temperatures reaching up to 31°C (Figure 2b). The mean annual temperature is about 26°C (Figure 2b). Estimated annual potential evaporation falls between 1,500 mm and 1,700 mm, generally surpassing the average annual rainfall. Furthermore, the riparian plants in the Ngerengere River ecosystem primarily include species such as *Cyperus rotundus* (Sedges), *Phragmites australis* (Reeds), *Pennisetum purpureum* (Elephant grasses), *Typha domingensis* (Bulrush), *Phragmites mauritianus* (Phragmites), *Sesbania sesban* (Sesbania), and *Ficus sycomorus* (Ficus).

Moreover, the river supports several socioeconomic activities, including domestic water supply, irrigation, industrial use, and livestock watering, particularly for the Ngerengere Maasai community.[14] The Morogoro region is located approximately 190 km southwest of Dar es Salaam.[14,29,39] The region experiences a tropical climate, with the highest temperatures, averaging 33°C, occurring between November and December, while the lowest temperatures, around 16°C, are recorded between June and August. According to the 2022 census, the Morogoro region has a population of 3,197,104, with Morogoro municipality accounting for 315,866 residents.[14]

2.2. Methods

2.2.1. Data acquisition and processing

The study used both spatial and non-spatial datasets derived from primary and secondary sources. Primary data included Landsat satellite imagery retrieved within the Google Earth Engine (GEE), and field-based observations, while secondary data were sourced from peer–reviewed literature and government reports

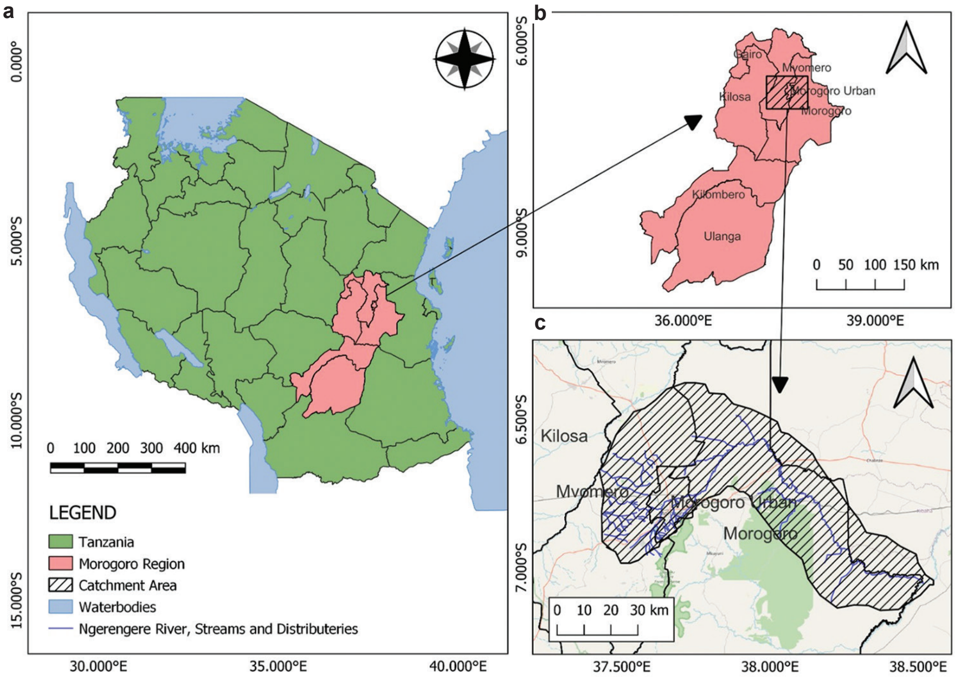

Figure 1. Map showing the location of Morogoro region (a), Morogoro municipality (b), and the Ngerengere River catchment area (c) in Tanzania

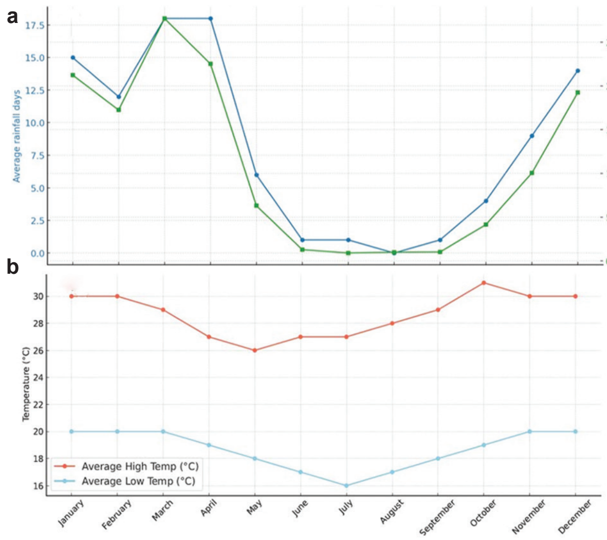

Figure 2. Average rainfall (a) and temperature (b) at Ngerengere River catchment in Morogoro from 2013 to 2024

Data source: https://www.worldweatheronline.com/ngerengere-weather-averages/morogoro/tz.aspx

