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Land Use Land Cover (LULC) and Normalized Difference Vegetation Index (NDVI) Change Analysis in the Umiam River Watershed of Meghalaya, using Sentinel–2 Imagery

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ABSTRACT

Untreated sewage and municipal waste are discharged into the Umiam reservoir through the Umiam River, its primary water source. The rivers Umkhrah and Umshyrpi, which pass through the Shillong agglomeration area, are documented as being of concern, but Land Use Land Cover (LULC) changes in the watershed of the Umiam River are not addressed. Sentinel-2 satellite imagery for the post-monsoon period from 2016 to 2020 was analyzed to understand LULC dynamics within the study area. Six LULC classes from Level I of Anderson's classification were identified using a maximum likelihood classifier (MLC) supervised classification, with mean land shares recorded as: Agricultural land (10.97%), barren land (2.27%), built-up area (6.28%), forest (42.82%), rangeland (37.14%), and water bodies (0.52%). Net increases were recorded in rangeland (4.69%), agricultural land (1.68%), built-up area (1.15%), barren land (0.36%), and water bodies (0.18%), while forest cover decreased by 8.06% across the study period. LULC findings were compared with NDVI results, which recorded a mean of agricultural land (8.72%), barren land (1.80%), built-up area (5.23%), forest (44.35%), rangeland (39.75%), and water bodies (0.16%). In support of LULC trends, net increases in NDVI were recorded in rangeland (3.09%), agricultural land (2.45%), built-up area (0.85%), barren land (0.30%), and water bodies (0.09%). In comparison, 6.77% decrease in forest cover occurred across the study period. Overall accuracies of 85% and 85.50% were achieved in 2016 and 2020, respectively, for LULC classification. Kappa coefficients of 0.811 (2016) and 0.818 (2020) were rated almost perfect in the Kappa statistics. The contribution of anthropogenic activities in the watershed towards the reservoir's degradation is indicated by the LULC and NDVI dynamics across the study period. This study will enable further identification, prioritization, execution and monitoring of management interventions to restore the reservoir's health.

Keywords Anderson's classification, LULC chang-

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es, NDVI, Supervised classification, Umiam river watershed.

INTRODUCTION

Wetlands are regarded as vital, productive, and ecologically sensitive systems that are rich in biodiversity (NESAC 2021). As one of the planet's most fragile, productive and adaptive ecosystems (Bassi *et al*. 2014, Turner *et al*. 2000), they are critical ecological zones that contain a broad range of plant and animal species that have adapted to changing water levels and are impacted by origin, location, water regime, dominating species, and soil features (Space Applications Center 2009, 2013). However, this is rapidly degrading due to natural and anthropogenic factors, including changes in land and marine use, climate change, pollution, and invasive species (Meli *et al.* 2014). Despite providing 47% of global ecosystem value (Xu *et al.* 2019), wetlands have lost 64% of their area since 1900 (RAMSAR 2016). Consequently, this necessitates constant monitoring and improved management policies. Ramsar sites are primarily located in Europe and Asia, with 92% of Africa's wetland area designated as protected. Inland, marine, and coastal wetlands are prevalent in Europe, Africa and Asia (Xu *et al.* 2019). Globally, riverine wetlands accounted for 38% of the total representation, followed by lacustrine wetlands (27%), estuarine wetlands (18%), and palustrine wetlands (17%) (Meli *et al.* 2014).

Specific wetland types were not identified during initial investigations conducted by Indian organizations between 1989 and 1998, leading to contradictory results. The first scientific mapping was conducted by the Space Applications Center (SAC), Ahmedabad, using satellite data from 1992–1993. Wetlands were classified according to the Ramsar Convention's definition and published in the National Wetland Atlas 2011, which provided a more realistic picture of wetland status in India (Bassi *et al.* 2014). The areal extent of India's wetlands is being rapidly decreased by climate change, with natural and artificial water spread being affected across inland and coastal areas from post-monsoon to peak summer periods (Bassi *et al*. 2014; Dar *et al.* 2020; Devi *et al.* 2017; Kumar *et al.* 2019; RAMSAR 2016). However, Ramsar sites have been the primary focus of the currently accessible research.

Currently, 99 wetlands of international importance are hosted by India, covering 1,384,140 ha out of 2528 sites globally, with a total surface area of 253,182,460 ha (RAMSAR 2026). Within Meghalaya, 221 natural inland wetlands (28,103 ha) and 38 artificial inland wetlands (1717 ha) are identified, alongside 167 wetlands with area < 2.25 ha (167 ha) (Space Applications Center 2009, pp 19, 61). Through mapping conducted with IRS LISS III data from 2005–2006 and updated under NWIA phase II from 2017-2018, 85 wetlands were lost, and three new ones were discovered (NESAC 2021). Among these, the Umiam reservoir is recognized as one of the three crucial wetlands (Space Applications Center, 2009), and recorded as Meghalaya's only wetland under India's National Wetlands Conservation Programme (MoEF 2009).

