



Landscape transformation in tropical monsoonal Wayanad district of Western Ghats, India: Spatiotemporal analysis (1991–2021) and projections using NDVI-based vegetation dynamics

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Abstract

Over the past three decades, Wayanad district in the Western Ghats mountains of Kerala, India has undergone notable ecological changes in vegetation, land use, and hydrology. This study uses NDVI-based spatiotemporal analysis to examine vegetation health and land cover dynamics from 1991 to 2021, with future projections for 2031 and 2041 using the CA-ANN model. Results show a significant increase in thick vegetation from 202.93 km² in 2001 to 1015.40 km² in 2021, indicating effective forest regeneration. Light vegetation has correspondingly declined, transforming into denser forest cover. Agricultural zones such as Meenangadi and Panamaram reveal seasonal NDVI fluctuations tied to farming practices. Barren lands, especially those affected by quarrying and urban growth, have varied over time, highlighting the need for targeted restoration. Water bodies show minor spatial variations linked to rainfall and management efforts. Projections indicate stabilization of thick vegetation at 47.51% and a reduction in barren land by 2041. The study underscores the value of NDVI and CA-ANN modelling for predicting land cover change and supports informed land-use planning and conservation to promote ecological resilience in the face of anthropogenic pressures.

Keywords: NDVI, LULC change, Wayanad, Western Ghats, Landsat OLI

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1 Introduction

Remote sensing technologies are vital for monitoring environmental changes and sustainable resource management. Satellite image-derived indices like the Normalized Difference Vegetation Index (NDVI) offer insights into vegetation health and landscape transformation (Yan et al., 2025). These tools are especially crucial in regions like India, where diverse ecosystems, rapid urbanization, and climatic variability pose significant challenges. The Normalized Difference Vegetation Index (NDVI), calculated from the red and near-infrared spectral bands (Houston et al., 1974–01), is a fundamental vegetation health indicator. Ranging from -1 to +1, NDVI values reflect vegetation density and vigor, with higher values indicating robust vegetation and

lower/negative values representing sparse or non-vegetated areas. Its widespread adoption stems from its simplicity and strong correlation with key biophysical parameters including leaf area index, chlorophyll content, and biomass, making it indispensable for ecological monitoring and vegetation studies.

Since its development, NDVI has served as a versatile tool for vegetation monitoring across multiple domains. Anyamba and Tucker (2012) established its utility for large-scale drought assessment using AVHRR data to analyze vegetation responses in the Sahel region. In the Indian context, Digavinti and Manikiam (2021) effectively employed LST and NDVI for evaluating forest fire impacts and post-disturbance regeneration, demonstrating its value for forest management. These studies highlight NDVI's broad

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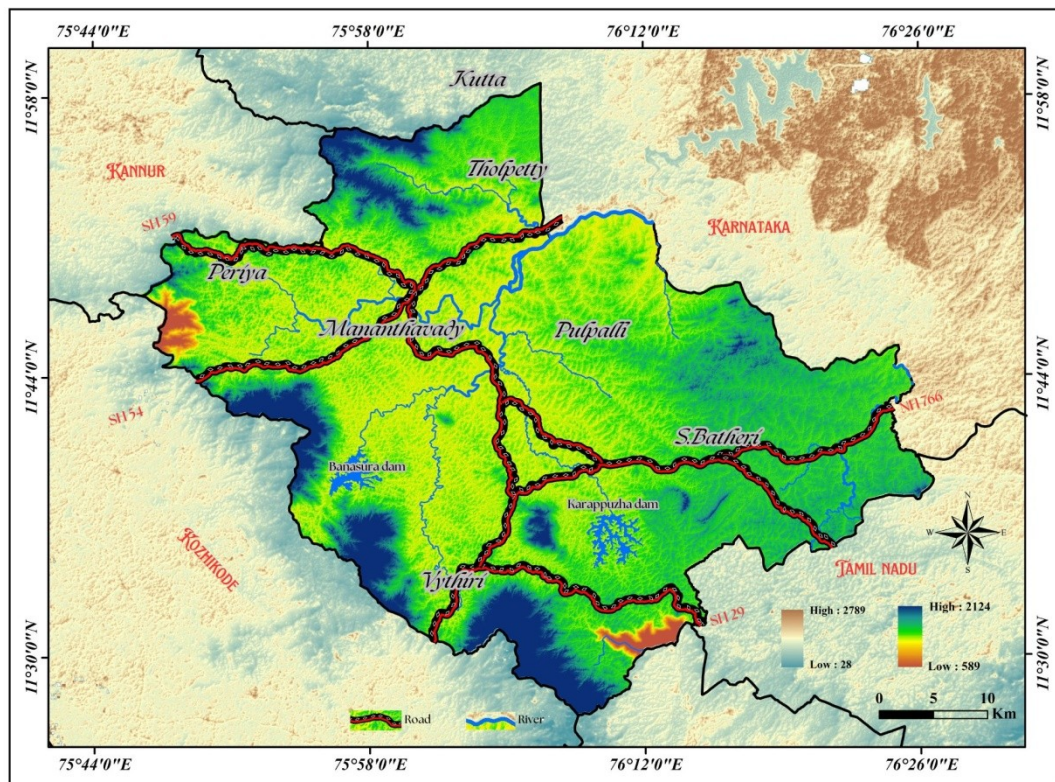


Fig. 1. Study area map – Wayanad District, Kerala, India.

applicability in agriculture, drought monitoring, deforestation tracking, and ecosystem health assessment.