(Table 1). A systematic approach was adopted using Landsat satellite imagery and spectral indices within the GEE platform[9,31] to analyze land cover changes in the Ngerengere River sub-catchment. The satellite data were obtained from the United States Geological Survey (USGS) database,[39] focusing on cloud-free Landsat 5 TM (2004) and Landsat 8 OLI/TIRS (2014 and 2024) images. These images were filtered based on the region of interest and processed to reduce cloud interference.[40] These Landsat images were integrated into the ArcGIS 2.8 and QGIS 8.10 to perform the classifications of each LULC.[41-43] Pre- and post-processing were both applied to the satellite images. Clouds, haze, shadows, and other disturbances must cause the least amount of contamination in input images to maximize classification accuracy.[2]

After image pre-processing, unsupervised classification followed by supervised classification was performed.[2,42,44] Supervised classification relies on pre-labeled training data to classify land cover, while unsupervised classification automatically groups pixels based on spectral similarity without prior labeling.[42] Supervised classification was employed in this study because it enables the use of known training samples, allowing for greater control and improved accuracy in identifying and mapping pre-defined land cover classes across the study area.[2,44] With the aid of Google Earth map, such change detection through image classification was performed through pixel-by-pixel comparison with the overall accuracy of over 80%.[41,45,46]

The LULC classification was carried out based on the Coordination of Information on the Environment

Table 1. Satellite images used for LULC change analysis and their characteristics

No.	Data type	Source	Resolution (m)	Bands	Path/Row	Cloud cover (%)	Date
1	Landsat 5 TM (2004)	USGS	30	1,2,3,4	148 – 49/36 – 37	10	March 28, 2004
2	Landsat 8 OLI	USGS	30	2,3,4,5	148 – 49/36 – 37	10	June 17, 2014
3	Landsat 8 TIRS	USGS	30	1,2,3,4		10	April 26, 2024

Abbreviations: LULC: Land use and land cover; USGS: United States Geological Survey.

(CORINE) LULC classification system, which was selected due to its relevance to the landscape features of the study area.[7,47-49] The LULC was categorized into eight classes based on Anderson classifications: water, wetland, dense vegetation, sparse vegetation, grassland, built–up area, bare land, and shrubland (Table 2). To enhance classification accuracy, spectral indices were applied, including the Modified Normalized Difference Water Index (MNDWI) for water detection, Enhanced Vegetation Index (EVI) for vegetation health, Normalized Difference Built-up Index (NDBI) for urban areas, Normalized Difference Burned Area Index (NDBaI) for fire-affected land, and Normalized Burn Ratio (NBR) for vegetated surfaces.[12,19,50] Logical expressions were used to assign pixels to appropriate land cover types, *that is*, water bodies, wetlands, vegetation, built-up zones, and bare areas.[18,31] Classified LULC maps were visualized using standardized color palettes and exported to Google Drive for further analysis.[6,12,24] The use of GEE enabled efficient, scalable, and reproducible land cover mapping, capitalizing on its robust cloud-based computational infrastructure.[2,15,51,52] Before classification, ground reference points were collected during fieldwork using GPS devices. These ground reference points were used to validate the classified images and ensure accuracy in associating image pixels with actual land use/cover types on the ground.[53]

To predict LULC in 2034, we employed the Cellular Automata–Markov (CA-Markov) model, a widely used spatial modeling approach that combines the strengths of Markov chain analysis and CA. The Markov chain component was used to analyze LULC transitions between 2004, 2014, and 2024, generating a transition probability matrix that estimates the likelihood of land cover class changes over time. The CA component incorporated spatial context by simulating how these transitions would propagate across space based on neighborhood effects. The model was implemented using the Land Change Modeler in TerrSet software. Key drivers of land change – such as proximity to roads, rivers, elevation, and slope – were included to improve prediction accuracy. Calibration was performed using LULC maps from 2004 and 2014, while validation was carried out by comparing the model's 2024 prediction with the actual 2024 classified map. Satisfactory validation results enabled the use of the calibrated model to simulate LULC distribution for the year 2034 under a business-as-usual scenario, assuming the continuation of past trends without major policy or land management interventions. This approach allowed for spatially explicit prediction of future land cover patterns, providing critical insights for planning and conservation efforts.

Table 2. The categories of LULC classes and their descriptions as used in the study

Description	Code	Land cover type
Area covered with water	WT	Water
Water-saturated land area	WL	Wetland
Area covered with dense vegetation	DV	Dense vegetation
Area covered with sparse vegetation	SV	Sparse vegetation
Area covered by sparse trees with dense grasses	GL	Grassland
Developed land area	BA	Built–up areas
Area of land without vegetation	BL	Bare land
Area covered with shrubs	SL	Shrubland