These areas provide essential ecosystem services, though they are threatened by both natural and anthropogenic disturbances (Meghalaya State Pollution Control Board 2020 ; WAPCOS Limited 2012). WAPCOS Limited (2012) reported an 8% reduction in the reservoir's storage capacity between 1965 and 1990. A 12.69 Mm^3 reduction in the storage capacity, with an average sedimentation rate of 25.7 ham/100 sq. m./year, was reported by TVIPL's hydrographic survey of the reservoir in 2004 (Marak *et al.* 2014). An estimated 40,000 cu.m. of silt is deposited into the reservoir annually according to the Integrated Basin Development and Livelihoods Promotion Program (2014). As the reservoir is fed by Wah[a] Umkhrah and Umshyrpi, which flow through densely populated areas in Shillong city, pollutants are carried to the reservoir by these primary sources. Furthermore 2025 million liters (Integrated Basin Development and Livelihoods Promotion Program 2014) untreated sewage and municipal waste are discharged into Wah Umkhrah by 20 major drains and into Wah Umshyrpi by 12 major drains (Directorate of Urban Affairs 2022). However, no published document was found that discusses land-use change within the Wah Umiam watershed.

The earth's surface has been modified by the spatial distribution of erosion, accelerated by several morphological factors combined with anthropogenic activities (Warjri 2025), such as inadequate land use and forest clearing. Once nutrient-rich topsoil is degraded, the sub-surface soil is exposed, and the soil's water content decreases, thereby increasing its susceptibility to erosion (Handique *et al.* 2023). Significant environmental risk is posed by sedimentation in reservoirs due to anthropogenic disturbances, including soil erosion, forest cover changes (Bhattacharyya *et al*. 2015; Ewunetu *et al.* 2021; Kosmas *et al.* 2014; Land and Water Division 2003 ; Meghalaya State Pollution Control Board 2020 ; Orewere *et al.* 2020 ; WAPCOS Limited 2012), and land use patterns, thus limiting water spread and endangering watersheds. The Ramsar Convention on Wetlands was established to prevent global wetland degradation due to human interventions, emphasizing the need for a comprehensive understanding of these ecosystems (Daryadel and Talaei 2014).

Environmental risks are assessed, zoning maps are created, and RS and GIS data are utilized for flood zoning, inventory, irrigation, cropping, water quality analysis, and habitat mapping within the scope of wetland management. In land change studies, land cover, transformations, rates, and primary factors causing change are examined, with pre-monsoon and post-monsoon data sets being used to assess from-to-change (Elias and Chand 2019; Hu *et al.* 2018; Mondal *et al.* 2017; Sharma *et al.* 2012; Xu *et al.* 2019). Rapid, comprehensive, and periodic monitoring and mapping of land use and land cover, and wetland resources are enabled by GIS and remote sensing data using indicators such as hydrology, vegetation, soil types, and topographic situations (Hu *et al.* 2018; Wu 2018). Nine major land use classes at Level I of the Anderson *et al.* (1976) classification system were used to derive these indicators. Within this system, Level I categories are further subdivided into thirty-seven Level II sub-classes.

[a]Rivers are locally called Wah in the Khasi dialect of Meghalaya.

MATERIALS AND METHODS

Study Area

The Umiam river originates in the East Khasi hills district of Meghalaya as a conglomeration of various drainage channels, formed primarily by the confluence of Wah Umkhrah and Wah Umshyrpi into Wah Ro-Ro (Directorate of Urban Affairs 2022). It is the primary water source to the Umiam reservoir; thereafter, the flow culminates into the Kopili river in Morigaon district of Assam (Directorate of Urban Affairs 2022). The watershed, which measures 187.96 Sq. Km. (18795.62 ha) is located between 25°28'00"N to 25°38'30"N Latitude, 91°41'30" E to 91°56'30" E Longitude, and an altitude of 940 m (MSL) (Fig. 1). The Umiam reservoir, built in 1965 by the Assam State Electricity Board, spans 10.158 sq. km. with a storage capacity of 181.42 Mm^3 (18142 ham) at a Full Reservoir Level (F.R.L.) of 981.46 m/3220 ft. (WAPCOS Limited 2012). Post creation of the new state of Meghalaya on January 1, 1972, control and management of the Umiam reservoir were transferred to the Meghalaya State Electricity Board.

