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Spatio-Temporal Assessment of Land Degradation Neutrality (LDN) status in Chhattisgarh, India (2001–2022) Using Trends.Earth

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ABSTRACT

The present study entitled "Spatio-Temporal Assessment of Land Degradation Neutrality (LDN) status in Chhattisgarh, India (2001–2022) Using Trends.Earth" assesses land degradation change from 2001 to 2022 using the Trend. Earth plugin within QGIS, integrating satellite-based datasets such as MODIS (MOD13Q1), ESA-CCI, and ISRIC Soil Grids to evaluate changes in land use/land cover (LULC), land productivity, and soil organic carbon (SOC) in accordance with SDG indicator 15.3.1. The analysis reveals that the total geographical area (135,169 km²) experienced moderate land use transitions, marked by a notable increase in built-up areas (+434.5 km²; +2.1%) and minor declines in agricultural (−472 km²) and forest land (−261.7 km²), indicating expanding urbanization and conversion pressures. The land degradation assessment shows that 97.36% of land cover remained stable, 1.02% improved, and 1.62% degraded. SOC levels were largely stable (98.53%), with minimal improvement (0.69%) and degradation (0.66%). Land productivity trends demonstrated strong growth, with 77.57% of the area showing improvement and only 2.56% showing decline. The overall SDG 15.3.1 indicator indicates that 76.59% of the total area is improved, 18.52% remains stable, and only 4.14% is degraded. These results suggest that the region is largely stable and ecologically resilient, with positive vegetation and soil health trends; however, localized degradation and urban expansion highlight the need for sustainable land management strategies and policy interventions to maintain land degradation neutrality (LDN) and ensure long-term landscape sustainability.

Keywords: *LDN; Trends.Earth; SOC; MODIS; SDG15.3.1.*

1. Introduction

Land degradation is one of the crucial environmental and developmental challenges of the 21st century, threatening ecosystem functions, productivity, and the well being of the human population. The United Nations Convention to Combat Desertification (UNCCD) formally incorporated the concept of Land Degradation Neutrality (LDN) within the 2030 Agenda for Sustainable Development as part of Sustainable Development Goal (SDG) 15.3. LDN aims to ensure that the amount and quality of land resources necessary to sustain ecosystem services and enhance food security remain stable or improve over a defined temporal and spatial scale (Minelli et al., 2017). The operationalization of SDG indicator 15.3.1 "proportion of land that is degraded over total land area" relies on three globally standardized sub-indicators: land cover and land cover change, land productivity, and soil organic carbon (SOC) dynamics (Sims et al., 2017; Orr et al., 2017).Remote sensing technologies enable comprehensive, spatially explicit monitoring of land degradation drivers and trends at multiple scales (Mbow et al., 2015; Fensholt et al., 2013). Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) derived from MODIS satellite data are widely used proxies for land productivity and vegetation health (Tucker, 1979; Pettorelli et al., 2005). Cloud-based platforms like Trends.Earth facilitate the standardized processing of remote sensing data to quantify land cover changes, productivity trajectories, and carbon stock variations, enhancing transparency and comparability for LDN assessments (Sims et al., 2021; Gorelick et al., 2017).

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Globally, satellite-derived proxies such as NDVI have proven effective in assessing net primary productivity (NPP) variations to depict the trajectory of ecosystem productivity (Fensholt et al., 2013; Prince, 2019). Vegetation decline associated with land surface disruption and soil erosion parallels NDVI reductions documented elsewhere (Reith et al., 2021; Schillaci et al., 2022). Employing Trends.Earth, this study quantifies LDN trajectories by grouping MODIS NDVI series into degraded, stable, and improved classesconsistent with the UNCCD "one-out, all-out" principle, where any decline in one sub-indicator yields classification as degraded (Sims et al., 2019). By enabling the use of high-temporal-resolution MODIS imagery combined with local data (Amani et al., 2020; Gorelick et al., 2017), by computing vegetation productivity trajectories based on annual maximum NDVI rather than mean values a refinement that enhances sensitivity to canopy dynamics while reducing noise from bare soil and atmospheric interference (Markos et al., 2023). Temporal NDVI trends from 2001–2022 encapsulate both anthropogenic and climatic influences on land condition in the state. Chhattisgarh, characterized by its diverse forest ecosystems and agrarian economy, is increasingly prone to land degradation due to deforestation, shifting cultivation, mining activities, and unsustainable land use practices. Despite its vulnerability, comprehensive LDN assessments integrating geospatial techniques and SDG Indicator 15.3.1 for this region remain limited (Singh et al., 2023; Cowie et al., 2018). Implementing such assessments is crucial for furnishing policymakers with spatially explicit evidence to guide restoration efforts and achieve LDN targets (Feng et al., 2022; Sims et al., 2021).

This study assesses LDN in Chhattisgarh from 2001 to 2022 by integrating geospatial methodologies using the Trends.Earth platform aligned with SDG Indicator 15.3.1. Satellite remote sensing datasets including MODIS NDVI, alongside ancillary data on SOC, enable robust characterization of land cover dynamics, productivity changes, and soil carbon stocks over two decades.