2.2.2. Spectral indices calculation

To enhance the differentiation of land cover types, several spectral indices were computed each chosen for its ability to highlight specific land surface features.[51] The MNDWI (Equation I) enhances the detection of open water bodies by suppressing built–up land noise, making it particularly effective for identifying aquatic features.[2,11,54] The EVI (Equation II) improves sensitivity to vegetation, especially in high biomass areas, by reducing atmospheric and canopy background noise, thus supporting accurate vegetation assessment.[17,55,56] The NDBI (Equation III) highlights urban and built-up areas by contrasting developed surfaces with vegetated or bare areas, while the NDBaI (Equation IV) detects recently burned regions by emphasizing the spectral signature of charred vegetation. The NBR (Equation V) further assists in identifying both vegetated and non-vegetated surfaces, making it suitable for monitoring burn severity and vegetation health.[1,57,58]

$$MNDWI = \frac{Green - SWIR}{Green + SWIR} \quad \text{(I)}$$

$$EVI = G\left(\frac{NIR - Red}{(NIR + C1)(Red - C2)(Blue + L)}\right) \quad \text{(II)}$$

$$NDBI = \left(\frac{SWIR - NIR}{SWIR + NIR}\right) \quad \text{(III)}$$

$$NDBaI = \frac{SWIR + Thermal - NIR}{SWIR + Thermal + NIR} \quad \text{(IV)}$$

$$NBR = \frac{NIR - SWIR}{NIR + SWIR} \quad \text{(V)}$$

Where, Green = Green band (e.g., Band 3 in Landsat 8);
SWIR = Shortwave Infrared band (e.g., Band 6 in Landsat 8);
NIR = Near-Infrared (e.g., Band 5 in Landsat 8);
Red = Red band (e.g., Band 4);
Blue = Blue band (e.g., Band 2);
L = Canopy background adjustment (typically 1);
C_1, C_2 = Coefficients for atmospheric resistance (typically $C_1 = 6$, $C_2 = 7.5$);
G = Gain factor (typically 2.5);
Thermal = Thermal Infrared (e.g., Band 10 or 11 in Landsat 8).

The calculated indices were then applied through a rule–based classification approach to categorize land cover types. Water bodies were identified in areas where EVI values were <0, indicating low vegetation reflectance typical of open water. Wetlands were detected in non-water pixels where MNDWI was greater than or equal to −0.2, capturing regions with significant moisture content. We classified vegetation where NBR values exceeded 0.4, indicating the presence of healthy plant cover. Within the vegetation class, dense vegetation, *that is*, forests, were further identified by NBR values of 0.6 or higher, while sparse vegetation or shrubland corresponded to NBR values below 0.6. Built-up areas were distinguished by pixels where NDBI exceeded −0.15 and NDBaI was ≤0.15, signifying urban or developed zones. Bare land was classified as non-vegetated and non-built-up areas, generally representing exposed soil or barren terrain.[59,60] This rule-based classification framework allowed accurate and consistent land cover mapping by leveraging the spectral characteristics of each land cover type. The integration of spectral indices with logical conditions significantly improved classification accuracy, as demonstrated in recent remote sensing studies.[2,33,61]

2.2.3. Visualization, export, and accuracy assessment

According to previous studies,[1,62] a pre-defined color palette was applied to the classified land cover map to enhance visual interpretation, with each land cover class assigned a distinct and easily recognizable color. Leveraging the capabilities of GEE significantly streamlined the image processing and visualization workflow, ensuring efficiency, consistency, and reproducibility throughout the analysis.[2,57] The use of cloud-based platforms, *for ex*ample, GEE, has proven highly effective for large-scale land cover classification, offering scalable, accessible, and robust tools that support researchers and practitioners in conducting spatial analysis and environmental monitoring.[16,54] Furthermore, the classification accuracy of all four images (2004, 2014, 2024, and 2034) in the study was assessed by an error matrix using Google Earth and land use maps. Accuracy assessment was essential for evaluating the reliability of land cover classification by comparing results with reference data. It involved overall accuracy, producer’s and user’s accuracy, and Kappa statistics. Assessing both classified and predicted maps validated the model’s performance and supported its use in environmental monitoring, land management, and spatial planning. The Kappa coefficient was used to measure the actual agreement in this validation, beyond what would be expected by chance. It is widely applied in LULC accuracy assessments to quantify the level of true agreement. To ensure that even smaller land cover classes were represented, a stratified random sampling approach was adopted during the accuracy assessment. The overall accuracy metric was calculated using Equation VI to assess the classification performance of the entire image, while the percentage change in LULC was quantified using Equation VII.

$$Overall\ accuracy = \frac{\sum(Correctly\ classidied\ pixels)}{\sum(Total\ number\ of\ reference\ pixels)} \quad \text{(VI)}$$

$$Percentage\ change = \frac{(Current\ LULC\ area - Previous\ LULC\ area)}{(Previous\ LULC\ area)} \quad (VII)$$

2.2.4. Human activities performed along the Ngerengere River catchment

Between March and April 2025, systematic field surveys were conducted along ten 150-m transects to assess anthropogenic activities contributing to LULCCs within the Ngerengere River sub-catchment. Observed activities were geolocated using GPS devices to enable accurate spatial mapping and analysis. In addition, spectral indices – including the Normalized Difference Vegetation Index, NDBI, and MNDWI – were applied to satellite imagery to detect and monitor spatial patterns of environmental change, such as deforestation, urban expansion, and water body shrinkage. These approaches allowed for the integration of field-based observations with remotely sensed data to evaluate the extent and impact of anthropogenic activities within the catchment.