The Western Ghats and eastern India have been focus areas for Landsat-based assessments, with studies by Reddy et al. (2016) demonstrating its effectiveness in monitoring forest degradation, deforestation, and biomass distribution in biodiversity-rich and ecologically fragile zones. In arid and semi-arid regions, NDVI has been crucial for evaluating agricultural vulnerability and climate-induced stress, as evidenced by Kaushalya et al. (2014), who analyzed seasonal vegetation responses to rainfall variability.

NDVI has also played a pivotal role in land-use/land-cover (LULC) change detection, enabling long-term monitoring of vegetation dynamics and human impacts. Singh et al. (2016) applied NDVI to assess LULC trends across India's agro-ecological zones, revealing its sensitivity to both environmental and socio-economic drivers. At a global scale, Anyamba and Tucker (2005) utilized multi-decadal NDVI data to examine vegetation anomalies linked to ENSO events and worldwide drought patterns, underscoring its value in climate-vegetation interaction studies. Recent advancements in satellite platforms such as MODIS, Landsat 8, and Sentinel-2 have significantly improved the spatial and temporal resolution of NDVI datasets. These enhancements support finer-scale studies and facilitate near-real-time vegetation monitoring (Chaves et al., 2020).

The integration of NDVI with GIS, machine learning, and climate modelling has significantly expanded its applications, ranging from precision agriculture to urban ecology and environmental forecasting. In land-use/land-cover (LULC) change analysis, NDVI has been instrumental in tracking vegetation dynamics and anthropogenic im-

pacts, supported by increasingly sophisticated modelling approaches. Among these, Cellular Automata (CA) and Artificial Neural Networks (ANNs) have emerged as powerful tools for simulating complex, non-linear land-use transitions (Charif et al., 2012). CA models excel at capturing spatial interactions through neighbourhood-based transition rules, while ANNs decode intricate patterns from historical data. Combined as CA-Markov models (Al-sharif and Pradhan, 2013), they enable robust simulations of future landscape changes, enhancing sustainable land management and planning efforts.

The MOLUSCE plugin in QGIS (2021) integrates multiple algorithms (logistic regression, WoE, MCE, Monte Carlo) for robust LULC change analysis. Its ANN-based framework effectively captures complex land-use transitions, particularly in heterogeneous landscapes (Muhammad et al., 2022). When calibrated with historical satellite data and spatial predictors (DEM, slope, road networks), the tool reliably projects future scenarios under varying environmental and socioeconomic conditions (Sang et al., 2011). Researchers have successfully applied this approach for urban expansion forecasting and structural transformation analysis (Muhammad et al., 2022), demonstrating its utility in spatiotemporal NDVI dynamics and land-use evolution studies.

1.1 Study Area

Wayanad district (Fig. 1) is located in Kerala's north-eastern Western Ghats. The study area covers approximately 2,132 sq. km and is characterized by rugged high-land plateaus, with elevations ranging from 700 to 2,100 m above mean sea level. The region's Archaean basement

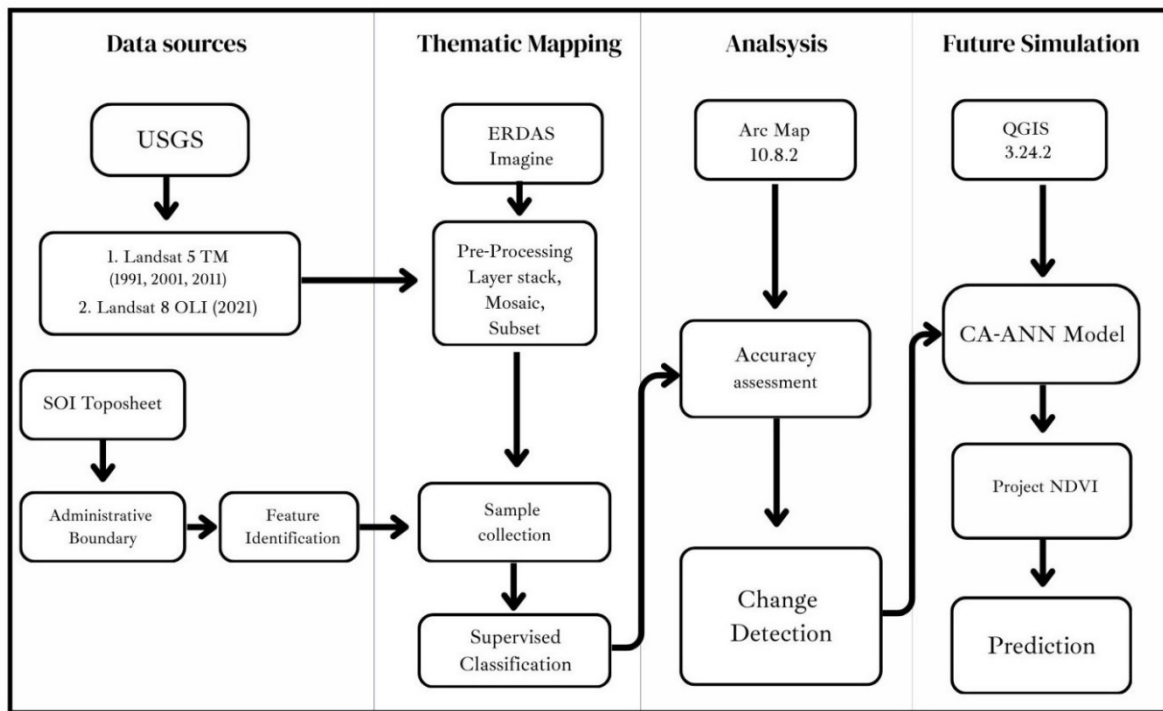


Fig. 2. Flowchart of methodology.