2. Materials and Methodology

2.1. Study Area

Chhattisgarh, located in central India, extends between latitudes 17°46′ to 24°05′ N and longitudes 80°15′ to 84°20′ E **(Fig. 1)**. Chhattisgarh has a population of about 25.5 million, of which nearly 70% are engaged in agriculture as their primary livelihood. The state has a net-snow area of about 4.65 million hectares (Mha), accounting for nearly 34% of its total geographical area (TGA) of approximately 13.8 Mha. The study area is categorized into three distinct agro-climatic zones: the Bastar Plateau, the Chhattisgarh Plains, and the Northern Hills. The Chhattisgarh Plains and Northern Hills together cover 20 districts, namely Balod, Balodabazar, Bemetara, Bilaspur, Dhamtari, Durg, Gariyaband, Janjgir, Kabirdham, Korba, Korea, Mahasamund, Mungeli, Raipur, Raigarh, Rajnandgaon, Surajpur, and Sarguja. In contrast, the Bastar Plateau consists of seven districts: Bastar, Bijapur, Dantewada, Kanker, Kondagaon, Narayanpur, and Sukma. The region has a tropical climate, marked by hot summers, cool winters, and a rainy season primarily influenced by the southwest monsoon. The average annual rainfall across the study area is about 1400 mm.

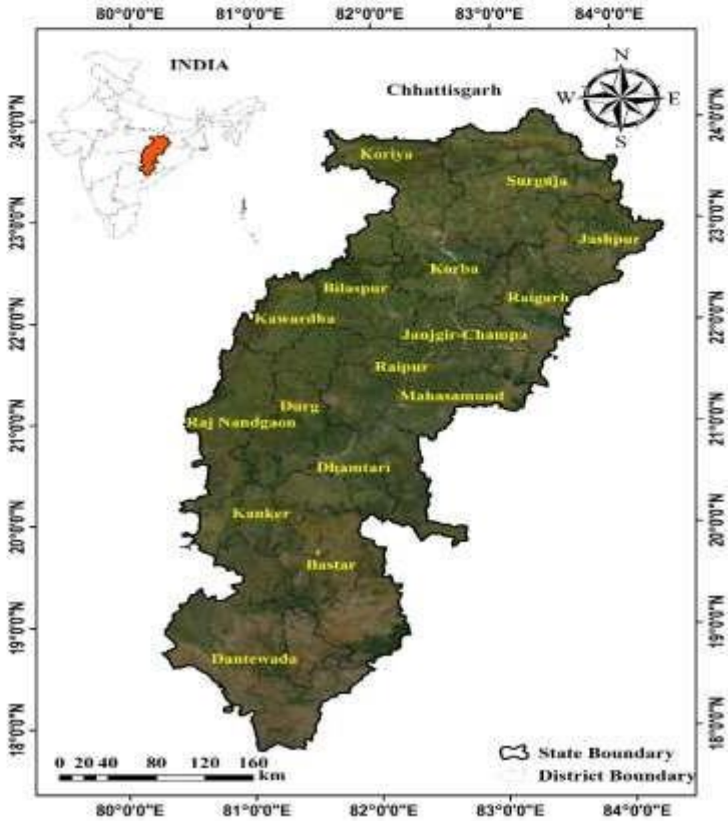

Fig. 1. Location map of the study area

2.2. Data (Trends.earth)

The MOD13Q1 Version 6 dataset was utilized in Trends.Earth to derive vegetation indices. This dataset, a Level 3 product from the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the Terra satellite, is generated every 16 days with a spatial resolution of 250 meters. The MOD13Q1 product offers two primary vegetation indices: the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI). For this 16-day composite product, the algorithm identifies and selects the highest-quality pixel from all observations within the 16-day period, based on criteria such as minimal cloud cover, optimal viewing angle, and the highest NDVI or EVI value. This data source was preferred over the AVHRR dataset available in Trends.Earth due to its finer spatial resolution (250 m compared to 1 km) and extended temporal coverage (2001-2022), encompassing the entire monitoring period.

Another dataset incorporated in Trends.Earth is the ESA Climate Change Initiative (ESA-CCI) dataset, which spans the period from 1992 to 2020 with a spatial resolution of 300 meters. It is utilized for monitoring land cover changes by reclassifying its 22 original categories into the seven land cover classes required for UNCCD reporting: forest, grassland, cropland, wetland, artificial area, bare land, and water (Friedl et al.,2022). The default reclassification matrix provided by Trends.Earth was applied. To assess the initial soil organic carbon (SOC) layer, the ISRIC Soil Grids global dataset (250 m resolution) was utilized, which offers spatial predictions of various soil properties across six standard depth intervals (Cherif et al.,2023).

The SDG 15.3.1 indicator is assessed by analyzing changes in three key sub-indicators land productivity, land cover, and soil organic carbon (SOC) to determine whether land degradation has increased, remained stable, or decreased. As per UNCCD guidelines, each country must report land degradation across its entire territory for the baseline period (2001–2015), which serves as the reference for measuring progress toward SDG target 15.3 and Land Degradation Neutrality (LDN).

In this study, land degradation was evaluated over a 22-year period (2001–2022). The land productivity sub-indicator was analyzed using long-term (trajectory), short-term (state), and spatial (performance) trends. The trajectory assessed productivity change from 2001–2022, while the state compared productivity between 2013–2015 and 2001–2012 for the baseline, and between 2020–2022 and 2005–2019 for the reporting period. Performance was determined by comparing productivity across similar land cover areas during 2001–2015 and 2016–2022.Finally, the three sub-indicators were integrated using the “one-out, all-out” principle, meaning a land unit is classified as degraded if any sub-indicator shows degradation. This provides the total proportion of degraded land within the study area.