3. Results

3.1. Classification accuracy assessments

Table 3 presents the accuracy assessments of the LULC classifications for the years 2004, 2014, 2024, and 2034. The overall accuracies ranged from 82.27% to 88.98%, with corresponding Kappa values between 0.78 and 0.85.

3.2. Historical trends of LULCCs from 2004 to 2024 along the Ngerengere River catchment

The analysis of LULCCs from 2004 to 2024 in the Ngerengere River catchment revealed notable transformations in landscape composition, primarily driven by anthropogenic activities, as illustrated in Table 4. The results showed a marked decline in vegetated areas over the two decades, accompanied by a significant increase in bare land and built–up areas (Table 4).

In 2004, sparse vegetation was the dominant land cover type in the Ngerengere River catchment, covering 50.92% (1416 km^2) of the total area. This was followed by bare land, which accounted for 30.56% (850 km^2), and shrubland at 11.21% (312 km^2) (Table 4 and Figure 3). Grassland made up 5.57% of the total area (155 km^2), while built–up areas were minimal, covering only 0.67% (19 km^2). Dense vegetation and wetlands were extremely limited, occupying just 0.04% (1 km^2) and 0.04% (1 km^2), respectively (Table 4 and Figure 3). Water bodies covered 0.98% (27 km^2) of the area. The predominance of sparse vegetation and bare land indicates that the river catchment was largely characterized by semi–arid conditions with limited forest cover (Figure 3).

By 2014, the Ngerengere River catchment experienced marked LULCCs, reflecting intensified human activity and environmental pressures (Table 4 and Figure 4). Bare land expanded significantly to 44.42% of the total area (1235 km^2), indicating increasing land degradation, possibly from overgrazing, deforestation, and poor land management practices (Table 4). In contrast, sparse vegetation area declined to 33.29% (925.86 km^2), suggesting a reduction in vegetative cover that may be linked to continued anthropogenic disturbance. Built–up areas saw a substantial rise to 5.44% (151.23 km^2), highlighting rapid urban expansion and population growth within the river catchment.

Table 3. Accuracy statistics of LULC maps produced from satellite imageries

Class	2004		2014		2024		2034	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
Dense vegetation	88.46	84.15	84.78	92.86	71.70	95.00	87.68	83.26
Shrub	60.00	78.26	75.00	61.54	82.34	68.29	84.3	86.28
Wetland	60.00	92.31	76.92	83.33	100.00	72.73	77.15	76.34
Water	100.00	77.55	96.55	87.50	100.00	97.67	82.73	81.73
Built–up area	86.36	95.00	90.32	96.55	90.70	88.64	78.23	79.02
Bare land	91.67	84.62	100.00	75.00	100.00	95.24	82.34	72.73
Sparse vegetation	84.09	88.70	76.54	78.00	85.72	87.02	100.00	87.50
Grassland	90.81	95.06	92.54	95.23	81.36	73.39	60.00	91.27
Overall accuracy	83.96		86.58		88.98		82.27	
Kappa statistic	0.78		0.80		0.85		0.79	

Abbreviations: AU: User's accuracy; PA: Producer's accuracy.

Table 4. LULCC (in km^2) between 2000 and 2034 along the Ngerengere River sub–catchment

Land cover	2004		2014		2024		2034	
	km^2	%	km^2	%	km^2	%	km^2	%
Dense vegetation	1.0	0.04	10.01	0.36	198.09	7.13	92.57	3.33
Grass land	155	5.57	204.34	7.36	145.95	5.25	141.1	5.08
Wetland	1.0	0.04	2.50	0.09	13.62	0.49	3.06	0.11
Water	27	0.98	1.95	0.07	1.95	0.07	12.23	0.44
Built–up area	19	0.67	151.23	5.44	58.38	2.1	25.3	0.91
Bare land	850	30.56	1235.08	44.42	1098.89	39.14	856.07	30.81
Sparse vegetation	1416	50.92	925.86	33.29	174.22	6.28	1449.19	52.13
Shrubland	312	11.21	249	8.97	1098.41	39.54	199.38	7.19
Total	2780	100	2780	100	2780	100	2780	100

Abbreviation: LULCC: Land use and land cover change.

