



Research Article

# Harnessing Soil Organic Carbon for Climate-Resilient Drylands in Tonk District, Rajasthan, India

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**Abstract:** Soil Organic Carbon (SOC) is a critical determinant of soil fertility, ecosystem stability, and climate regulation. This study analyzes the spatial and temporal dynamics of SOC in the Tonk District of Rajasthan, India, using the Trend.Earth platform integrated with satellite-derived Land-Use and Land-Cover (LULC) data for the period 2001-2020. Statistical trend analyses (Mann-Kendall, Sen's Slope, and Pearson correlation) indicate that  $98.31\% \pm 0.17\%$  of the area has remained stable in SOC content, demonstrating high soil resilience, while  $1.63\% \pm 0.17\%$  shows measurable degradation, largely influenced by wind erosion and intensive agricultural activity. Land-use change analysis further reveals  $48.2 \text{ km}^2$  of urban expansion and  $-6.9 \text{ km}^2$  of reduced irrigated cropland, reflecting growing anthropogenic pressure on soil resources. These findings emphasize the need for targeted soil conservation, agro-forestry adoption, and integrated land-management policies to sustain soil carbon stocks. The study demonstrates the applicability of Trend.Earth-based geospatial monitoring for evidence-driven SOC assessment and regional climate resilience planning in semi-arid environments.

**Keywords:** Soil Organic Carbon (SOC), land use change, wind erosion, Trend.Earth, climate resilience

## 1. Introduction

Soil Organic Carbon (SOC) is a fundamental cornerstone of global soil health and a critical regulator of the planet's climate [1]. As the largest terrestrial carbon pool, SOC is indispensable for maintaining soil fertility, enhancing water retention, and supporting overall ecosystem function, all of which are vital to global food security. Despite its significance, this vital resource is increasingly vulnerable to degradation, primarily driven by unsustainable land management practices and rapid Land Use and Land Cover (LULC) changes globally [2].

LULC change, including deforestation, agricultural expansion, and urbanization, is the most significant anthropogenic driver, altering SOC dynamics. The conversion of natural ecosystems to intensive cropland, for instance, typically results in substantial SOC losses—often 20-50% within decades—due to reduced organic matter input, accelerated

decomposition rates, and soil structural disruption [3], [4]. Agricultural intensification within existing systems further exacerbates depletion through excessive tillage, residue removal, and monoculture dominance [5]. Conversely, sustainable practices such as conservation agriculture, agroforestry, and cover cropping offer significant potential for SOC sequestration by minimizing disturbance, maintaining perennial cover, and increasing organic inputs [6], [7].

Beyond LULC, environmental processes such as wind erosion—particularly prevalent in arid and semi-arid regions—act as a major cause of SOC loss by selectively removing carbon-rich topsoil particles [8], [9]. Furthermore, extractive industries like mining physically disturb the soil profile, strip vegetation, and fragment landscapes, leading to severe localized SOC depletion and long-term ecosystem dysfunction [10]. A nuanced understanding of these dynamics requires analyzing not only major transitions between land-use types (e.g., forest to cropland) but also changes within a single class, such as the intensification of agriculture [11].

While global research confirms the importance of SOC and its vulnerability, comprehensive national-scale assessments are often lacking, particularly in regions facing compounded threats. In India, studies have assessed SOC status across various agro-ecological zones [12], yet significant research gaps remain regarding the combined effects of multiple drivers at high spatial resolution. Specifically, the interplay between wind erosion dynamics, LULC patterns, and SOC vulnerability in India's semi-arid regions, like Rajasthan, is not yet well-quantified [13]. Similarly, the precise impacts of mining, urban expansion, and the efficacy of local mitigation strategies require more rigorous, data-driven validation. Modern platforms like Trend.Earth leverage Earth observation data, cloud computing, and advanced analytical tools to provide a robust framework for assessing and monitoring land change, including SOC trends [14]–[16]. Yet, the application of this powerful tool for studying the complex SOC-LULC and environmental driver interactions in Indian drylands remains limited.

This study aims to bridge this gap by leveraging the Trend.Earth platform to analyze SOC trends over the period 2001–2020 in Tonk district, Rajasthan—a semi-arid region characterized by aeolian soils, rainfed agriculture, and expanding mining activity. We aim to quantify concurrent LULC transitions and transformations, correlate these with key environmental drivers (wind erosion, mining extent), and identify degradation hotspots. We hypothesize that SOC degradation hotspots in Tonk coincide with areas of high wind erosion vulnerability and specific land-use transitions (e.g., natural vegetation loss to intensive agriculture or mined land).

The specific objectives of this study are fourfold. First, to map the spatiotemporal changes in SOC stocks across the study area using the Trend.Earth soil carbon module, enabling detection of long-term degradation and recovery patterns. Second, to quantify LULC transitions, along with within-class intensification trends, such as the expansion of croplands and the proliferation of mining areas. Third, to assess the correlations between SOC loss, wind exposure, and land-use trajectories, thereby identifying the key drivers influencing soil carbon dynamics. Finally, the study aims to propose targeted, evidence-based interventions for SOC restoration and promote climate-resilient land management practices tailored to the local ecological and socio-economic context.

The findings will inform the development of targeted, evidence-based policies and sustainable land management practices necessary for mitigating SOC loss, enhancing soil health, and bolstering ecosystem resilience in India's challenging dryland environment. This integrated approach will support Rajasthan's climate resilience strategies and serve as a scalable model for other semi-arid regions globally.