The Trends.Earth plugin, developed by Conservation International, is a powerful QGIS-based platform recommended by the UNCCD for monitoring and reporting land degradation under SDG 15.3.1. It integrates global Earth Observation (EO) and national datasets, using a cloud-based system via Google Earth Engine for sub-indicator computation, while the final indicator is generated locally. In this study, Trends.Earth v1.0.8 was used following the guidelines of Sims et al. 2019. The indicator was calculated for the baseline period (2001-2015) and the reporting period (2016–2020), as per UNCCD recommendations. Although the short reporting period limits the detection of slow-changing variables such as SOC, it was adopted due to data constraints. For assessing vegetation productivity, the MODIS MOD13Q1 (NDVI) dataset was used, as it covers both periods (2001-2020) with consistent spatial and temporal resolution. NDVI trends were analyzed without climate calibration (RUE/WUE), which is appropriate for irrigated agricultural regions where water stress is minimal. Land productivity was analyzed for 2005-2020, classified into five categories-Declining, Early signs of decline, Stable but stressed, Stable, and Increasing-and reclassified into three SDG categories: Degraded, Stable, and Improved. The sub-indicators were combined using the “one-out, all-out” principle to determine the total proportion of degraded land, ensuring a consistent and standardized assessment of land degradation dynamics.

The SOC change sub-indicator was estimated by combining the initial SOC values from the Soil Grids dataset with a default transition matrix for land cover and SOC provided by Trends.Earth. The outputs generated by the Trends.Earth plugin were automatically imported into QGIS for further spatial analysis. All analyses were performed using QGIS Desktop 3.16.13, which is fully compatible with Trends.Earth version 1.

3. Results

3.1. Land Use Land Cover

The Land Use/Land Cover (LULC) analysis between 2001 and 2022**(Table 1)** indicates noticeable spatial transformations within the study area shown in (Fig.2&3), while the total geographical extent remained unchanged at 135,169 km². The most prominent change was observed in the built-up area, which expanded significantly from 210.3 km² to 644.8 km², marking an increase of 434.5 km² (2.1%)a clear indication of rapid urbanization and infrastructural development. Conversely, both open forest and agricultural land exhibited declines of 261.7 km² and 472.0 km², respectively, reflecting ongoing land conversion pressures due to urban expansion and shifting land-use practices. Sparse vegetation increased by 194.0 km², suggesting localized vegetation recovery or the expansion of degraded lands, while minor decreases were recorded in wetlands (-

0.1 km²) and barren lands (−0.2 km²), indicating relative stability of these categories. Water bodies expanded by 105.5 km², likely due to improved water management or the creation of reservoirs. Overall, these changes demonstrate a gradual transition from natural and agricultural landscapes toward more urbanized and semi-vegetated environments, underscoring the growing human influence on land resources andthe need for sustainable land management to maintain ecological balance and productive land use.

Table 1: Land Use Land Cover Details of the study area from (2001-2022)

	Area in (sq. km)		**Change in area**	
LULC Class	**2001**	**2022**	**(km²)**	**(%)**
Open forest	47756.2	47494.4	-261.7	0.0
Sparse Vegetation	1678.5	1872.5	194.0	0.1
Agricultural land	84695.7	84223.7	-472.0	0.0
Wetland	44.7	44.6	-0.1	0.0
Built up	210.3	644.8	434.5	2.1
Barren land	10.1	9.9	-0.2	0.0
Water body	773.5	879.0	105.5	0.1
Total:	**135169.0**	**135169.0**		