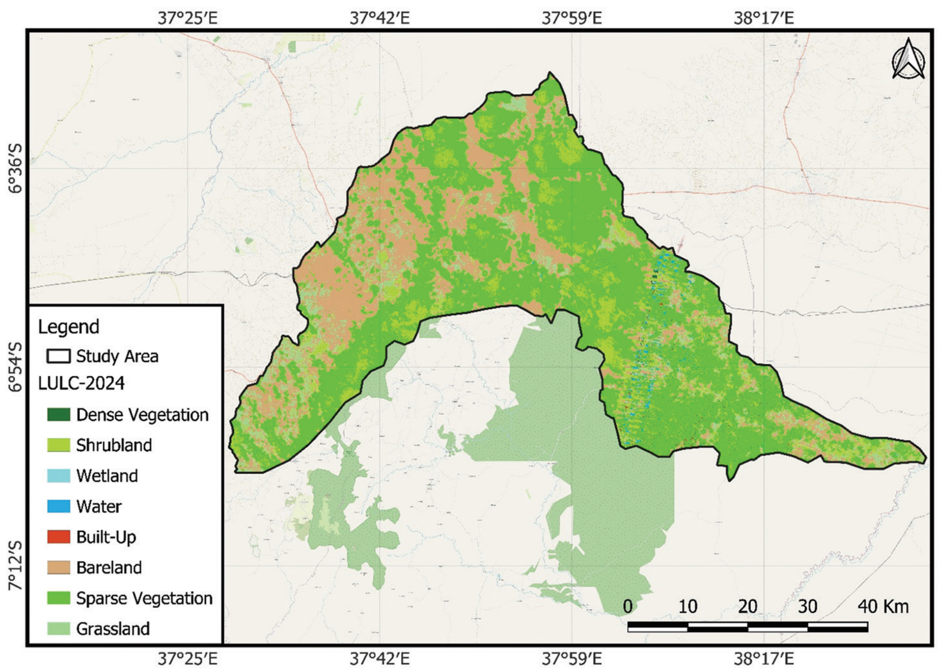

Figure 3. Spatial distribution of land cover in Ngerengere River catchment in 2004

Grassland area increased to 7.36% (204.37 km^2), and wetlands, though still limited, expanded slightly to 0.09% (2.50 km^2), pointing to changing vegetation dynamics that could be influenced by localized climate shifts or restoration initiatives (Table 4 and Figure 4). Most concerning, however, is the drastic reduction in water bodies from 27 km^2 in 2004 to just 1.95 km^2 in 2014 (Table 4 and Figure 4).

Land cover data for 2024 indicates a significant ecological shift in the Ngerengere River catchment, with shrubland emerging as the dominant land cover, accounting for 39.54% (1098.41 km^2) of the area (Table 4 and Figure 5). This change is accompanied by a slight area decline of bare land to 39.14% (1088.89 km^2). Notably, dense vegetation shows a substantial increase in area to 7.13% (198.09 km^2) (Table 4). While built–up areas decline to 2.1% (58.38 km^2), water bodies remain critically low, covering only 0.07% (1.95 km^2) (Table 4 and Figure 5).

3.3. Prediction of the LULCC for 2034 along the Ngerengere River catchment

The land cover projection for 2034 indicates continued ecological transformation within the Ngerengere River catchment (Table 4 and Figure 6). Sparse vegetation area is expected to expand significantly, covering

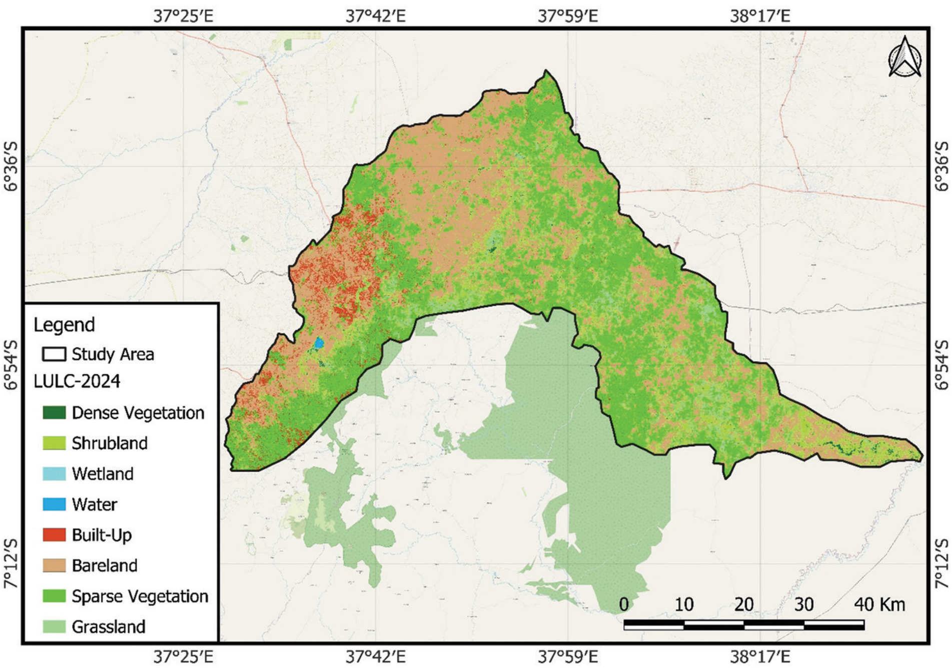

Figure 4. Spatial distribution of land cover in Ngerengere River catchment in 2014