Between 1965 and 1990, sedimentation reduced the reservoir's storage capacity by 8%, with dead and living storage decreasing by 21% and 4%, respectively (WAPCOS Limited 2012). TVIPL's hydrographic survey (2004) shows a decrease in reservoir storage capacity from 179.757 Mm^3 to 167.069 Mm3 over 25 years, with an average sedimentation rate of 25.7 ham/100 sq. km./year (Marak *et al.* 2014). The Umiam River's entry into the reservoir, characterized by mesotrophic to eutrophic conditions, was found to have higher sediment levels of nitrate and phosphorus (Ramanujam *et al.* 2020). Reports emphasize the need for preventive measures to control sedimentation in the Umiam reservoir (WAPCOS Limited 2012), primarily due to catchment-area erosion (Meghalaya State Pollution Control Board 2020). This study is proposed due to a lack of scientific data on LULC in the river's watershed.

Methodology

Data collection

For the analysis, suitable multi-temporal Sentinel-2 satellite images for post-monsoon periods ranging from September to December of 2016, 2018 and 2020 with a cloud cover of 0–5% were obtained from the

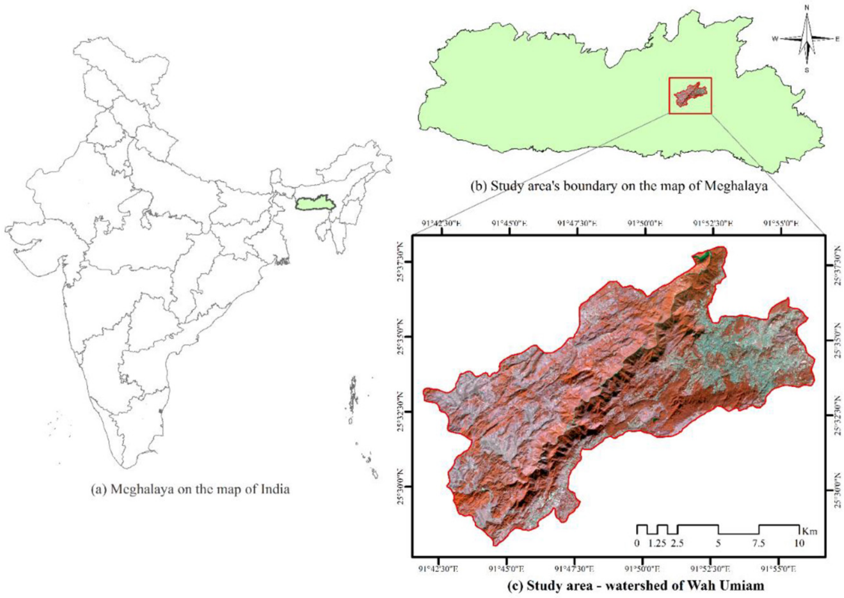

Fig. 1. (a) Meghalaya on the map of India, (b) the study area's boundary on the map of Meghalaya, (c) the study area - watershed of Wah Umiam.

USGS Earth Explorer. These images were chosen due to their spectral resolution (10 m), critical for modeling the land use and land cover change (LULC) maps. The watershed's boundary/study area for this study was determined with the assistance of the North Eastern Space Applications Center (NESAC) using 78O series topographical maps (Space Applications Center 2007) at a 1:50,000 scale, generated by the Survey of India. This watershed boundary is utilized as the primary data source. The choice of scale is based on the Department of Space's 1992 IMSD mission, in which remote sensing data were combined with conventional information to create 1:50,000 scale watershed-level land and water resource development plans (Kasaragod and Hegde 2002).

Land Use and Land Cover classification

Assessing Land Use and Land Cover (LULC) change is considered imperative for understanding the human-nature relationship. Advancements in remote sensing technology and GIS tools have enabled easier monitoring of changes in LULC from the past to the present. Various algorithms are used to detect these changes, with satellite data being the primary source for recent data (Chughtai *et al.* 2021; Tempa *et al.* 2024). In this study, traditional change detection methodologies for LULC information are evaluated for the study area. This was achieved using the post-classification method combined with a maximum likelihood classifier (MLC) for supervised classification of spatial-temporal data from Sentinel–2. Compared to other approaches, the maximum likelihood classifier has been employed most frequently in the past and to the present, and great accuracy has been achieved in all areas (Chughtai *et al.* 2021 ; Moisa *et al.* 2025; Nasrin & Barman 2025; Pathan *et al.* 2021 ; Tarmizi and Rizwan 2024 ; Tempa *et al.* 2024; Ullah *et al.* 2023).