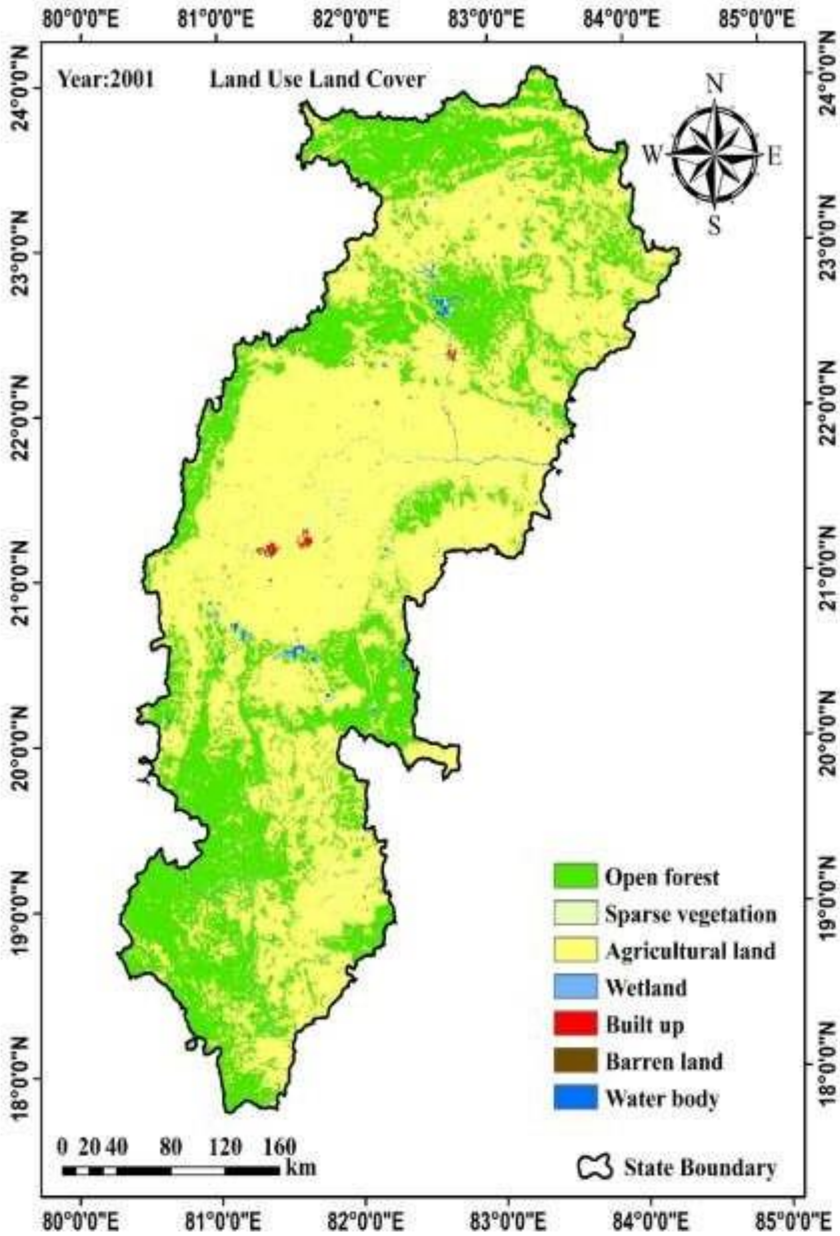

Fig. 2. Land Use Land Cover map of the study area of the year 2001.

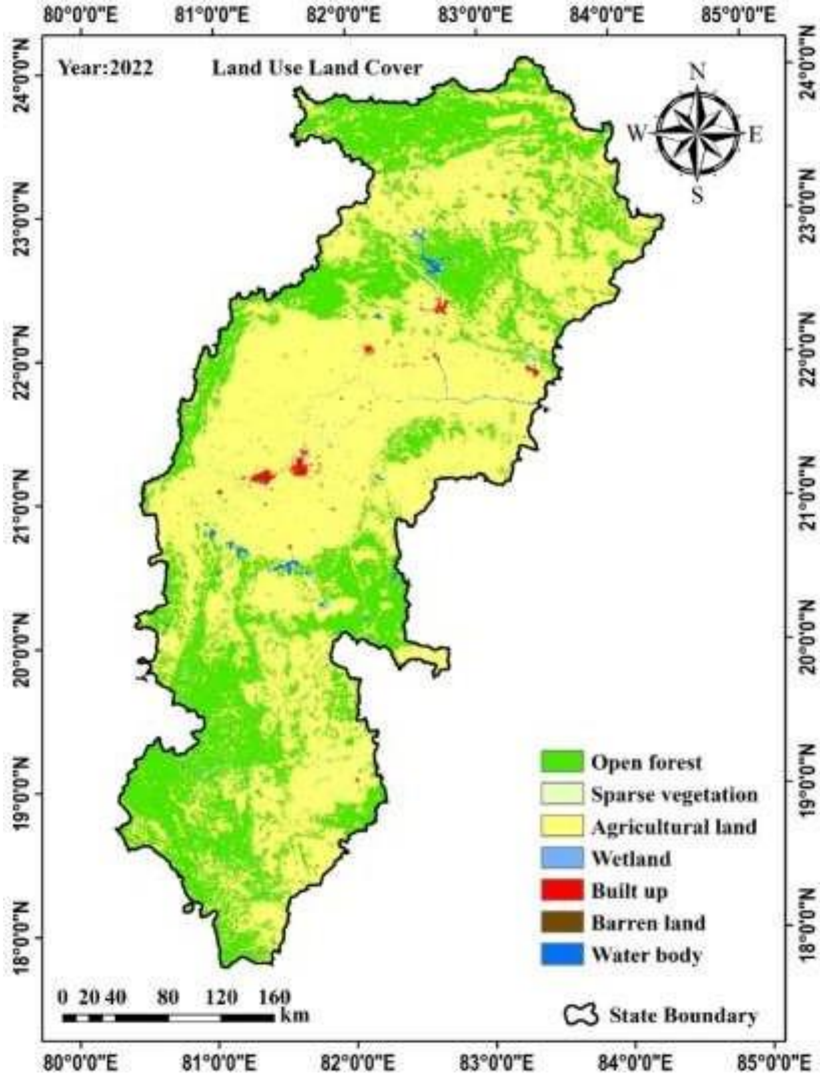

Fig. 3. Land Use Land Cover map of the study area of the year 2022.

3.2. Land Cover Degradation

The land cover degradation assessment **(Table 2)** based on land cover change reveals that most of the study area remained stable, covering approximately 131,605.48 km² (97.36%) of the total land area (135,168.99 km²) shown in (Fig.4). This indicates that most of the land maintained its existing condition without significant degradation or improvement during the study period. A relatively small portion of land, about 2,190.99 km² (1.62%), was classified as degraded, suggesting localized areas affected by processes such as deforestation, soil erosion, or unsustainable land use practices. Conversely, 1,372.52 km² (1.02%) of the area showed improvement in land cover, reflecting successful vegetation regeneration or land restoration efforts, possibly due to conservation measures or natural recovery. No areas were reported with missing data, ensuring comprehensive spatial coverage. Overall, the results indicate that while the region remains largely stable, targeted attention is needed in degraded zones to achieve land degradation neutrality and sustain long-term ecosystem health.