(charnockites/gneisses) has been sculpted into steep escarpments and narrow valleys through prolonged weathering. Hydrologically, the Kabini river system drains the district, which possesses moderate-to-good groundwater potential through both shallow weathered and deep fractured aquifers. These hydrogeological characteristics, combined with cool, moist climatic conditions, support diverse agricultural systems and rich biodiversity within this ecologically sensitive zone.

2 Materials and Methods

2.1 Data Collection

Administrative boundaries were obtained from Survey of India toposheets. The satellite datasets were acquired from the United States Geological Survey Earth Explorer portal (<https://earthexplorer.usgs.gov/>). The study area was covered by two Landsat scenes with path/row combinations of 144/052 and 145/052. Multi-temporal satellite imagery from Landsat 5 Thematic Mapper (TM) for the years 1991, 2001, and 2011, along with Landsat 8 Operational Land Imager (OLI) for 2021, was used to derive the Normalized Difference Vegetation Index (Table 1). To ensure data reliability and consistency, all selected images had less than 5% cloud cover.

Table 1. Data acquisition details.

Satellite	Acquisition Date	Path/Row	Year	Resolution
Landsat 5 TM	12-Feb-91	144/052	1991	30 m
	03-Feb-91	145/052	1991	
	23-Feb-01	144/052	2001	
	03-Mar-01	145/052	2001	
	01-Mar-11	144/052	2011	
	01-Mar-11	145/052	2011	
Landsat 8 OLI	02-Mar-21	144/052	2021	
	09-Mar-21	145/052	2021	

Image preprocessing was carried out prior to analysis. The preprocessing steps included radiometric calibration and atmospheric correction to minimize sensor and atmospheric effects and to ensure comparability between multi-temporal images. Atmospheric correction was performed using standard methods to convert digital numbers to surface reflectance. All datasets were clipped to the study area and projected to WGS 1984 UTM Zone 43N for spatial consistency.

NDVI analysis classified the area into four categories (light/thick vegetation, barren land, water) using standardized thresholding. Classification accuracy was validated through GPS ground truthing, random sampling, and kappa coefficient assessment (Fig. 2).

To retrieve NDVI using Landsat 4-5, the following formula was used (USGS, 2025):

$$\text{NDVI} = (\text{Band 4} - \text{Band 3}) / (\text{Band 4} + \text{Band 3}). \quad (1)$$

To retrieve NDVI using Landsat 8-9, the following formula was used:

$$\text{NDVI} = (\text{Band 5} - \text{Band 4}) / (\text{Band 5} + \text{Band 4}). \quad (2)$$

Thresholds on NDVI values are used to classify areas (Laksono et al., 2020) into thick vegetation (NDVI > 0.6), light vegetation (NDVI 0.3-0.6), barren land (NDVI < 0.2), water bodies (NDVI < 0).

2.2 Prediction and Model Validation

Using NDVI datasets from 2011 and 2021, along with relevant explanatory variables and transition matrices, the study projected NDVI for 2031. The MOLUSCE plugin in QGIS (2021) was utilized for this analysis, employing its