The methodology adopted involved the collection of appropriate satellite images, image pre-processing, and identifying the LULC classification scheme based on Anderson's classification (Anderson *et al.* 1976, p. 8). Training sample data was selected, followed by image classification and change detection. The LULC classification was derived using the Maximum Likelihood (ML) algorithm, drawing inspiration from Chughtai *et al.* (2021), Moisa *et al.* (2025), Nasrin & Barman (2025), Pathan *et al.* (2021), Tarmizi and

Rizwan (2024), Tempa *et al.* (2024), and Ullah *et al.* (2023). Bands 2, 3, 4 and 8 (R, G, B and NIR) with 10 m spatial resolution were utilized, and images were pre-processed for analysis in ArcMap 10.4. The net change in area (N) during the study period, annual change in area (A_N), and annual rate of change in area (A_R) were analyzed using the change algorithms in Equation 1, Equation 2 and Equation 3 (Seyam *et al.* 2023; Tarmizi and Rizwan 2024).

$$N = \frac{Area_{Te} - Area_{Ts}}{\sum_{i=1}^{n} Area_{Te}} \times 100$$

Equation 1: Net change in area during the study period

$$A_N = \frac{Area_{Te} - Area_{Ts}}{T_p}$$

Equation 2: Annual change in area during the study period

$$A_R = \frac{Area_{Te} - Area_{Ts}}{\sum_{i=1}^{n} Area_{Te} \times T_P} \times 100$$

Equation 3: Annual rate of change in area during the study period

Where $Area_{Te}$ is the area of LULC classes at the end of the study period, $Area_{Ts}$ is the area of LULC classes at the start of the study period, $\sum_{i=1}^{n} Area_{Te}$ is the total area of the watershed, and T_p is the time interval of the study period.

Accuracy assessment

Post image classification and change analysis, it is imperative to assess the accuracy of the findings. The assessment involves two crucial procedures: *Generating a confusion matrix from an attribute table and interpreting it by calculating change algorithms* (Seyam *et al.* 2023 ; Tarmizi and Rizwan 2024). Each LULC class was assigned to polygons using stratified random sampling across all classified images (Tarmizi and Rizwan 2024) to evaluate the accuracy of the classification. Two hundred reference points (locations) were assigned to the classified images, each with a designated code representing its LULC class. These points were overlaid on Google Earth as a reference source and cross-referenced with the LULC map to generate a confusion matrix. The degree of classification accuracy is displayed by the matrix (Seyam *et al.* 2023), with reference data (User Value) and classified data (Producer Value) represented by the columns (ground truth) and rows, respectively. Additionally, kappa statistics (Jenness and Wynne 2007) were used to assess the accuracy of this study.

Correctly identified points for each class are represented by the main diagonal of the matrix. Off-diagonal cells represent incorrectly identified pixels, indicating discrepancies between the reference and classified data, known as commission and omission errors. Commission errors were quantified by summing off-diagonal column cells above and below a class's primary diagonal, while classification reliability was determined through Producer's accuracy. Omission errors were similarly identified by summing off-diagonal pixels in row cells, representing pixels from one class that were inadvertently assigned to others (Seyam *et al.* 2023). The User's accuracy (U_A), Producer's accuracy (P_A), Overall accuracy (O_A) (Seyam *et al.* 2023; Tarmizi and Rizwan 2024), and Kappa coefficient (K) (Rwanga and Ndambuki 2017) were calculated by the change algorithms in Equation 4, Equation 5, Equation 6 and Equation 7.

$$U_A = \frac{\text{Total number of correct pixels in a row of an LULC class}}{\text{Total number of pixels in a row of that class derived from reference data}}$$

Equation 4: User's accuracy

$$P_A = \frac{\text{Total number of correct pixels in a column of an LULC class}}{\text{Total number of pixels in a column of that class derived from reference data}}$$

Equation 5: Producer's accuracy

$$O_A = \frac{\text{Total number of correctly classified pixels}}{\text{The sum of pixels derived from the User's reference data}} \times 100$$

Equation 6: Overall accuracy

$$K = \frac{Obs—Exp}{1—Exp}$$

Equation 7: Kappa coefficient

Normalized Difference Vegetation Index (NDVI)

The supervised classification was compared with an NDVI analysis to verify the identified LULC changes. NDVI analysis of remote sensing data effectively identifies vegetation health, distinguishes land cover types, and assesses land-use changes (Akbar *et al.* 2019; B. Huang & Wang 2020; S. Huang *et al*. 2021; Tarmizi and Rizwan 2024). NDVI ranges from -1.0 to 1.0 was established by NDVI (2018) and USGS (2021). Within this range, low values (0.1 or less) were associated with features such as barren land, sand, and snow, whereas moderate values (0.2 to 0.5) corresponded to sporadic vegetation, such as grassland. High NDVI indices (0.6 to 0.9) are observed where dense vegetation cover was present. The change in vegetation density and cover during the study period was assessed using Equation 8 (Tarmizi and Rizwan 2024) to analyze LULC changes concerning vegetation cover.

$$\mathbf{NDVI} = \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED})}$$

Equation 8: Normalized Difference Vegetation Index

Where NIR is the near-infrared reflectance (Band 8), and RED is the red reflectance (Band 4) of Sentinel-2 data.