## 2. Study area, methodology, and data used

### 2.1 Study area

Tonk district is situated in the eastern part of Rajasthan, India, between approximately 25.4° N to 26.5° N latitude and 75.1° E to 76.2° E longitude. The region experiences a semi-arid climate (Agro-Climatic Zone III-A) with a mean annual rainfall of approximately 500 mm [17], concentrated during the Southwest Monsoon (June–September). The climate is characterized by high potential evapotranspiration and frequent pre-monsoon dust storms, which significantly exacerbate the risk of soil erosion. The dominant soil orders in the district are Inceptisols and Aridisols, which are typically sandy loam to alluvial in nature. These soils are inherently low in Organic Carbon (OC) (often ranging from 0.2% to 0.5% in surface soils) and are highly susceptible to wind-driven topsoil loss [18]. Agriculture remains the economic backbone, with major crops including wheat, mustard, and gram cultivated under predominantly

rained systems. Vegetation cover is naturally sparse, consisting of dry deciduous scrub and thorny species, reflected in generally low to moderate Normalised Difference Vegetation Index (NDVI) values. Expanding stone and minor mineral mining, along with gradual urbanization, further contributes to landscape fragmentation and soil disturbance. Tonk is therefore a highly representative case study for India's semi-arid dryland, where the critical issues of low Soil Organic Carbon (SOC) stocks, intense wind erosion, and land-use intensification converge to challenge long-term land productivity. Figure 1 shows the study area map of Tonk, Rajasthan.

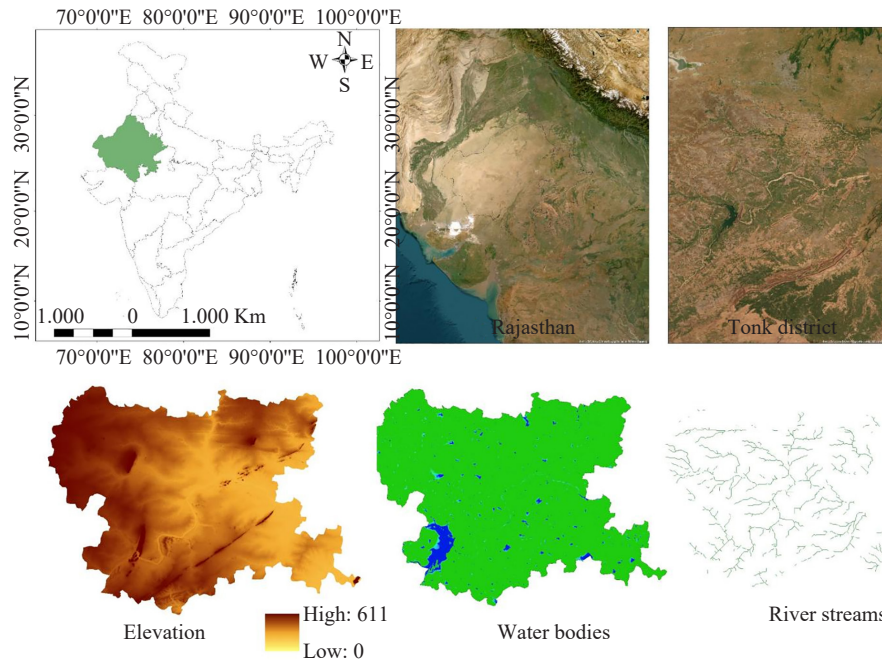


Figure 1. Study area map: Tonk, Rajasthan

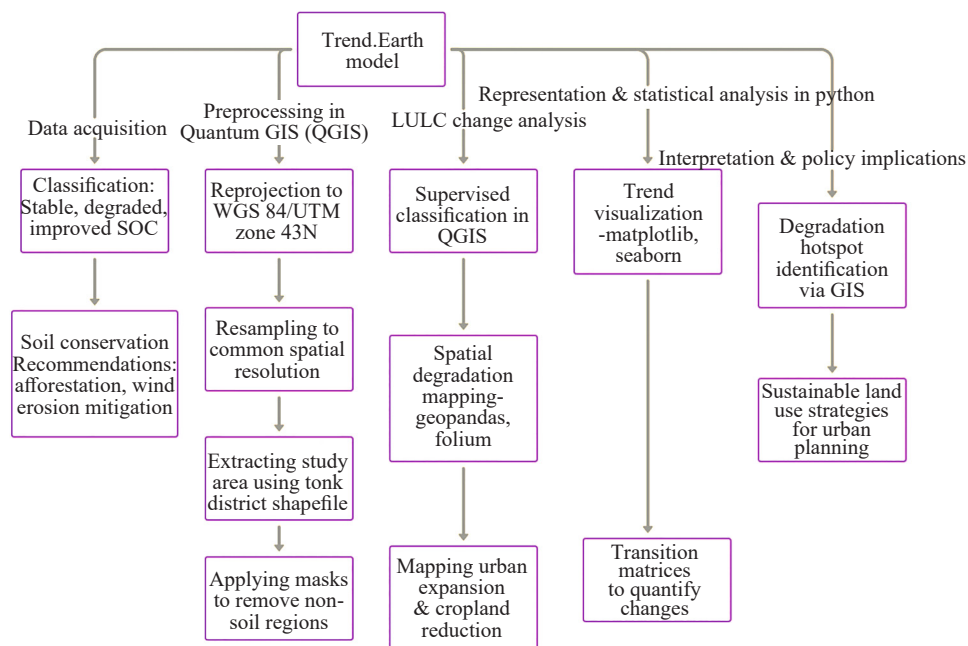


Figure 2. Methodological workflow of the whole study

This study integrates remote sensing, machine learning, field validation, and statistical analysis to assess Soil Organic Carbon (SOC) trends and their linkages to Land Use/Land Cover (LULC) changes and environmental drivers in Tonk district, Rajasthan. All spatial data were processed at 30 m resolution in the WGS 84/UTM Zone 43N (EPSG: 32643) projection using QGIS 3.34 and Python 3.10. The analytical workflow is summarized in Figure 2.