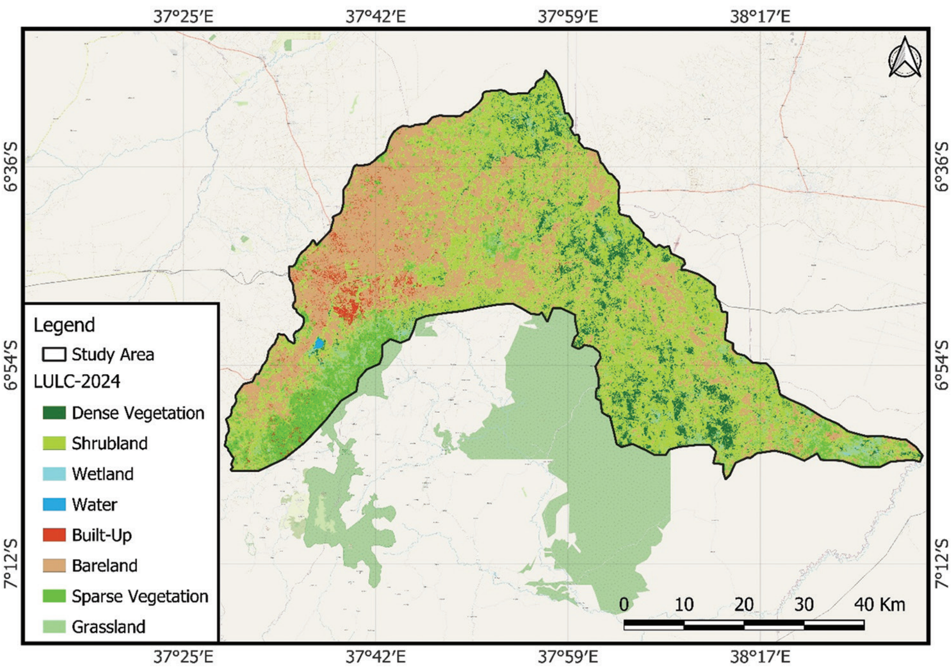

Figure 5. Spatial distribution of land cover in Ngerengere River catchment in 2024

52.13% (1,449.19 km^2), while bare land is projected to decline in area to 30.81% (856.07 km^2). Moreover, dense vegetation area is expected to decrease to 3.33% (92.57 km^2) and built–up area is predicted to decline to 0.91% (25.3 km^2). Importantly, water bodies are expected to show a modest increase, rising to 0.44% (12.23 km^2).

3.4. Human activities performed along the Ngerengere River catchment

During the field survey, we observed that the LULCCs negatively impact the hydrology and the Ngerengere River. Extensive degradation of natural habitats across the Ngerengere River catchment was primarily driven by widespread and intensifying anthropogenic activities.

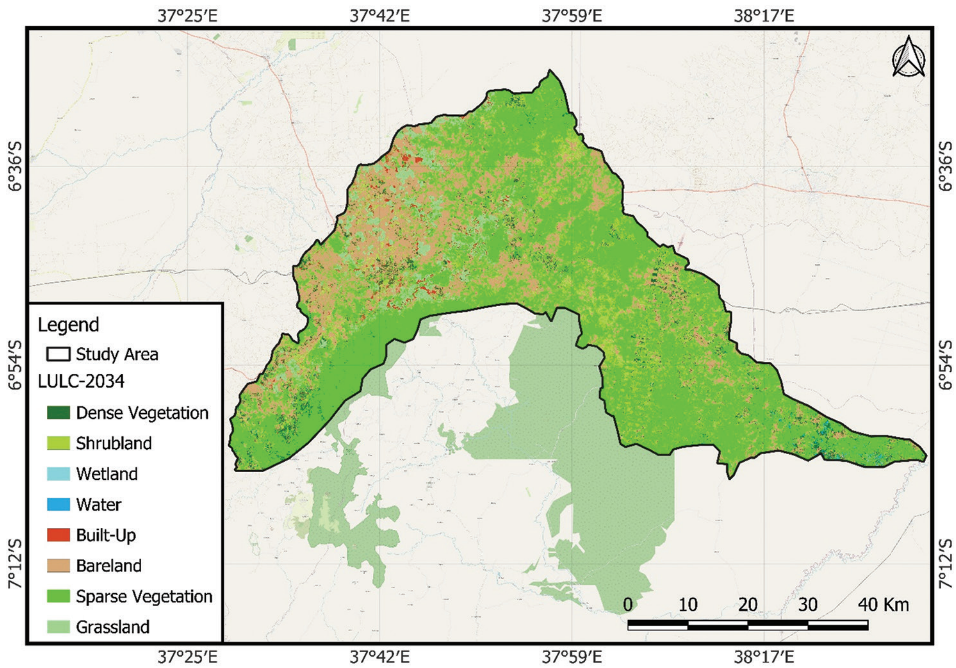

Figure 6. Spatial distribution of future land cover in Ngerengere River catchment in 2034

Agriculture emerged as the most frequent and dominant land–use practice with 38% frequency of occurrence (Figure 7), with large expanses of forested land cleared and converted into farmlands/bareland to support both crop cultivation and livestock rearing key livelihood strategies for most local communities. Subsistence farming was documented in nearly all surveyed locations, highlighting the high frequency and intensity of this activity (Figure 8). These field observations closely align with the satellite-based LULC analysis, showing that sparse vegetation declined by 17.6% between 2004 and 2014, followed by a further 27.01% decrease from 2014 to 2024, indicating ongoing deforestation and land degradation. This loss of vegetation cover correlates with the reported increase in bareland (by 8.58% over two decades), reflecting soil exposure due to clearing and overuse. Built-up areas initially increased from 0.67% in 2004 to 5.44% in 2014, suggesting rapid urban and rural settlement expansion, but declined to 2.1% by 2024 – possibly due to land abandonment or reclassification.