RESULTS AND DISCUSSION

Land use and land cover classification

Satellite imagery found suitable for the analysis was dated 13.12 2016 and 22.12 2020. Based on the methodology described in Land Use and Land Cover classification, processed images were classified at Level I of Anderson *et al.* (1976, p. 8) by the maximum likelihood supervised classification system. The classifications identified were Urban or Built-up land, Agricultural land, Rangeland, Forest land, Water, and Barren land (Table 1).

Table 1. LULC system delineated based on supervised classification (Anderson *et al.*1976).

Class name	Description
1 Agricultural land	Cropland and pasture, orchards, groves, vineyards, nurseries, and ornamental horticulture areas
2 Barren land	Dry salt flats, beaches, sandy areas other than beaches, bare exposed rocks,strip mines, quarries and gravel pits, transitional areas, mixed bar ren land
3 Built-up land	Residential, commercial, and services, transportation, industrial and commercial complex, mixed urban or built-up land, other urban or built-up land
4 Forest	Deciduous, evergreen, and mixed forest land
5 Rangeland	Herbaceous rangeland, shrub and brush rangeland, mixed rangeland
6 Water	Streams, canals, lakes, reservoirs, bays and estuaries.

Across the study period, the mean land share observed was agricultural land – 10.97%, barren land – 2.27%, built-up area – 6.28%, forest – 42.82%, rangeland – 37.14%, and water bodies – 0.52. The area occupied by each LULC class, along with the net change, annual change and annual rate of change during the study period, is illustrated in Fig. 2 and Table 2. The net change in area (N), annual change in area (A_N), and the annual rate of change (A_R) were calculated using Equation 1, Equation 2 and Equation 3.

The following observations were made from the change analysis:

a) Agricultural land: 1903.11 ha (10.13%) of the land was occupied by agricultural land in 2016, which increased to 2219.61 ha (11.81%) in 2020. A net increase of 316.50 ha (1.68%) was observed with an annual change of 0.42% (79.12 ha/year) during the study period.

b) Barren land: Barren land comprised 392.16 ha (2.09%) of the watershed in 2016, which increased to 459.91 ha (2.45%) in 2020. With a net increase of 67.74 ha (0.36%), an annual increase of 0.09% (16.94 ha/year) was observed during the study period.

c) Built-up area: 1072.79 ha (5.71%) of the watershed was occupied by built-up area in 2016, which increased to 1288.95 ha (6.86%) in 2020. With an increase of 54.04 ha/year (0.29%), a net increase of

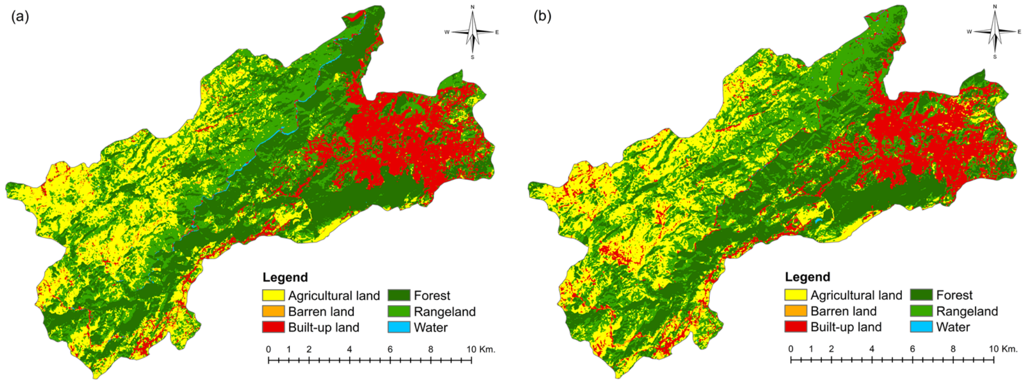

Fig. 2. Land Use and Land Cover maps for (a) 13.12.2016, and (b) 22.12.2020.

216.15 ha (1.15%) was observed from 2016 to 2020.

d) Forest: Forest land decreased from 8805.61 ha (46.85%) in 2016 to 7290.23 ha (38.79%) in 2020. This represents a net decrease of 1515.38 ha (8.06%), decreasing at an annual rate of 2.02% (378.85 ha/year).

e) Rangeland: Rangeland increased from 6540.73 ha (34.80%) in 2016 to 7421.45 ha (39.48%) in 2020. A net increase of 880.71 ha (4.69%) was observed with an annual change of 1.17% (220.18 ha/year) during the study period.

f) Water bodies: Water bodies comprised 81.21 ha (0.43%) of the watershed in 2016, which increased to 115.48 ha (0.61%) in 2020. With a net increase of 34.26 ha (0.18%), an annual increase of 0.05% (8.57

Table 2. Land Use Land Cover change analysis during the study area.