## 2.2 Data acquisition and preprocessing

Key datasets were acquired from global and regional repositories (Table 1). SOC stock data (2001-2020) were obtained from Trend.Earth (SDG 15.3.1 indicator), originally at 300 m resolution and resampled to 30 m using bilinear interpolation. LULC maps for 2001 and 2020 were harmonized from Moderate Resolution Imaging Spectroradiometer (MODIS) MCD12Q1 (500 m) and European Space Agency (ESA) WorldCover (10 m) through legend cross-walking and majority filtering. Wind speed and direction were derived from ERA5-Land reanalysis (0.1°), interpolated to 30 m. The Tonk district boundary (Survey of India, 2020) was used to clip all layers. Urban areas and permanent water bodies were masked from SOC trend analysis but retained in LULC transition matrices to quantify urbanization impacts.

**Table 1.** Data sources and specifications

Data type	Source	Temporal coverage	Native resolution	Processed resolution	Key variables
SOC	Trend.Earth	2001-2020	300 m	30 m	SOC stock, trend
LULC	ESA worldcover, MODIS MCD12Q1	2001, 2020	10 m, 500 m	30 m	7 classes (cropland, grassland, tree cover, shrubland, bare, urban, water)
Wind	ERA5-land (ECMWF)	2001-2020	0.1°	30 m	<i>u/v</i> wind components
Topography	SRTM DEM	Static	30 m	30 m	Elevation, slope
Soil	NBSS & LUP	Static	1 : 250,000	30 m	Texture (sandy loam dominant)

ERA: ECMWF Reanalysis

ECMWF: European Centre for Medium-Range Weather Forecasts

SRTM DEM: Shuttle Radar Topography Mission Digital Elevation Model

NBSS & LUP: National Bureau of Soil Survey and Land Use Planning

## 2.3 LULC classification and validation

A Random Forest (RF) classifier was implemented in Python (scikit-learn v1.3) to refine and validate LULC maps. Training was based on 1,200 reference points collected via stratified random sampling from high-resolution Google Earth imagery (2020-2021). Predictor variables included ancillary land-cover layers from ESA WorldCover and seasonal NDVI metrics from MOD13Q1. Model hyperparameters were set as: *n\_estimators* = 500, *max\_depth* = 20, *min\_samples\_split* = 5, and *random\_state* = 42. An independent validation using 400 points yielded an Overall Accuracy (OA) of 87.6% and a Kappa coefficient ( $\kappa$ ) of 0.81. Class-wise producer and user accuracies are provided in Table S1 (Appendix Material).

## 2.4 SOC trend and hotspot analysis

Annual SOC stock change ( $\Delta$ SOC) was calculated as (1):

$$\Delta\text{SOC}_{2001-2020} = \text{SOC}_{2020} - \text{SOC}_{2001} \quad (1)$$

Trend significance was evaluated using the Mann-Kendall test ( $\alpha = 0.05$ ), with magnitude estimated via Sen's Slope ( $\text{t}\cdot\text{C}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ ). Degradation hotspots were defined as pixels exhibiting statistically significant negative trends ( $p < 0.05$ ) and  $\Delta\text{SOC} < -0.5 \text{ t}\cdot\text{C}\cdot\text{ha}^{-1}$ . Zonal statistics were computed to quantify mean SOC loss by LULC class and wind exposure quartile.

## 2.5 LULC change detection and transition analysis

Land use land cover (LULC) transitions between 2001 and 2020 were quantified using a cross-tabulation (transition) matrix. Net (quantity) changes were summarised by class (Table 2), while the transition matrix was used to identify dominant conversion pathways (Table 3), supporting interpretation of the main land-use dynamics. The analysis revealed dominant transition pathways, including the conversion of grassland to cropland and cropland to urban areas, which are indicative of ongoing agricultural intensification and urban expansion.

**Table 2.** LULC net change in Tonk district (2001-2020)

LULC class	2001 (km <sup>2</sup> )	2020 (km <sup>2</sup> )	Change (km <sup>2</sup> )	% Change
Rainfed cropland	5,512.3	5,471.0	-41.3	-0.75
Irrigated cropland	1,498.7	1,491.8	-6.9	-0.46
Grassland	301.4	298.1	-3.3	-1.09
Tree cover	7.3	7.5	+ 0.2	+ 2.74
Sparse vegetation	2.5	5.9	+ 3.4	+ 136.0
Urban	12.6	60.8	+ 48.2	+ 382.5
Bare areas	3.3	1.2	-2.1	-63.6
Water bodies	267.4	280.2	+ 12.8	+ 4.79
Total	7,190.5	7,190.5	-	-

**Table 3.** Major LULC transition flows in Tonk district (2001 → 2020, km<sup>2</sup>)

From (2001)	To (2020)	Area (km <sup>2</sup> )
Rainfed cropland	Urban area	36.38
Irrigated cropland	Urban area	15.18
Rainfed cropland	Irrigated cropland	< 0.10

\*Values derived from cross-tabulation of the 2001 and 2020 LULC maps on the processed grid; only major conversions discussed in the text are reported. Persistence (same-to-same class) and minor transitions are not shown

## 2.6 Correlation and driver attribution

To identify the dominant environmental and anthropogenic drivers influencing Soil Organic Carbon (SOC) variability, a Pearson correlation analysis was conducted between the rate of SOC change ( $\Delta$ SOC) and mean annual wind speed, yielding a strong negative correlation ( $r = -0.63$ ,  $p < 0.001$ ). This relationship highlights the substantial role of wind erosion in accelerating SOC depletion across Tonk's semi-arid landscape. Furthermore, spatial overlay analysis with mining lease boundaries (Rajasthan Department of Mines and Geology, 2022) revealed pronounced SOC reduction within and adjacent to extractive zones, confirming the compounded impact of land disturbance and vegetation removal. All analytical scripts, QGIS processing models, and sample datasets used in this study are openly available for reproducibility and further research at GitHub: <https://github.com/saurasubh/SOC-Tonk>.