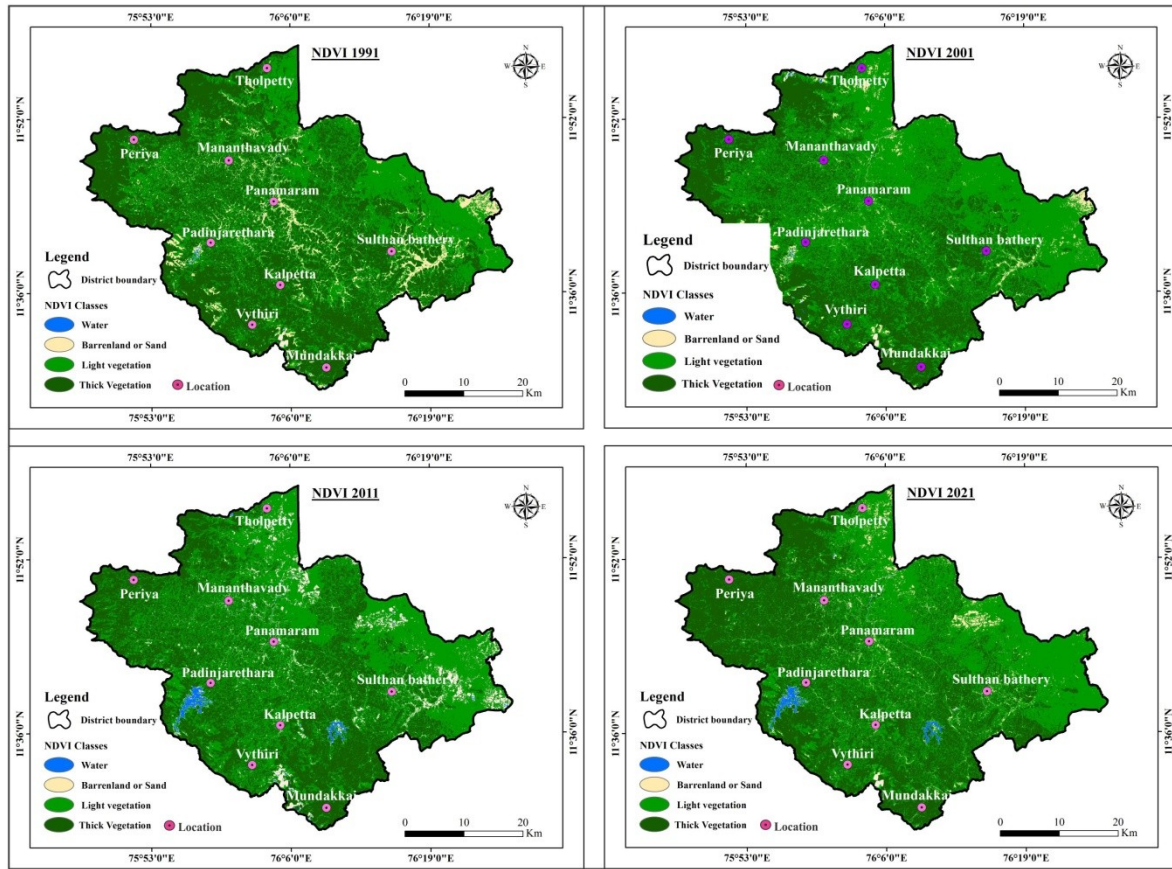


Fig. 3. NDVI change map.

built-in validation tools to assess model accuracy. The validation process produced a kappa coefficient of 0.99, demonstrating strong agreement between actual and simulated NDVI data. Furthermore, a comparative analysis of observed and projected NDVI images confirmed the model's reliability.

2.3 Change Analysis and Transition Potential Modelling

For the Artificial Neural Network (ANN) training process, the model was configured with 1000 iterations, a 1×1 pixel neighbourhood size, a learning rate of 0.100, 10 hidden layers, and a momentum value of 0.05. This configuration facilitated the generation of a robust learning curve and accurate projection of NDVI for 2031. After confirming robust validation results, the calibrated model was applied to generate a simulated NDVI scenario for 2031 (Fig. 2). This projection offers critical insights into anticipated vegetation trends and spatial patterns within the study area, supporting informed decision-making for land management and environmental planning.

2.4 Annual Rate of Change (ARC)

To evaluate the temporal dynamics of NDVI, the annual rate of change (ARC) was calculated for each class. This metric quantifies the percentage change per year over a given time period and provides insight into the rate at which specific NDVI types are expanding or declining. The

ARC was derived by computing the difference in area between the final year and the initial year, dividing this difference by the area in the initial year and the duration of the time interval, and then expressing the result as a percentage (Mathewos et al., 2022). The formula used for this calculation is presented in equation (3):

$$\text{ARC (\%)} = \frac{F_y - I_y}{I_y} \times 100, \quad (3)$$

where, ARC is the annual rate of change in percentage, I_y is the area of the NDVI class in the initial year, F_y is the area of the NDVI class in the final year, and t is the time interval in years between the two observations.

3 Results

3.1 Spatio-temporal Change Analysis of NDVI

The study area, covering 2130.6 km², underwent significant transformations in vegetation cover, barren land, and water bodies between 1991 and 2021, as revealed by NDVI classifications (Fig. 3; Table 2). Thick vegetation, which initially covered 405.35 km² in 1991, sharply declined to 202.93 km² by 2001, indicating a period of severe degradation. However, this trend reversed in subsequent decades, with coverage rebounding substantially to 880.13 km² in 2011 and further increasing to 1015.40 km² by 2021, nearly restoring early 1990s levels. Light vegetation exhibited a contrasting pattern. It expanded from 1699.94 km² in 1991 to 1909.18 km² in 2001, becoming the dominant land cover.

Table 2. NDVI classes for 1991–2021 (area in km²) and annual rate of change (ARC).

Class	1991 Area in km ²	2001 Area in km ²	2011 Area in km ²	2021 Area in km ²	ARC 1991–2021 (%)
Thick vegetation	405.35	202.93	880.13	1015.4	3.11
Light vegetation	1699.94	1909.18	1135.03	1038.81	-1.63
Barrenland	22.11	8.74	96.61	61.83	3.49
Water	3.21	9.75	18.81	14.52	5.16

Table 3. Temporal changes 1991–2001.

Class	1991 Area in km ²	2001 Area in km ²	Δ	1991%	2001%	Δ %
Thick vegetation	405.35	202.93	-202.42	19.03	4.83	-14.20
Light vegetation	1699.94	1909.18	+209.24	79.80	94.30	14.54
Barrenland	22.11	8.74	-13.37	1.04	0.41	-0.63
Water	3.21	9.75	6.54	0.15	0.46	0.31

Table 4. Temporal changes 2001–2011.

Class	2001 Area in km ²	2011 Area in km ²	Δ	2001%	2011%	Δ %
Thick vegetation	202.93	880.13	677.2	4.83	41.31	36.50
Light vegetation	1909.18	1135.03	-774.21	94.30	53.27	-41.04
Barrenland	8.74	96.61	87.87	0.41	4.53	4.13
Water	9.75	18.81	9.06	0.46	0.88	0.42

Table 5. Temporal changes 2011–2021.