Furthermore, trees were being harvested extensively for construction, and most notably, fuelwood collection (Figure 7). Fuelwood collection stood out as another major and frequent activity (with 30% frequency of occurrence), which was observed to occur on a daily basis. Timber production and settlement expansion were also evident throughout the river catchment, fueled by rapid population growth and the growing demand for housing, roads, schools, and other infrastructure.

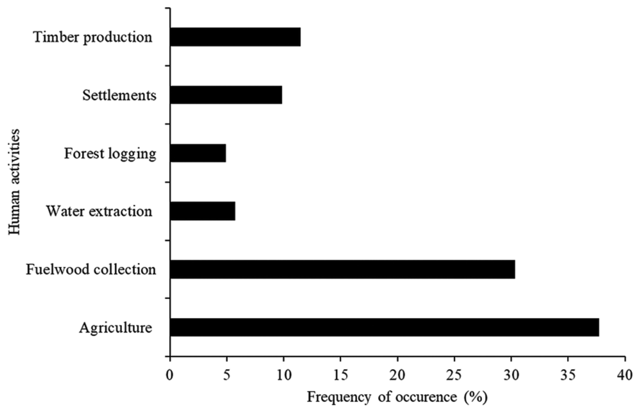

Figure 7. Frequency of occurrence of human activities along Ngerengere River catchment

4. Discussion

This study examined LULCCs in the Ngerengere River catchment from 2004 to 2024 and projected changes for 2034. Accuracy assessments for the classified maps showed high reliability, supporting the credibility of the results.[39] The findings revealed significant landscape transformation driven mainly by human activities, particularly agricultural expansion and settlement growth. The current study revealed that the Ngerengere River catchment has undergone notable landscape transformations between 2004 and 2024, largely driven by anthropogenic pressures. Over the years, a considerable reduction in vegetated

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Figure 8. Pictures of (a) the Ngerengere River sub–catchment at Tangeni; (b) agricultural activities along or near the catchment; (c) banana plantation; and (d) the Ngerengere River
Source: Photo by Nkinda R., captured in March 2025.

cover has occurred, paralleled by an increase in bare land and built–up areas. These shifts mirroring global trends, where LULCCs have been used, are influenced by agricultural expansion, urbanization, and climate variability.[10,12,40] In the early 2000s, sparse vegetation and bare land dominated the landscape, reflecting the semi–arid nature of the region and the limited presence of dense forest.[39,40] This composition likely stemmed from ongoing deforestation, overgrazing, and soil degradation, which progressively reduced forest cover. By the mid-2010s, changes in land cover became more pronounced, indicating intensified land use and environmental pressures. The expansion of bare land suggested worsening land degradation, while the growth of built-up areas highlighted rapid urban expansion.[63,64] A simultaneous decline in sparse vegetation pointed to continued encroachment and disturbance. Although grasslands and wetlands saw slight increases, they remained minimal, and the sharp reduction in water bodies during this period raised concerns about prolonged dry spells and overextraction of water resources.

The expansion of built-up land between 2000 and 2014 could be primarily driven by population growth, especially in areas near the river catchment, as the region's agricultural potential attracted people and accelerated settlement development during that period.[28,29] On the other hand, the observed decline in built-up areas in 2024 could reflect constraints on settlement expansion, or changes in population distribution.[65] In addition, this decline in built-up land can be attributed to the informal and non-permanent nature of many earlier settlements.[27,28] Over time, residents in these areas were relocated, particularly due to actions by government authorities – most notably the Pangani River Basin Authority – who enforced environmental regulations by removing individuals residing or farming within 60 m of the river.[27,28,38] These interventions may contribute to the reduction in built-up land by 2024. Alongside this, a shift in land cover composition became evident, with shrubland emerging as the dominant cover. However, the projected decrease in shrubland by 2034 is likely due to the gradual transition from sparse vegetation to mature shrubland – a process that takes time, and not all areas may fully regenerate within that period. A slight reduction in bare land might indicate stabilization in some previously degraded areas, while the noticeable increase in dense vegetation suggests that restoration initiatives may be producing positive outcomes.[66,67] Nonetheless, persistent hydrological stress – highlighted by the negligible water coverage – continues to underscore the impacts of ongoing drought conditions and unsustainable water use.

Moreover, projections for 2034 suggest further ecological transformation, with sparse vegetation expected to dominate. This could be attributed to sustained restoration efforts or natural vegetation recovery influenced by climatic factors.[68] A decline in bare land aligns with expectations of successful rehabilitation, although a predicted reduction in dense vegetation indicates lingering threats, such as logging and agricultural encroachment.[68,69] The forecasted drop in built-up areas may reflect improved enforcement of land use regulations, while the modest return of surface water could signal early success in water conservation efforts.[70] In general, the continued ecological transformation projected for 2034 further emphasizes the long-term impact of LULCCs on the catchment. The dominance of subsistence farming across almost all surveyed areas, combined with deforestation and unsustainable land practices, is likely to exacerbate soil erosion, reduce groundwater recharge, and alter streamflow patterns – thereby, compromising the hydrological balance of the Ngerengere River system.