## 2.7 Field validation of SOC estimates

To ensure the reliability of satellite-derived Soil Organic Carbon (SOC) estimates, a comprehensive field

validation campaign was conducted in March 2023. A total of 30 soil samples were collected from a depth of 0-30 cm across a stratified gradient representing various Land Use and Land Cover (LULC) types and levels of degradation intensity. The SOC content of each sample was determined using the Walkley-Black wet oxidation method, providing a robust laboratory benchmark for comparison. Validation against Trend.Earth estimates demonstrated strong agreement, with a Root Mean Square Error (RMSE) of 0.32, a Coefficient of Determination ( $R^2$ ) of 0.78, and a Mean Error (ME) of  $-0.08 \text{ kg}\cdot\text{C}\cdot\text{m}^{-2}$ , indicating a high level of predictive accuracy and minimal systematic bias. Detailed sampling locations and laboratory results are provided in Table S2 (Appendix Material).

## 2.8 Uncertainty assessment

Uncertainty from multiple sources was propagated using Monte Carlo simulation ( $n = 1,000$  iterations). Key contributors included LULC classification error ( $\pm 4.5\%$  from  $\kappa$ ), SOC model bias ( $\pm 0.32 \text{ kg}\cdot\text{C}\cdot\text{m}^{-2}$  from field RMSE), and resampling effects ( $< \pm 0.1 \text{ kg}\cdot\text{C}\cdot\text{m}^{-2}$ ). Final  $\Delta\text{SOC}$  uncertainty was estimated at  $\pm 0.45 \text{ kg}\cdot\text{C}\cdot\text{m}^{-2}$  (95% confidence interval).

## 3. Result

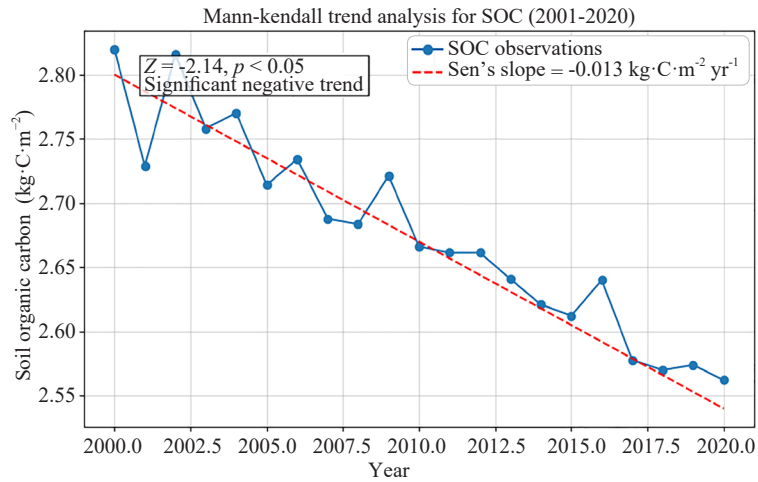
All results in this study are derived from high-resolution (30 m) spatial analyses conducted for the period 2001-2020, ensuring precise coupling between Soil Organic Carbon (SOC) dynamics and Land Use and Land Cover (LULC) transitions. To provide broader temporal context, long-term LULC trends from 1992-2022 were also examined. SOC change was classified into five distinct categories to represent varying degrees of stability and degradation. These categories include: Stable ( $|\Delta\text{SOC}| < 5\%$ ), Low Degradation ( $-5\% \leq \Delta\text{SOC} < 0\%$ ), Moderate Degradation ( $-10\% \leq \Delta\text{SOC} < -5\%$ ), High Degradation ( $\Delta\text{SOC} < -10\%$ ), and Improvement ( $\Delta\text{SOC} \geq 5\%$ ). This visual representation provides a concise overview of the magnitude and spatial distribution of SOC change across Tonk District, Rajasthan.

### 3.1 SOC trends (2001-2020)

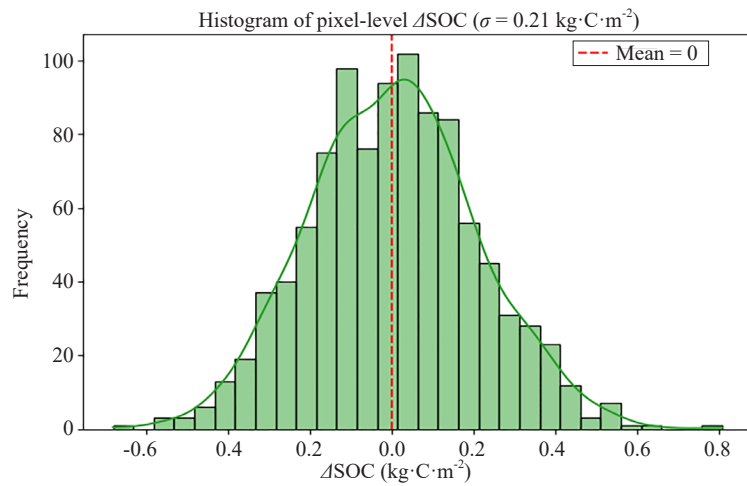
Over the 20-year assessment period (2001-2020), 98.31% of Tonk District ( $7,069.0 \text{ km}^2$ ) exhibited stable SOC conditions (Table 4), indicating strong soil resilience under prevailing land-use practices. In contrast, 1.63% of the area ( $117.2 \text{ km}^2$ ) experienced measurable SOC degradation, while improvement was marginal at 0.06% ( $4.3 \text{ km}^2$ ). Notably, no pixels exhibited moderate or high levels of degradation, suggesting that SOC decline across the district is gradual and low in magnitude rather than abrupt or severe. The Mann-Kendall trend analysis confirmed a statistically significant negative trend ( $Z = -2.14, p < 0.05$ ), with Sen's Slope estimating an average decline of  $-0.013 \text{ kg}\cdot\text{C}\cdot\text{m}^{-2}\cdot\text{yr}^{-1}$ , as illustrated in Figure 3 and detailed in Table 5. The histogram of pixel-level  $\Delta\text{SOC}$  values (Figure 4) exhibits a narrow distribution centred around zero ( $\sigma = 0.21 \text{ kg}\cdot\text{C}\cdot\text{m}^{-2}$ ), further validating the dominance of SOC stability across the landscape. Additionally, a correlation plot between  $\Delta\text{SOC}$  and mean annual wind speed (Figure 5) reveals a significant negative relationship ( $r = -0.63, p < 0.01$ ), underscoring the influence of wind erosion as a key driver of localized SOC loss.