Table2: Summary of Land Cover degradation from 2001-2022

Land Cover Class	Area (sq km)	% of total land area
Land area with improved land cover:	1,372.52	1.02%
Land area with stable land cover:	131,605.48	97.36%
Land area with degraded land cover:	2,190.99	1.62%
Land area with no data for land cover:	0.00	0.00%
Total land area:	135,169.0	100.00%

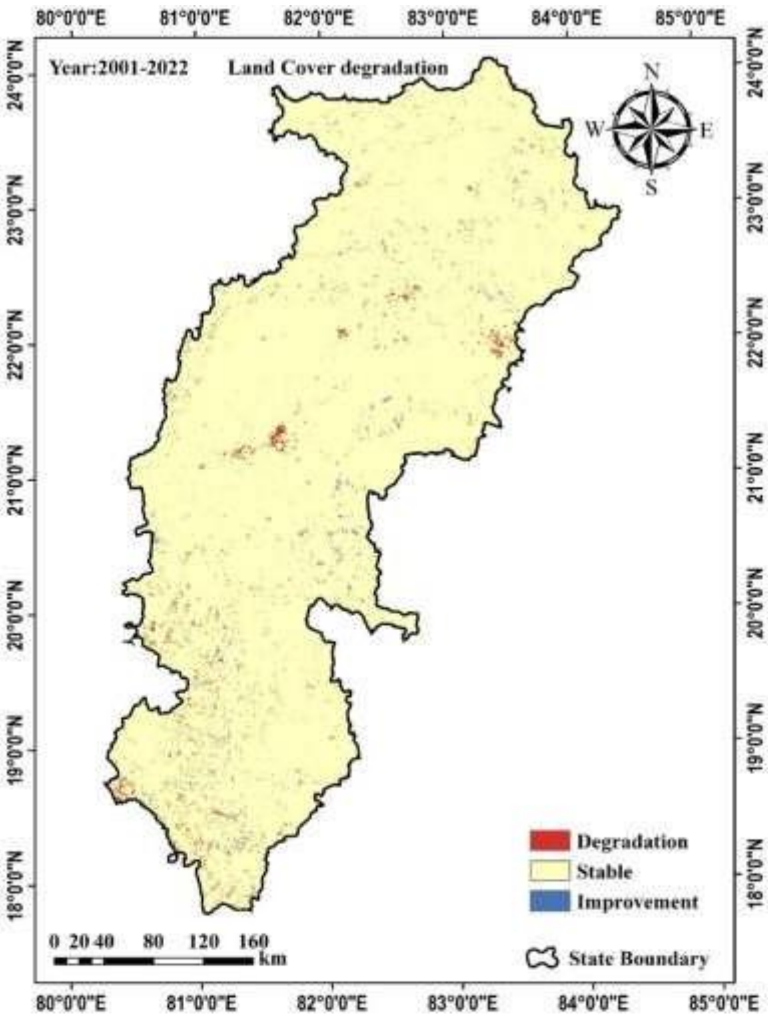

Fig. 4. Land Cover degradation map from 2001-2022

3.3. Soil Organic Carbon

The assessment of Soil Organic Carbon degradation (SOCD) (Table 3) status indicates that most of the study area maintained stable SOC levels, accounting for 132,415.37 km² (98.53%) of the total land area (134,395.5 km²) shown in the (Fig.5, 6 and 7). This stability reflects minimal changes in soil carbon dynamics, suggesting that the region's soils are largely in equilibrium under existing land use and management practices. A relatively small portion of land, approximately 930.67 km² (0.69%), exhibited improved SOC, which may be attributed to vegetation recovery, sustainable land management, or organic matter enhancement through conservation practices. Conversely, about 892.27 km² (0.66%) of the area showed SOC degradation, likely resulting from soil erosion, deforestation, or agricultural intensification leading to organic matter depletion. Additionally, 157.15 km² (0.12%) of land lacked data, representing a negligible portion of the total. Overall, these findings suggest that SOC levels across the study area are largely stable, with only marginal zones showing improvement or degradation, highlighting the importance of maintaining current management practices while reinforcing restoration measures in degraded areas to sustain soil health and carbon storage potential.

Table3: Summary of Soil Organic Carbon Degradation from 2001-2022

SOC Degradation Class	Area (sq km)	% of total land area
Land area with improved soil organic carbon:	930.67	0.69%
Land area with stable soil organic carbon:	132,415.37	98.53%
Land area with degraded soil organic carbon:	892.27	0.66%
Land area with no data for soil organic carbon:	157.15	0.12%
Total land area:	134,395.5	100.00%