Field observations further reinforce the findings of this study, revealing that LULCCs are adversely affecting the hydrology and ecological integrity of the Ngerengere River. These on-the-ground insights closely align with the satellite-based LULC analysis, which shows, for instance, a 17.6% decline in sparse vegetation between 2004 and 2014, followed by an additional 27.01% decrease from 2014 to 2024. This consistent downward trend highlights ongoing deforestation and land degradation across the catchment, confirming the significant environmental pressure driven by human activities. Agricultural expansion is the most pervasive land use activity, with 38% frequency, driven by the need for crop cultivation and livestock grazing. This land conversion has often come at the expense of forested areas, contributing to habitat degradation.[29,71] Subsistence farming was observed in nearly all surveyed locations, affirming its dominance as a livelihood strategy. Fuelwood collection emerged as another major activity, reported at a 30% frequency, occurring daily across many areas. This intensive dependence on natural resources reflects economic vulnerability and highlights mounting pressure on forest ecosystems.[72] Additional activities, including timber harvesting, settlement expansion, and the development of informal market centers, may have compounded land degradation and landscape fragmentation. These findings echo previous studies that have linked anthropogenic activities to river ecosystem degradation.[8,10,73]

The cumulative effects of deforestation and land clearing are increasingly visible in the form of soil erosion, biodiversity loss, and deteriorating water quality. As vegetation is removed, reduced infiltration and increased runoff can lead to seasonal water scarcity and sedimentation of water bodies.[67] This directly threatens agricultural productivity, ecosystem health, and water security in the Morogoro region. Given these challenges, there is a pressing need to adopt integrated and sustainable land-use planning approaches.[67,74] Conservation-oriented strategies such as agroforestry, regulated logging, community-led reforestation, and participatory forest management can help reverse degradation trends.[66,67] Moreover, public awareness and environmental education initiatives must be scaled up to promote resource stewardship and reduce unsustainable practices.[15,75] Without timely and coordinated intervention, the ecological and socioeconomic consequences of ongoing LULCC may jeopardize the sustainability of both natural systems and community livelihoods in the Ngerengere River catchment.[67,76] Overall, the integration of remote sensing data and field observations clearly indicates that human–driven LULCC is a major threat to the sustainability of the Ngerengere River and its surrounding ecosystems. Immediate attention to sustainable land management and conservation interventions is critical to mitigate further ecological and hydrological degradation.

5. Limitations

While this study provides valuable insights into LULCCs within the Ngerengere River catchment, several limitations should be acknowledged. The analysis relied primarily on Landsat imagery with a 30-m spatial resolution, which, although widely available and historically comprehensive, limited the detection of fine-scale changes in heterogeneous or mixed–use landscapes. Classification accuracy was affected by cloud cover, atmospheric conditions, and seasonal variability, despite efforts to minimize these through image preprocessing and ground–truthing. Misclassifications were particularly common between spectrally similar classes, such as sparse vegetation and shrubland, cropland and barren land, or plantation forests and orchards. Ground-truthing was also constrained by limited spatial coverage and access to remote areas, which may have introduced sampling bias. In addition, the study focused mainly on biophysical drivers of change and did not fully incorporate complex socio-economic, institutional, or political factors that influence land use decisions. The 2034 projections were based on historical trends and assumptions, without accounting for future uncertainties such as policy shifts, technological developments, or climate change impacts – which, although recognized, were treated as a constant rather than modeled directly. Finally, the use of secondary data for historical validation may have introduced inconsistencies or reduced the precision of results.

6. Conclusion

Overall, the study revealed that between 2004 and 2024, extensive areas of forested land within the Ngerengere River catchment were cleared and converted into croplands for cultivating crops such as bananas, cassava, and maize. This land conversion reflects growing pressure from subsistence farming and population expansion. The observed increase in shrubland and sparse vegetation, alongside changes in bare land and built-up areas, indicates ongoing ecological degradation, habitat fragmentation, and shifting land use patterns. The application of GEE enabled high-resolution spatial and temporal analysis, making it an effective tool for monitoring and projecting land cover changes. These findings highlight the urgent need for sustainable land management, reforestation efforts, and active community engagement to restore ecological integrity and support long-term environmental and socioeconomic resilience. Despite these valuable insights, the study had several shortcomings, such as limited detection of fine-scale changes due to the use of medium-resolution imagery and under-exploration of socioeconomic and institutional drivers. Therefore, future research should utilize high-resolution satellite data, integrate socioeconomic and policy analysis, and incorporate climate change modeling. In addition, long-term hydrological monitoring and evaluation of current land use policies are essential. Developing scenario-based spatial models that account for multiple variables will enhance

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Conflict of interest

The authors declare they have no competing interests.

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Availability of data

Data are available from the corresponding author upon reasonable request.

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