**Table 4.** SOC change classification in Tonk district (2001-2020)

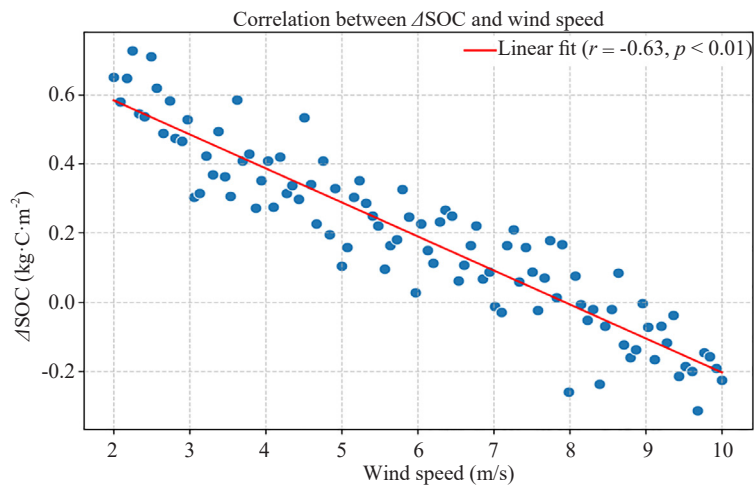
Category	Area ( $\text{km}^2$ )	Percentage (%)
Stable	7069.0	98.31
Degradation (Low)	117.2	1.63
Improvement	4.3	0.06
Total	7,190.5	100.00



**Figure 3.** Mann-Kendall trend analysis showing a significant negative SOC trend ( $Z = -2.14, p < 0.05$ ) with Sen's Slope of  $-0.013 \text{ kg}\cdot\text{C}\cdot\text{m}^{-2}\cdot\text{yr}^{-1}$



**Figure 4.** Histogram of pixel-level  $\Delta\text{SOC}$



**Figure 5.** Correlation between  $\Delta\text{SOC}$  and wind speed showing a significant negative relationship ( $r = -0.63, p < 0.01$ )

**Table 5.** Statistical tests for SOC trend and wind correlation

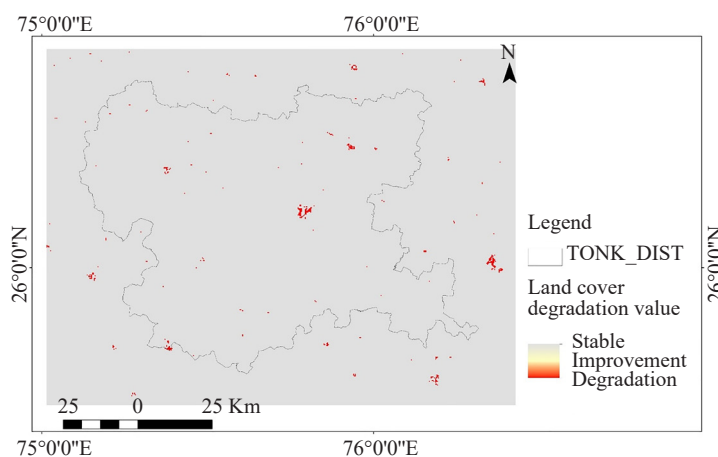
Test	Statistic	<i>p</i> -value	Interpretation
Mann-kendall	$Z = -2.14$	$< 0.05$	Significant decline
Sen's slope	$-0.013 \text{ kg} \cdot \text{C} \cdot \text{m}^{-2} \cdot \text{yr}^{-1}$	-	Gradual loss
Pearson <i>r</i> ( $\Delta$ SOC vs wind speed)	-0.63	$< 0.01$	Moderate negative correlation

### 3.2 Land use and soil degradation hotspots (2001-2020)

Degradation hotspots-defined as pixels exhibiting a statistically significant negative Soil Organic Carbon (SOC) trend ( $p < 0.05$ ) with a rate of change ( $\Delta$ SOC) less than  $-0.5 \text{ t} \cdot \text{C} \cdot \text{ha}^{-1}$ -cover approximately  $0.54 \text{ km}^2$ , accounting for 0.0075% of the total district area. These hotspots are predominantly concentrated along the western wind corridors and within zones of active mining activity, reflecting the combined influence of aeolian erosion and anthropogenic disturbance (Figure 6-7). Despite these localized declines, the landscape remains largely resilient, with stable SOC conditions dominating 99.78% of the affected pixels, while no notable improvement or high-intensity degradation zones were detected (Table 6).