Class	2011 Area in km ²	2021 Area in km ²	Δ	2011%	2021%	Δ %
Thick vegetation	880.13	1015.40	135.27	41.31	47.66	6.35
Light vegetation	1135.03	1038.81	-96.22	53.27	48.76	-4.52
Barrenland	96.61	61.83	-34.78	4.53	2.90	-1.63
Water	18.81	14.52	-4.29	0.88	0.68	-0.20

However, its extent declined consistently thereafter, reducing to 1135.03 km² in 2011 and 1038.81 km² in 2021, suggesting a possible transition to thicker vegetation or other land-use changes. Barren land displayed a non-linear trend, decreasing from 22.11 km² in 1991 to 8.74 km² in 2001, followed by a sharp increase to 96.61 km² in 2011. By 2021, it had partially recovered to 61.83 km², though remaining significantly higher than 1991 levels. Water bodies, the smallest NDVI category, gradually increased from 3.21 km² in 1991 to 9.75 km² in 2001 and 18.81 km² in 2011, likely due to climatic or anthropogenic factors. A slight reduction occurred by 2021 (14.52 km²), though the overall trend remained one of expansion.

The NDVI analysis from 1991 to 2001 indicates major shifts in vegetation and land use patterns across the study region. Thick vegetation experienced a sharp decline of 202.42 km², dropping from 19.03% to 4.83%, potentially due to deforestation, urban expansion, or agricultural encroachment. Conversely, light vegetation expanded by 209.24 km², increasing from 79.77% to 94.31%, which may reflect transitional land states or the conversion of dense forest into more open vegetation. Barren land decreased slightly by 13.37 km², while water bodies increased by 6.54 km² (Table 3).

The decade between 2001 and 2011 witnessed remarkable changes in NDVI dynamics within the study area (Table 4). Thick vegetation increased significantly by 677.20 km², rising from 4.83% to 41.33%, indicating strong greening trends likely due to reforestation, natural succession, or improved vegetation health. Meanwhile, light vegetation experienced a substantial decline of 774.15 km², falling from 94.31% to 53.27%, suggesting a transition toward denser

vegetation or land use intensification. Barren land expanded by 87.87 km², and water bodies grew by 9.06 km².

Between 2011 and 2021, NDVI changes in the study area were relatively moderate compared to the previous decade (Table 5). Thick vegetation continued to expand, increasing by 135.27 km², with its share rising from 41.31% to 47.66%. Light vegetation decreased slightly by 96.22 km², declining from 53.27% to 48.76%, which may indicate further transition into denser canopy or conversion to other land uses. Barren land saw a reduction of 34.78 km², and water bodies also declined by 4.29 km².

3.2 NDVI Transition Matrix

The NDVI transition matrix for 1991 to 2001 shows that water areas shifted primarily to barren land (0.398) and thick vegetation (0.237), with a smaller portion remaining as water (0.209). Barren land showed a strong transition to light vegetation (0.479), while a portion remained unchanged (0.330). Light vegetation mainly shifted to thick vegetation (0.712), while some remained as light vegetation (0.253). Thick vegetation was most stable, retaining a high value (0.952) within the same class and showing minimal transition to other categories (Table 6).

Between 2001 and 2011 (Table 7), water mostly transitioned to thick vegetation (0.541) and light vegetation (0.359), with less retained as water (0.074). Barren land shifted mainly to light vegetation (0.536), while some remained barren (0.327). Light vegetation was largely stable (0.786), with smaller transitions to barren land (0.130) and thick vegetation (0.073). Thick vegetation partly remained unchanged (0.521) and partly turned into light vegetation (0.460).

Table 6. NDVI transition matrix from 1991–2001.

Year	1991–2001				
	NDVI Class	Water	Barren land	Light vegetation	Thick vegetation
1991	Water	0.209	0.208	0.415	0.168
	Barren land	0.008	0.048	0.863	0.081
	Light vegetation	0.002	0.003	0.704	0.291
	Thick vegetation	0.012	0.006	0.143	0.839

Table 7. NDVI Transition matrix from 2001–2011.

Year	2001–2011				
		Water	Barren land	Light vegetation	Thick vegetation
2001	Water	0.074	0.026	0.359	0.541
	Barren land	0.043	0.327	0.536	0.095
	Light vegetation	0.011	0.130	0.786	0.073
	Thick vegetation	0.006	0.013	0.460	0.521

Table 8. Transition matrix from 2011–2021.

Year	2021				
		Water	Barren land	Light vegetation	Thick vegetation
2011	Water	0.696	0.068	0.117	0.119
	Barren land	0.010	0.303	0.614	0.073
	Light vegetation	0.000	0.029	0.719	0.252
	Thick vegetation	0.000	0.003	0.182	0.816

Table 9. Gains and losses of each category.

Classes	1991–2001 Area km ²	2001–2011 Area km ²	2011–2021 Area km ²
Thick vegetation	-202.42	677.2	135.27
Light vegetation	209.24	-774.21	-96.22
Barrenland	-13.37	87.87	-34.78
Water	6.54	9.06	-4.29

From 2011 to 2021 (Table 8), water remained largely stable (0.696), with minor transitions to thick vegetation (0.119) and light vegetation (0.117). Barren land mostly changed to light vegetation (0.614), while some remained barren (0.303). Light vegetation was moderately stable (0.719) and also transitioned to thick vegetation (0.252). Thick vegetation showed high stability (0.816), with some conversion to light vegetation (0.182).