LULC classes	13.12.2016		22.12.2020		Net change (N)		Annual rate of change	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha) (A_N)	Area (%) (A_R)
Agricultural land	1903.11	10.13%	2219.61	11.81%	316.50	1.68%	79.12	0.42%
Barren land	392.16	2.09%	459.91	2.45%	67.74	0.36%	16.94	0.09%
Built-up land	1072.79	5.71%	1288.95	6.86%	216.15	1.15%	54.04	0.29%
Forest	8805.61	46.85%	7290.23	38.79%	–1515.38	–8.06%	–378.85	–2.02%
Rangeland	6540.73	34.80%	7421.45	39.48%	880.71	4.69%	220.18	1.17%
Water	81.21	0.43%	115.48	0.61%	34.26	0.18%	8.57	0.05%
Total	**18795.62**	**100%**	**18795.62**	**100%**	–	–	–	–

Table 3. Confusion matrix for 13.12.2016.

LULC classes	Agricultural land	Barren land	Built-up	Forest	Rangeland	Water	User's accuracy
Agricultural land	**11**	1	0	1	5	0	**18**
Barren land	1	**6**	0	0	2	1	**10**
Built-up	0	2	**8**	0	2	0	**12**
Forest	2	0	0	**79**	5	0	**86**
Rangeland	2	1	0	4	**62**	0	**69**
Water	0	1	0	0	0	**4**	**5**
Producer's accuracy	**16**	**11**	**8**	**84**	**76**	**5**	**200**

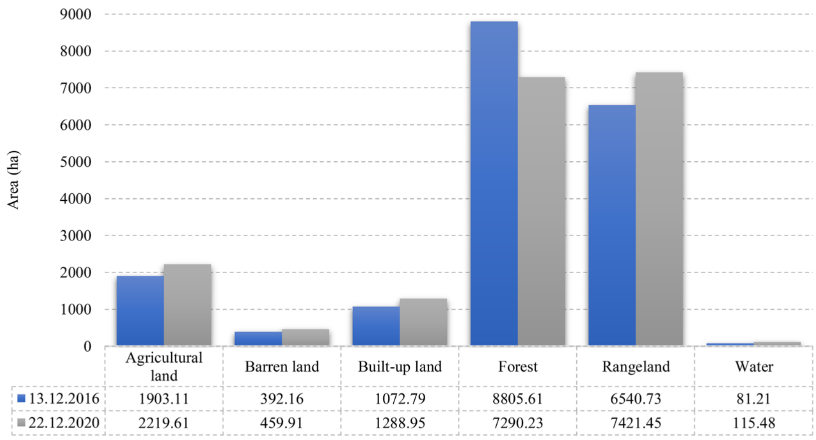

Fig. 3. Extent of Land Use Land Cover change during the study period.

Table 4. Confusion matrix for 22.12.2020.

LULC classes	Agricultural land	Barren land	Built-up	Forest	Rangeland	Water	User's accuracy
Agricultural land	**10**	1	0	0	3	0	**14**
Barren land	1	**6**	0	0	1	2	**10**
Built-up	0	0	**10**	0	2	0	**12**
Forest	3	0	0	**74**	4	0	**81**
Rangeland	3	1	0	7	**65**	0	**76**
Water	0	1	0	0	0	**6**	**7**
Producer's accuracy	**17**	**9**	**10**	**81**	**75**	**8**	**200**

ha/year) was observed during the study period.

The extent of the LULC change is represented in Fig. 3.

2. Accuracy assessment

The accuracy of the analysis in Land Use and Land Cover classification was assessed by plotting the confusion matrix in Table 3 and Table 4, and by calculating the User's accuracy (U_A), Producer's accuracy (P_A), Overall accuracy (O_A), and Kappa coefficient (K).

The following were observed from the accuracy assessment:

Table 5. Users' and Producers' accuracy for 2016 and 2020.

Land Use Land Cover classes	13.12.2016		22.12.2020	
	U_A	P_A	U_A	P_A
Agricultural land	61.11%	68.75%	71.43%	58.82%
Barren land	60%	54.55%	60%	66.67%
Built-up	66.67%	100%	83.33%	100%
Forest	91.86%	94.05%	91.36%	91.36%
Rangeland	89.86%	81.58%	85.53%	86.67%
Water	80%	80%	85.71%	75%

Table 6. Overall accuracy and Kappa coefficient for the study period.