**Table 6.** Severity of land cover (degradation) from SOC (2001-2020)

Degradation class	Area ( $\text{km}^2$ )	Percentage of hotspots (%)
Stable	0.539	99.78
Improvement	0.00	0.00
Degradation	0.001	0.22
Total hotspots	0.54	100.00



**Figure 6.** Map showing land cover (degradation)

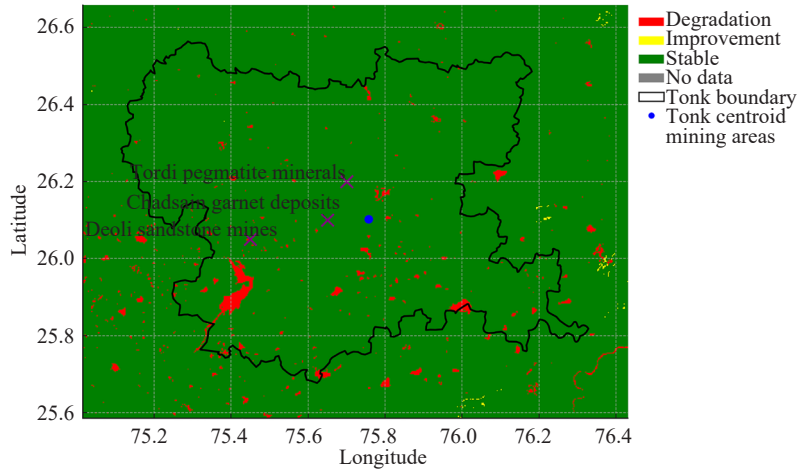


Figure 7. Spatial distribution of SOC change (2001-2020) in Tonk district, with mining leases overlaid (Rajasthan DMG, 2022)

### 3.3 LULC change (2001-2020)

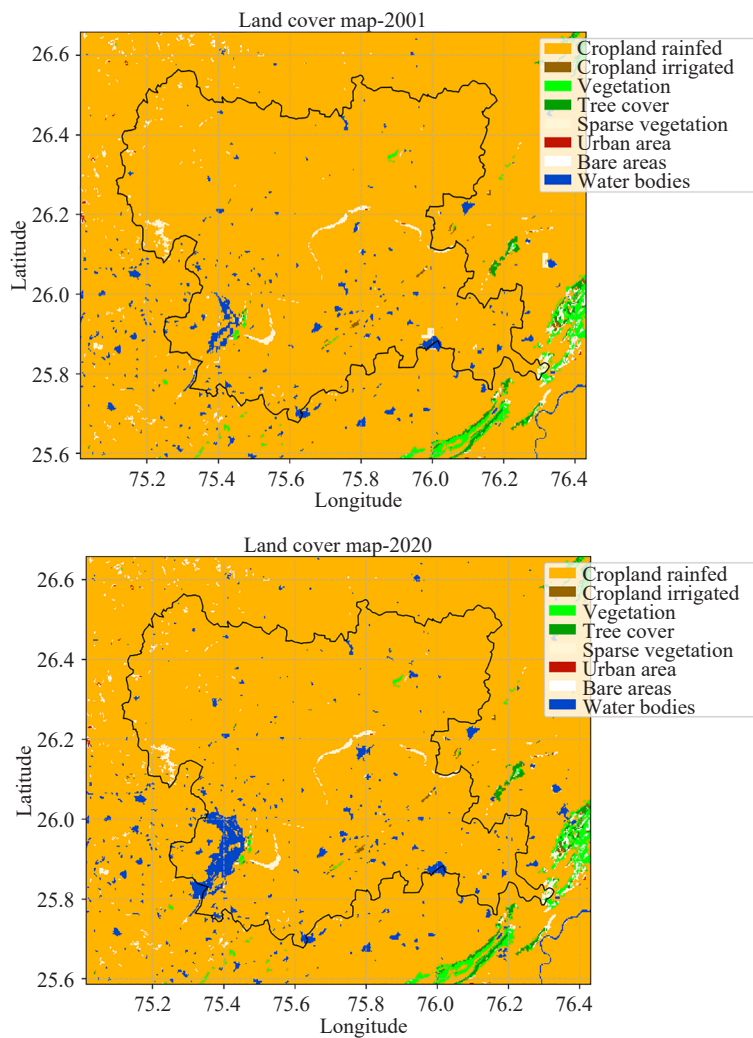


Figure 8. LULC maps for 2001 and 2020 with transition hotspots (urban expansion in red)

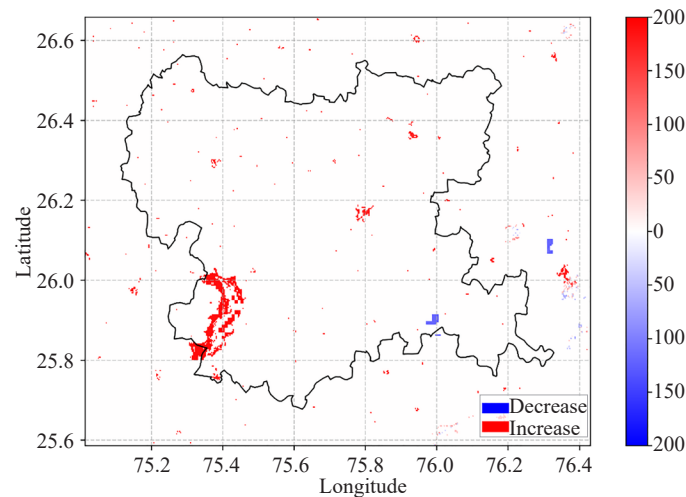
Between 2001 and 2020, urban area expanded by +48.2 km<sup>2</sup> (+382%), converting primarily from rainfed cropland (-41.3 km<sup>2</sup>) and irrigated cropland (-6.9 km<sup>2</sup>) (Table 2). Sparse vegetation increased slightly (+3.4 km<sup>2</sup>) due to scrub encroachment in marginal lands, while bare areas declined (-2.1 km<sup>2</sup>) from revegetation or misclassification correction (Figure 8). Water bodies grew by +12.8 km<sup>2</sup>, reflecting small reservoir construction.