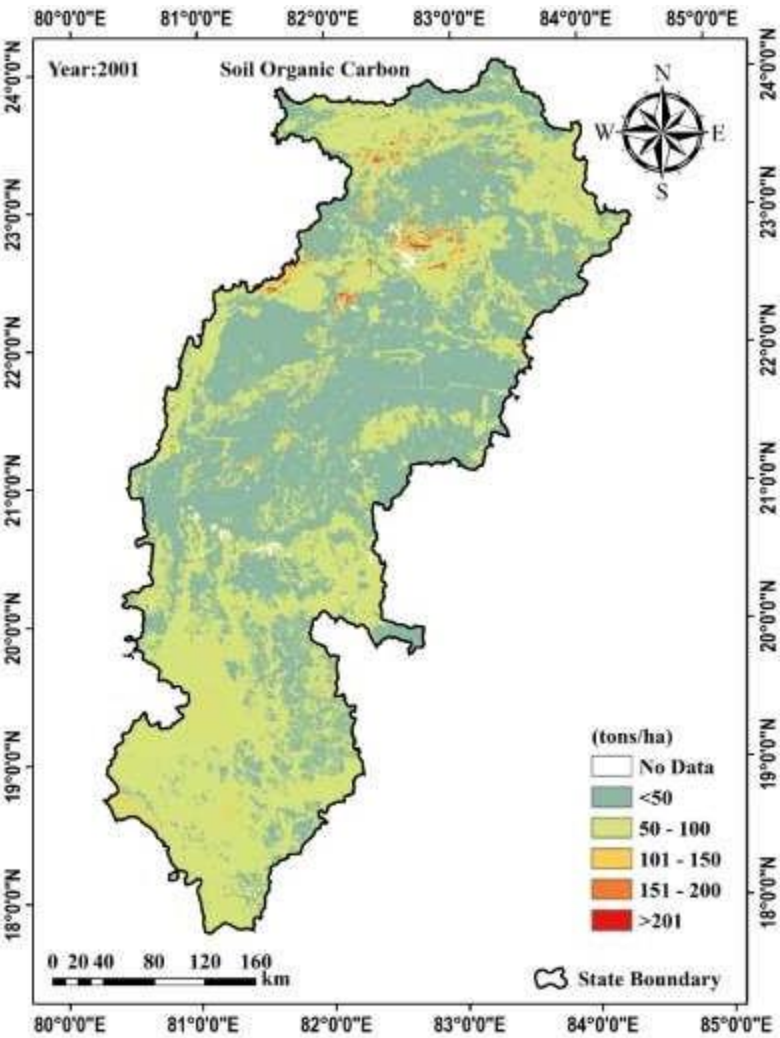

Fig. 5. Soil organic carbon map of the year 2001.

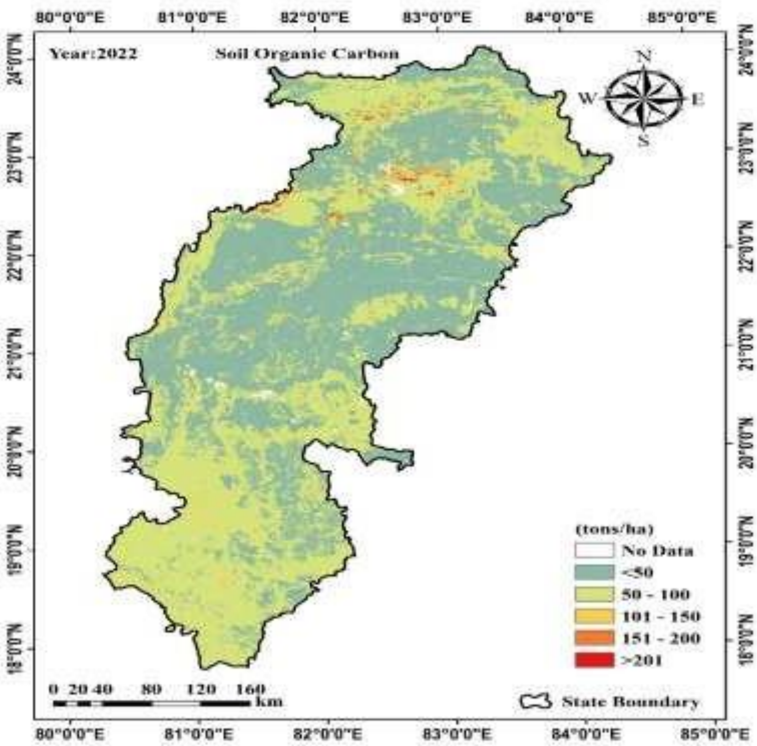

Fig. 6. Soil organic carbon map of the year 2022.