3.3 Gains and Losses in NDVI Classes

The NDVI-based analysis reveals significant shifts in Wayanad's vegetation cover over three decades. The initial period (1991–2001) saw a striking transformation, with thick vegetation declining sharply (-202.42 km²) while light vegetation expanded by a nearly comparable magnitude (209.24 km²), suggesting widespread forest degradation or thinning (Table 9). This trend reversed in the following decade (2001–2011), as thick vegetation recovered substantially (677.20 km²) at the expense of light vegetation (-774.21 km²), indicating possible forest regeneration or successful conservation efforts. The most recent period (2011–2021) showed continued but more gradual recovery, with thick vegetation expanding modestly (135.27 km²) as light vegetation receded further (-96.22 km²).

The subsequent decade (2001–2011) marked a substantial recovery of thick vegetation (677.2 km²) and a sharp decline in light vegetation (-774.21 km²), suggesting regrowth or afforestation efforts. However, from 2011 to 2021, the increase in thick vegetation slowed (135.27 km²), while light vegetation and barren land declined (-96.22 km² and -34.78

km², respectively), reflecting a stabilization trend. Water bodies showed minor fluctuations across the decades, indicating minimal influence on overall vegetation dynamics. Fig. 4 illustrates NDVI gains and losses during the period 1991–2021 using a bar graph.

3.4 Transition Potential Modelling and Model Validation

The study employed the MOLUSCE plugin in QGIS, which incorporates established algorithms for transition potential modelling including Artificial Neural Networks (ANN), weights of evidence, multicriteria evaluation, logistic regression, and cellular automata (CA). For NDVI transition modelling and future projections, integrated Cellular Automata-Artificial Neural Network (CA-ANN) approach was implemented. Utilizing historical NDVI data (1991–2021) combined with relevant spatial variables, the model generated projections of NDVI distribution for 2021 (Fig. 5). Model performance was rigorously assessed by comparing these projections against actual 2021 NDVI observations. The validation results demonstrated excellent predictive accuracy, with an overall accuracy of 96.64% and a kappa coefficient of 0.9 (Table 10). These robust validation metrics confirm the model's reliability for analyzing long-term NDVI trends and support its use for future landscape change projections.

3.5 Prediction of NDVI

The NDVI-based projections for Wayanad district over the decade from 2031 to 2041 highlight notable ecological

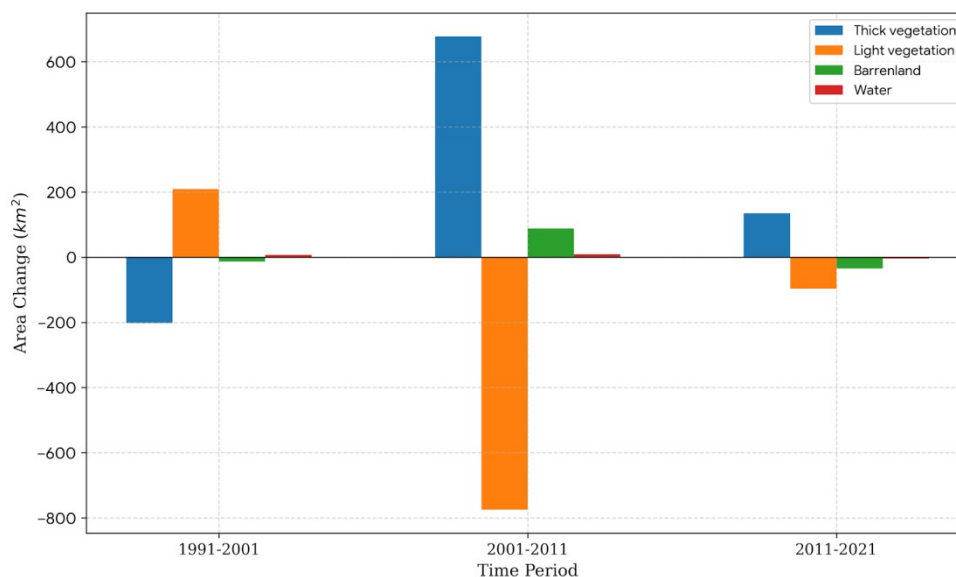


Fig. 4. NDVI gains and losses (1991–2021).