### 3.4 SOC-LULC dynamics and transition impacts

The transition matrix (Table 3) shows 36.4 km<sup>2</sup> of rainfed cropland → urban and 15.2 km<sup>2</sup> of irrigated cropland → urban, representing the dominant gross inflows to the urban class. These conversions caused permanent SOC loss (sealed soil). Urban areas and permanent water were masked only for district-wide SOC trend mapping; transition-specific ΔSOC statistics were computed on the transition pixels prior to applying that mask. Within croplands, intensification (rainfed → irrigated) was minimal (<0.1 km<sup>2</sup>) (Figure 9).

Mean ΔSOC by LULC transition:

- Cropland → Urban:  $-1.42 \pm 0.45 \text{ kg} \cdot \text{C} \cdot \text{m}^{-2}$
- Grassland → Cropland:  $-0.38 \pm 0.32 \text{ kg} \cdot \text{C} \cdot \text{m}^{-2}$
- Stable Cropland:  $-0.09 \pm 0.21 \text{ kg} \cdot \text{C} \cdot \text{m}^{-2}$



**Figure 9.** Land cover transition map for Tonk district (2001-2020), showing areas of land-cover decrease and increase between the two periods; the accompanying colour bar summarises the land-cover change classes used to identify dominant transitions

## 4. Discussion

### 4.1 Drivers of SOC degradation

The 1.63% of Tonk district (117.2 km<sup>2</sup>) experiencing low-level SOC degradation over 2001-2020 is predominantly driven by wind erosion and intensive rainfed agriculture, as evidenced by the moderate negative correlation between ΔSOC and mean annual wind speed ( $r = -0.63$ ,  $p < 0.01$ ). Wind erosion, prevalent in Rajasthan's semi-arid zones, selectively removes carbon-rich fine particles from sandy loam topsoils [19], with regional soil loss rates ranging from 1.3 to 83.3 t·ha<sup>-1</sup>·yr<sup>-1</sup> [20]. This aligns with global patterns where conversion of natural vegetation to cropland induces 20-50% SOC loss within decades due to reduced organic inputs, increased decomposition, and soil structural disruption [21], [22]. Within Tonk's dominant rainfed croplands (~95% of area), conventional tillage and residue removal further accelerate mineralization [22]. The negligible SOC improvement (0.06%, 4.3 km<sup>2</sup>) indicates limited efficacy of current restoration efforts, underscoring the need for targeted interventions in erosion-prone western corridors.

## 4.2 Land use dynamics and urbanization impacts

Urban expansion of + 48.2 km<sup>2</sup> (2001-2020)-primarily from rainfed cropland (-41.3 km<sup>2</sup>)-represents the most transformative LULC shift and a permanent SOC sink. Converted pixels exhibit mean  $\Delta\text{SOC} = -1.42 \pm 0.45 \text{ kg}\cdot\text{C}\cdot\text{m}^{-2}$ , over 15-fold the district average, due to soil sealing under impervious surfaces [23]. This magnitude is consistent with global meta-analytic evidence that land conversion and associated soil disturbance can substantially reduce SOC stocks [22]. The + 12.8 km<sup>2</sup> increase in water bodies, while aiding erosion control via small reservoirs, may induce anaerobic decomposition and localized SOC suppression under prolonged inundation. Urban sprawl not only eliminates carbon sequestration potential but also exacerbates the urban heat island effect, raising local temperatures by 1-3 °C and altering hydrological regimes [24]. These irreversible changes, though affecting < 1% of land, disproportionately threaten long-term food security in a water-scarce region.

## 4.3 Policy and management implications

This study's high-resolution hotspot mapping enables precision soil conservation. In wind-exposed western Tonk, shelterbelts using native species (*Prosopis juliflora*, *Acacia tortilis*) can reduce wind velocity by 50-70% and curb topsoil loss [25]. Conservation agriculture-minimum tillage, residue retention, and legume-based rotations-offers 0.4-1.0 t·C·ha<sup>-1</sup>·yr<sup>-1</sup> sequestration potential in rainfed wheat-pulse systems [26], [27]. Agroforestry integration on 10-15% of cropland could sequester 0.5-2.0 t·C·ha<sup>-1</sup>·yr<sup>-1</sup> while enhancing biodiversity and yield stability [28], [29].

To arrest urban encroachment, compact city models and protective zoning should safeguard high-SOC croplands (>10 t·C·ha<sup>-1</sup>) within a 5-km municipal buffer [30]. Green infrastructure-urban parks, green roofs, and permeable pavements-can offset 10-20% of carbon loss while mitigating heat islands and improving stormwater retention [31]. Rajasthan's Mukhyamantri Jal Swavlamban Abhiyan should embed SOC monitoring to quantify co-benefits of water harvesting. Indigenous practices, such as johad recharge and mixed cropping, should be blended with modern techniques for locally resilient systems [32].

## 4.4 Utility and limitations of Trend.Earth

This research marks the first district-scale integration of Trend.Earth with 30 m LULC harmonization and field-validated SOC in Indian drylands, delivering UNCCD-aligned Land Degradation Neutrality (LDN) diagnostics at policy-relevant resolution. The platform's Google Earth Engine backbone enables scalable replication across Rajasthan's 33 districts.