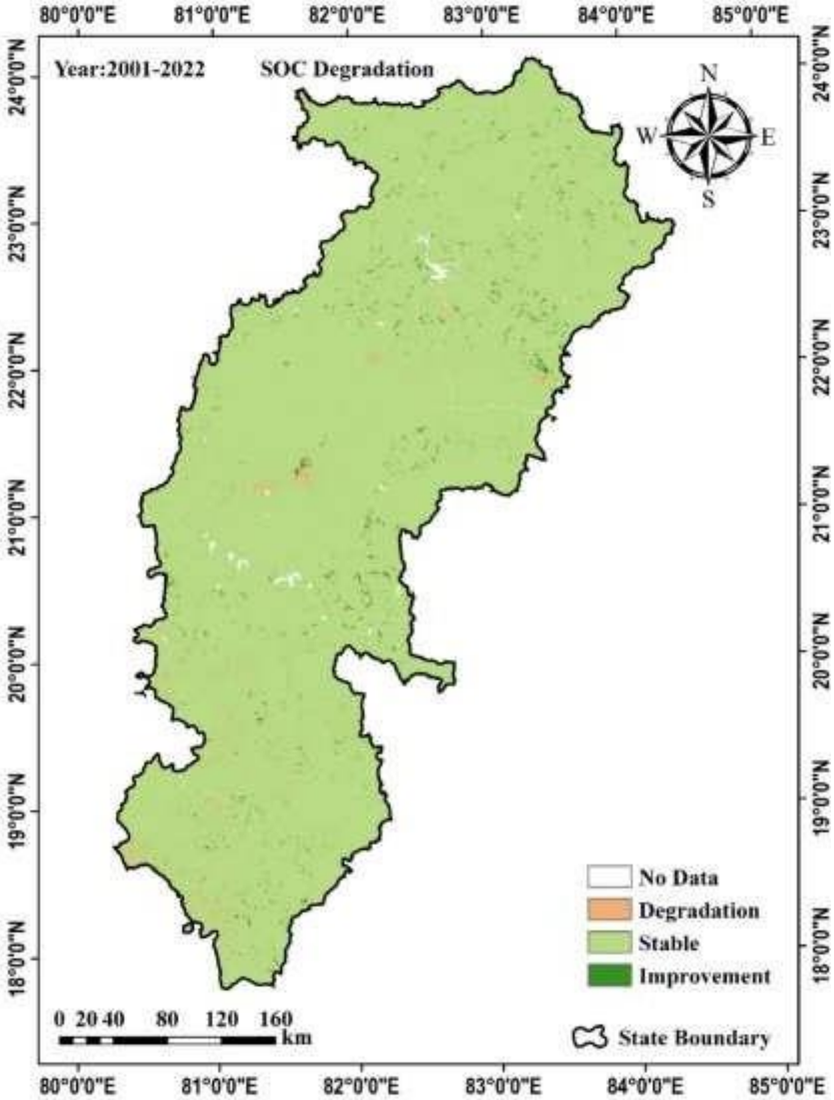

Fig. 7. Soil organic carbon degradation map from 2001-2022.

3.4. Land Productivity Status

The analysis of land productivity status **(Table 4)** indicates that a substantial portion of the study area experienced improvement during the assessment period shown in **(Fig 8)**. Approximately 104,856.93 km² (77.57%) of the total land area (135,169.0 km²) showed improved productivity, suggesting enhanced vegetation growth and overall ecosystem performance, likely influenced by favorable climatic conditions, effective land management practices, or agricultural intensification. Meanwhile, 26,148.06 km² (19.34%) of land maintained stable productivity, indicating consistent land performance without major degradation or improvement. However, about 3,455.70 km² (2.56%) of the area exhibited degraded productivity, reflecting localized declines possibly caused by loss of soil fertility, overexploitation, or environmental stress factors such as drought and land misuse. A small fraction, 708.30 km² (0.52%), had no productivity data, representing negligible uncertainty in coverage. Overall, the results demonstrate a positive trend in land productivity, with more than three-fourths of the area showing improvement, emphasizing a generally healthy landscape condition but also highlighting the need for targeted restoration in degraded zones to sustain long-term productivity.

Table 4: Summary of Land Productivity Status from 2001 to 2022

Land productivity Class	Area (sq km)	% of total land area
Land area with improved productivity:	104,856.93	77.57%
Land area with stable productivity:	26,148.06	19.34%
Land area with degraded productivity:	3,455.70	2.56%
Land area with no data for productivity:	708.30	0.52%
Total land area:	135,169.0	100.00%

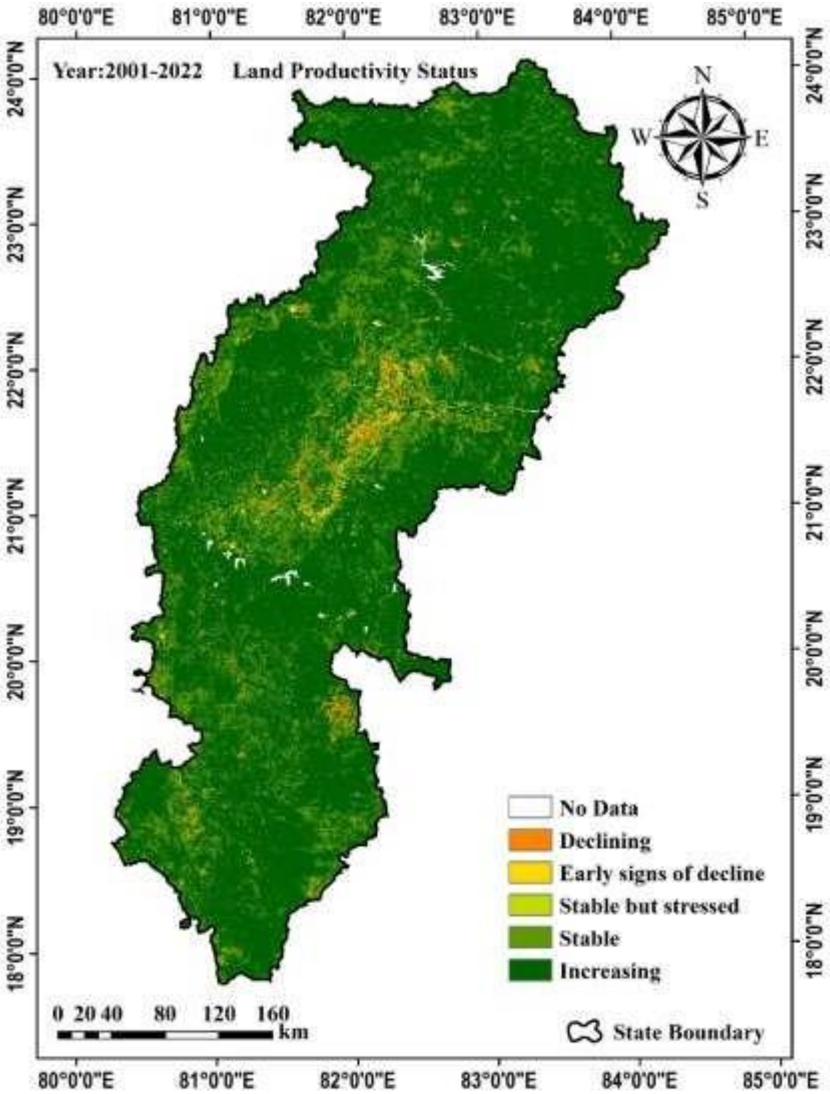

Fig. 8. Land Productivity map from 2001-2022.