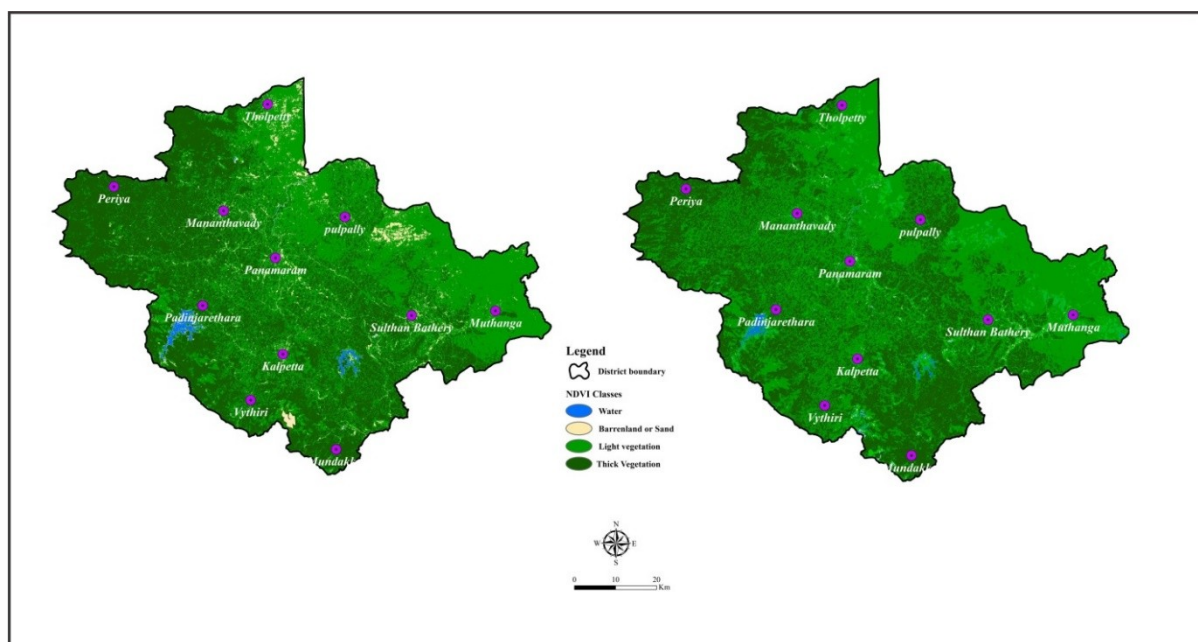


Fig. 5. Actual and projected NDVI 2021.

Table 10. Actual and projected NDVI 2021.

Classes	Actual		Projected		Accuracy	Kappa value ANN
	Area km ²	%	Area km ²	%		
Thick vegetation	1015.4	47.66	874.61	41.04	96.64	0.9
Light vegetation	1038.81	48.76	1147.7	53.86		
Barrenland	61.83	2.90	95.91	4.50		
Water	14.52	0.68	12.27	0.57		

transitions indicative of both vegetation recovery and localized degradation (Fig. 6). Thick vegetation is projected to increase from 1012.24 km² (47.51%) in 2031 to 1039.96 km² (48.91%) by 2041. This steady rise reflects a continued trend of forest densification, possibly resulting from ecological restoration, natural succession, or effective conser-

vation practices. Conversely, light vegetation is expected to exhibit a slight decline from 1013.43 km² (47.63%) to 1005.00 km² (47.08%), suggesting that areas with sparse or intermediate vegetation cover may be transitioning into denser forest classes, enhancing the region's overall vegetative biomass. Barren land is projected to rise from 62.81 km²

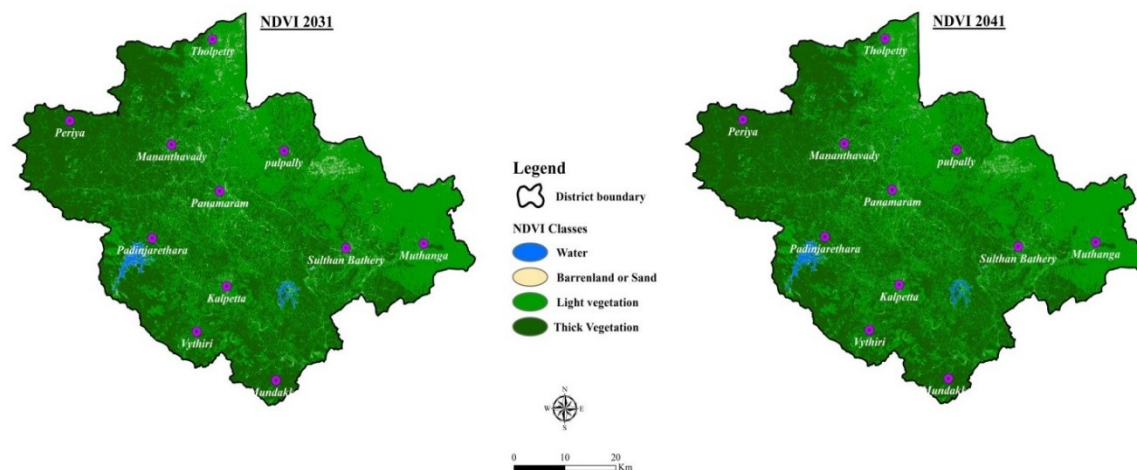


Fig. 6. Predicted NDVI 2031 and 2041.

(2.95%) to 71.56 km² (3.36%). Meanwhile, the area under water bodies is anticipated to marginally decline from 14.04 km² (0.67%) to 13.95 km² (0.65%), indicating relative hydrological stability with minor fluctuations. Importantly, the kappa coefficient – a statistical measure of model reliability – increases from 0.90 in 2031 to 0.94 in 2041, demonstrating high spatial accuracy and consistency in the model's predictive performance (Table 11).

Table 11. Predicted area statistics (2031 and 2041).