Accuracy parameter	2016	2020
Total number of correctly classified pixels	170	171
The sum of pixels derived from the User's reference data	200	200
Overall accuracy (O_A)	**85%**	**85.50%**
Kappa Coefficient	**0.811**	**0.818**

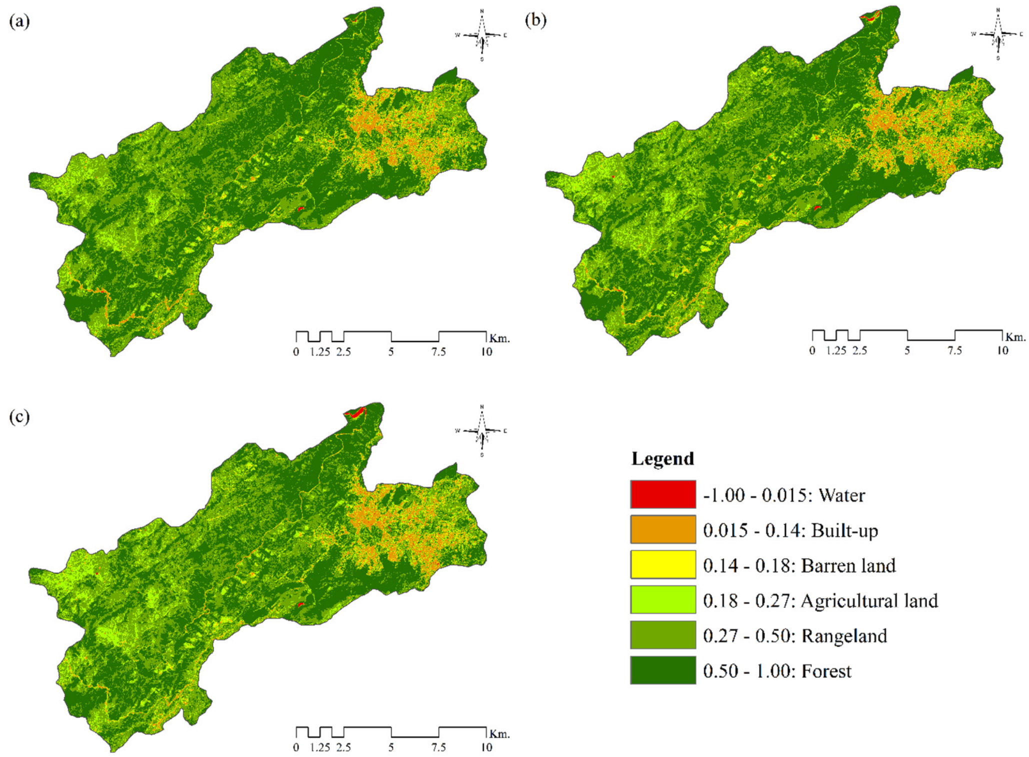

Fig. 4. NDVI maps for (a) 13.12.2016, (b) 23.12.2018 and (c) 22.12.2020.

a) From the confusion matrices (Table 3 and Table 4), the User's accuracy (U_A) and Producer's accuracy (P_A) for 2016 and 2020 are shown in Table 5.

b) The Overall accuracy (O_A) and Kappa coefficient (K) calculated (Equation 6 and Equation 7) for the study period are represented in Table 6. The Kappa analysis was rated almost perfect according to the Kappa statistics (Rwanga and Ndambuki 2017, p. 620).

Table 7. Reclassified NDVI range for the study period.

NDVI Range	Land Use Land Cover description
–1.00 – 0.015	Water
0.015 – 0.14	Built-up area
0.14 – 0.18	Barren land
0.18 – 0.27	Agricultural land
0.27 – 0.50	Rangeland
0.50 – 1.00	Forest/Dense vegetation

3. Normalized difference vegetation index (NDVI)

Large land areas, predominantly in Asia and Africa, degraded by anthropogenic activities, are affected by water and wind erosion (Jena *et al.* 2018). The North-Eastern hilly region of India is characterized by heavy soil erosion, loss of soil fertility, and deforestation (Bharadwaj *et al.* 2024; Choudhury *et al.* 2022), all of which cause acute environmental degradation and severe ecological imbalance. Vegetation may be quantified with the difference between near-infrared (NIR) light (strongly reflected) and red light (absorbed) measured by the NDVI index (GISGeography 2025). Raw satellite data is transformed into NDVI values using RS and GIS to measure vegetation type and health, density, and surface conditions (GISGeography, 2025; S. Huang *et al.* 2021; NDVI 2018).

Changes in vegetation's spatial distribution as an indicator of land degradation were assessed us-

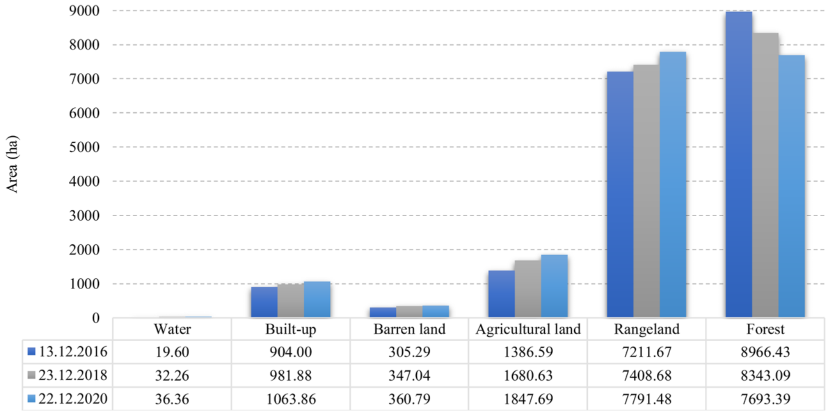

Fig. 5. LULC change trend during the study period identified by NDVI analysis.