3.5. LDN Status

The overall land degradation neutrality status **(Table 5)**reveals that most of the study areas have shown positive or stable conditions during the assessment period shown in **(Fig. 9)**. Out of the total 135,169.0 km², approximately 103,527.95 km² (76.59%) of land area was classified as improved, indicating substantial enhancement in vegetation productivity, soil condition, or land cover quality, likely due to effective land management practices, reforestation, and agricultural development. Around 25,034.45 km² (18.52%) remained stable, suggesting that these areas maintained consistent land condition without significant improvement or degradation. However, about 5,590.72 km² (4.14%) of land was identified as degraded, reflecting localized deterioration possibly caused by deforestation, soil erosion, over-cultivation, or climate-induced stress. A small fraction of land, 1,015.86 km² (0.75%), had no data, representing minimal uncertainty in analysis. Overall, the findings indicate that over three-fourths of the land area is either stable or improving, demonstrating a generally positive trend toward land restoration and productivity enhancement, though continued focus on mitigating degradation hotspots remains essential for achieving land degradation neutrality.

Table 5: Summary of LDN Status from 2001-2022

LDN Status Class	Area (sq km)	% of total land area
Land area improved:	103,527.95	76.59%
Land area stable:	25,034.45	18.52%
Land area degraded:	5,590.72	4.14%
Land area with no data:	1,015.86	0.75%
Total land area:	135,169.0	100.00%

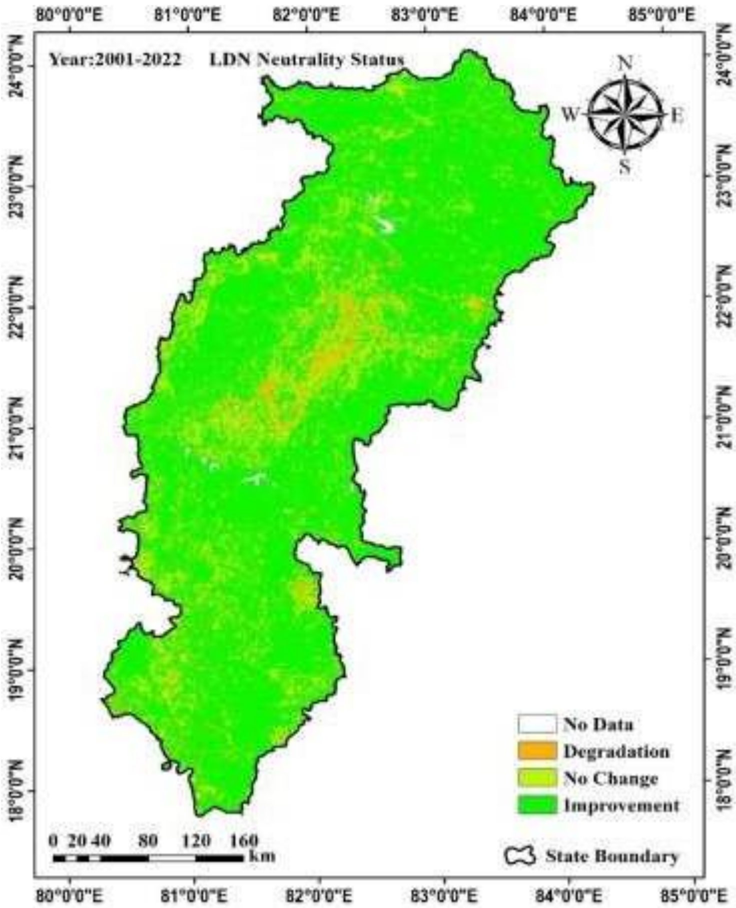

Fig. 9. Land Degradation Neutrality Status map from 2001-2022.

4. Conclusion

The comprehensive assessment of land degradation dynamics from 2001 to 2022 provides a detailed understanding of the spatial and temporal changes in land use/land cover (LULC), land productivity, and soil organic carbon (SOC) within the study area. The analysis carried out using the Trends.Earth plugin integrated with QGIS, revealed that most of the landscape has remained ecologically stable with notable signs of improvement in vegetation and productivity. The LULC analysis indicated moderate transformations over the past two decades, characterized by a substantial increase in built-up areas (2.1%) and a minor reduction in agricultural land (-472 km²) and open forest (-261.7 km²). These shifts reflect growing urbanization and land-use conversion pressures, while a slight increase in sparse vegetation and water bodies suggests localized regeneration and improved water management. In terms of land degradation status, most of the region (97.36%) maintained stable land cover, while only 1.62% showed degradation and 1.01% exhibited improvement. Similarly, SOC assessment indicated that 98.53% of the land retained stable carbon levels, with marginal areas showing improvement (0.69%) and degradation (0.66%), emphasizing that the region's soil is largely resilient under current management conditions. The land productivity assessment further highlighted a positive trajectory, with 77.57% of the area demonstrating improved productivity and only 2.56% showing decline, suggesting that vegetation vigor and biomass production have generally increased over time. When all sub-indicators were combined, the overall SDG 15.3.1 indicator showed that 76.59% of the land area is improved, 18.52% remains stable, and only 4.14% is degraded.

Overall, the findings indicate that the region exhibits a predominantly improving and stable landscape condition, with limited zones of active degradation. The positive trends in vegetation productivity and SOC stability point toward gradual ecosystem recovery and effective land management practices. However, the observed loss of agricultural and forest land to built-up areas underscores the need for sustainable land use planning, reforestation, and conservation-oriented policies to maintain long-term land degradation neutrality (LDN) and ecosystem resilience in alignment with SDG target 15.3.

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