NDVI Class	2031 (Area)		Kappa	2041 (Area)		Kappa
	km ²	%		km ²	%	
Water	14.04	0.67	0.90	13.95	0.65	0.94
Barren land	62.81	2.95		71.56	3.36	
Light vegetation	1013.43	47.63		1005.00	47.08	
Thick vegetation	1012.24	47.51		1039.96	48.91	

3.6 Temporal changes 2031–2041

The decadal NDVI analysis reveals remarkable stability in vegetation cover across the study area. Both thick and light vegetation classes demonstrated complete persistence, with 100% of their 2031 coverage remaining unchanged by 2041 (Table 12). This uniform stability suggests these vegetation types have reached ecological equilibrium, though it may also reflect constraints on further growth due to resource limitations or sustained land-use pressures. Barren lands showed moderate transformation, with 78% persistence and 22% transitioning to light vegetation, indicating gradual revegetation in some areas. Water bodies maintained near-complete stability (98% retention), with only 2% converting to light vegetation—changes likely attributable to seasonal drying patterns or marginal vegetative encroachment. The transition matrix (Table 13), paints a picture of overall landscape stability punctuated by localized changes. While the dominant vegetation classes appear resistant to change, the observed transitions in barren lands and marginal water areas suggest ongoing, though limited, ecological dynamics.

Table 12. Temporal changes 2031–2041.

Classes	2021–2031		2031–2041	
	Area in km ²	%	Area in km ²	%
Thick vegetation	24.88	21.85	-0.32	0.09
Light vegetation	-25.38	27.29	-8.43	8.43
Barrenland	0.98	6.06	8.75	62.69
Water	-0.48	0.48	0.00	25.01

Table 13. Transition matrix from NDVI categories to change 2031–2041 (%).

Classes	2031–2041			
	Water	Barren land	Light vegetation	Thick vegetation
water	0.98	0.00	0.02	0.00
barren	0.00	0.78	0.22	0.00
light	0	0	1	0
thick	0	0	0	1

4 Discussion

The analysis of NDVI classes in Wayanad District reveals a remarkable recovery of dense evergreen and semi-evergreen forests, particularly in ecologically significant zones like Tholpetty, Muthanga, and Pakshipathalam, where high NDVI values (0.6–0.8) reflect thriving vegetation. After initial declines between 1991 and 2001 due to deforestation and degradation, these forests have rebounded substantially, with thick vegetation cover expanding to 1015.40 km² by 2021. Moderate NDVI values (0.3–0.6) in Wayanad highlight light vegetation zones, including scrublands, grasslands, and agricultural areas, particularly in the fertile valleys of Meenangadi and Panamaram. These regions exhibit pronounced seasonal NDVI fluctuations, driven by crop cycles – especially rice cultivation during monsoon and winter seasons. While light vegetation dominated nearly 79% of the district in 1991, its coverage has since declined, reflecting urban expansion, agricultural intensification, and the gradual conversion of open areas into denser forests.

Barren lands, characterized by NDVI values below 0.2, include degraded zones such as quarries, deforested areas, and sites affected by road development. These areas have

experienced notable fluctuations over time – initially decreasing between 1991 and 2001, expanding during the 2011 infrastructure boom, and then partially recovering by 2021. Water bodies, identified by negative NDVI values, have also undergone changes, with notable expansions in reservoirs like Karapuzha and Banasura Sagar – from 3.21 km² in 1991 to 18.81 km² in 2011 – due to shifting precipitation patterns and water management interventions.

Together, these NDVI classes highlight a district undergoing both ecological recovery and human-induced pressure, with forests regenerating in certain areas while urbanization, agriculture, and land degradation continue to influence the landscape. The spatiotemporal analysis reveals not only the impact of past land use but also offers valuable projections for future conservation and land management efforts, especially in areas marked by significant vegetation loss or fragmentation.

5 Conclusions

The spatiotemporal NDVI-based analysis from 1991 to 2021, along with future projections up to 2041 using the CA-ANN model, reveals significant vegetation dynamics in Wayanad, shaped by both anthropogenic pressures and natural ecological processes. The sharp decline in thick vegetation during the 1990s reversed in the following decades, suggesting successful afforestation, conservation efforts, or favourable climatic conditions. Simultaneously, the gradual transition of light vegetation into thicker classes highlights a broader trend of vegetation densification and ecological succession. Barren lands and water bodies exhibited temporal fluctuations, reflecting localized disturbances such as quarrying, settlement expansion, and seasonal reservoir drawdowns rather than long-term degradation. Future predictions using the CA-ANN approach indicate a likely continuation of this greening trend, with thick vegetation expected to stabilize or expand, while barren areas are projected to decline. The model's strong performance for 2031 ($\kappa = 0.90$) lends confidence to near-term forecasts, though moderate accuracy for 2041 ($\kappa = 0.94$) suggests cautious interpretation for longer horizons. Overall, the study demonstrates the utility of NDVI time-series analysis combined with machine learning-based modelling in capturing nonlinear land cover transitions. These tools are essential for monitoring vegetation health, guiding sustainable land management, and informing conservation policy in the ecologically vital Western Ghats region.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT Author Statement

M. S. Sanjayan: Conceptualization, Methodology, Formal Analysis, Investigation, Resources, Writing-Original Draft, Writing-Review & Editing. **V. K. Brijesh:** Methodology, Validation, Formal Analysis, Data Curation, Writing-Review & Editing, Visualization, Supervision.

Data Availability

All data used in this study are available from the authors upon reasonable request.

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