Table 8. NDVI change analysis during the study period.

NDVI range	Land use and Land cover classes	13.12.2016 Area (ha)	13.12.2016 Area (%)	23.12.2018 Area (ha)	23.12.2018 Area (%)	22.12.2020 Area (ha)	22.12.2020 Area (%)	Net change 2016 to 2020 Area (ha)	Net change 2016 to 2020 Area (%)
-1.00 - 0.015	Water	19.94	0.11%	32.60	0.17%	36.70	0.20%	16.76	0.09%
0.015 - 0.14	Built-up	904.34	4.81%	982.22	5.23%	1064.20	5.66%	159.87	0.85%
0.14 - 0.18	Barren land	305.63	1.63%	347.38	1.85%	361.13	1.92%	55.51	0.30%
0.18 - 0.27	Agricultural land	1386.93	7.38%	1680.97	8.94%	1848.03	9.83%	461.10	2.45%
0.27 - 0.50	Rangeland	7212.01	38.37%	7409.02	39.42%	7791.82	41.46%	579.81	3.09%
0.50 - 1.00	Forest	8966.77	47.71%	8343.43	44.40%	7693.73	40.94%	–1273.04	–6.77%
	Total	**18795.62**	**100%**	**18795.62**	**100%**	**18795.62**	**100%**	**N.A.**	**N.A.**

ing NDVI analysis alongside the supervised LULC classification. The NDVI maps were reclassified into six LULC classes (Table 7) based on NDVI (2018), Tempa *et al.* (2024), and USGS (2021), and modified from Akbar *et al.* (2019).

Across the study period, forest (44.35%) and rangeland (39.75%) were the primary land covers identified by NDVI analysis, followed by agricultural land (8.72%), built-up areas (5.23%), barren land (1.80%), and water (0.16%). LULC changes analyzed during the study period are illustrated in Fig. 4 and summarized in Table 8.

A net increase in the area of rangeland (3.09%), agricultural land (2.45%), built-up areas (0.85%), barren land (0.30%), and waterbodies (0.09%) was observed during the study period, in contrast to a decline of 6.77% in forest area (Table 8). A trend identical to that in the Land Use and Land Cover classification is observed here. The decrease in forest cover recorded by the LULC and NDVI analyses corresponds to the overall decline in Meghalaya's forest cover (1.22%) from 2013 to 2023 (Forest Survey of India 2024). The contribution of anthropogenic activities is indicated by an increase in the area of agricultural land and built-up areas, coinciding with a decrease in forest cover, thereby making the land surface more vulnerable to erosion. The magnitude of area changes and total gain or loss of area is represented below (Fig. 5).

CONCLUSION

Untreated sewage, municipal waste, and silt are being discharged into the reservoir by the Umiam River, degrading it. Sentinel-2 images for the post-monsoon periods of 2016 to 2020 were analyzed using RS and GIS to identify additional indicators of degradation, alongside those documented in the evidence. Based on Anderson's classification (Level I), six Land Use Land Cover (LULC) classes were identified and listed in descending order of land share: Forest, rangeland, agricultural land, built-up area, barren land, and water bodies. A net increase in area of rangeland (4.69%), agricultural land (1.68%), built-up area (1.15%), barren land (0.36%) and water bodies (0.18%), while a decrease in forest cover (8.72%) was recorded by the LULC change analysis during the study period. This observation was supported by NDVI analysis, which showed an identical change pattern. A net increase in area of rangeland (3.09%), agricultural land (2.45%), built-up area (0.85%), barren land (0.30%), and water bodies (0.09%), while the NDVI analysis recorded a decrease in forest cover (6.77%) during the same period. An overall accuracy of 85% for 2016 and 85.50% for 2020 was achieved during ground truthing of the LULC analysis. The analysis fell within the almost-perfect range of the Kappa statistic, with Kappa coefficients of 0.811 (2016) and 0.818 (2020) achieved during the study period. Therefore, anthropogenic activities in the watershed, as an indicator of degradation, are evidenced by the increase in agricultural and built-up land and the consequent decrease in forest cover. These observations may inform monitoring and prioritization of sustainable land management to address the reservoir's degradation alongside the pollution of the Umiam River.

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