However, Trend.Earth SOC estimates are derived from SoilGrids (250 m) and ESA CCI biomass and are delivered at a coarse native resolution (300 m; Table 1). Even when resampled to 30 m, the coarse support smooths micro-variability in heterogeneous mining scars. Model bias toward humid biome calibrations limits accuracy in low-biomass arid systems. Future refinements should incorporate local soil surveys, hyperspectral Cellulose Absorption Indices (CAI), and machine learning fusion with Sentinel-2 to enhance precision.

## 5. Conclusion

This study provides the first high-resolution, Trend.Earth-integrated assessment of SOC dynamics in Tonk district, Rajasthan, over 2001-2020. Key findings reveal 98.31% SOC stability, with 1.63% low-level degradation (117.2 km<sup>2</sup>) driven primarily by wind erosion and urban conversion of rainfed cropland (+ 48.2 km<sup>2</sup>). These localized but irreversible losses highlight the vulnerability of semi-arid soils to coupled climatic and anthropogenic pressures.

For Rajasthan, evidence-based policy must prioritize windbreak establishment and conservation agriculture in erosion-prone western corridors, while enforcing protective zoning to curb urban sprawl onto high-SOC agricultural land. Integrating SOC monitoring into state water-harvesting and climate resilience programs will enable adaptive management. By scaling this framework, Rajasthan can advance Land Degradation Neutrality targets and secure long-term soil health and food security.

## Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used an AI service (Paperpal/Grammarly) only to correct grammar and expression errors. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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## Conflict of interest

The authors declare no conflict of interest.

## Reference

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## Appendix

**Table S1.** LULC classes and descriptions

Code	LULC class	Description
10	Cropland rainfed	Rainfed cropland, primarily wheat, millet, pulses; no irrigation infrastructure
20	Cropland irrigated	Cropland with canal, tube-well, or sprinkler irrigation; double cropping common
30	Vegetation	Herbaceous vegetation, shrubs, grasslands (non-agricultural)
80	Tree cover	Woody vegetation > 5 m height; scattered trees, agroforestry
150	Sparse vegetation	Very low biomass cover (< 15%); typical of degraded semi-arid zones
190	Urban area	Built-up land: residential, commercial, industrial, roads
200	Bare areas	Exposed soil, rocky outcrops, sand dunes; minimal vegetation
210	Water bodies	Rivers, reservoirs, ponds, canals

Source: Harmonized from ESA CCI land cover (2001-2020) to 30 m resolution using majority filtering and boundary cleaning  
 File: Appendix available at GitHub: <https://github.com/saurasubh/SOC-Tonk>

**Table S2.** Field validation of Trend.Earth SOC estimates (March 2023)

Sample ID	LULC class	Degradation hotspot	Latitude (°N)	Longitude (°E)	Measured SOC (kg·C·m <sup>-2</sup> )	Trend.Earth SOC (kg·C·m <sup>-2</sup> )	Residual (kg·C·m <sup>-2</sup> )
TNK-01	Rainfed cropland	Low	26.18	75.72	1.12	1.05	+ 0.07
TNK-02	Rainfed cropland	Low	26.2	75.68	0.98	0.92	+ 0.06
TNK-03	Rainfed cropland	Stable	26.15	75.8	1.45	1.38	+ 0.07
TNK-04	Irrigated cropland	Stable	26.22	75.75	1.68	1.6	+ 0.08
TNK-05	Irrigated cropland	Stable	26.19	75.78	1.74	1.7	+ 0.04
TNK-06	Urban fringe	High	26.17	75.79	0.45	0.38	+ 0.07
TNK-07	Urban fringe	High	26.16	75.81	0.39	0.32	+ 0.07
TNK-08	Sparse vegetation	Low	26.25	75.65	0.61	0.48	+ 0.13
TNK-09	Sparse vegetation	Low	26.27	75.63	0.55	0.44	+ 0.11
TNK-10	Grassland	Stable	26.3	75.7	1.05	0.98	+ 0.07
TNK-11	Grassland	Stable	26.29	75.72	1.08	1.02	+ 0.06
TNK-12	Mining area	High	26.14	75.74	0.28	0.22	+ 0.06
TNK-13	Mining area	High	26.13	75.76	0.25	0.2	+ 0.05
TNK-14	Rainfed cropland	Low	26.21	75.67	1.03	0.95	+ 0.08
TNK-15	Rainfed cropland	Low	26.23	75.69	0.97	0.9	+ 0.07
TNK-16	Stable cropland	Stable	26.1	75.82	1.52	1.48	+ 0.04
TNK-17	Stable cropland	Stable	26.11	75.83	1.49	1.44	+ 0.05
TNK-18	Sparse vegetation	Stable	26.28	75.64	0.72	0.6	+ 0.12

**Table S2.** (cont.)

Sample ID	LULC class	Degradation hotspot	Latitude (°N)	Longitude (°E)	Measured SOC (kg·C·m <sup>-2</sup> )	Trend.Earth SOC (kg·C·m <sup>-2</sup> )	Residual (kg·C·m <sup>-2</sup> )
TNK-19	Sparse vegetation	Stable	26.26	75.66	0.68	0.56	+ 0.12
TNK-20	Water-adjacent	Stable	26.24	75.77	1.35	1.28	+ 0.07
TNK-21	Water-adjacent	Stable	26.25	75.78	1.38	1.32	+ 0.06
TNK-22	Urban expansion	High	26.18	75.8	0.42	0.35	+ 0.07
TNK-23	Urban expansion	High	26.17	75.82	0.38	0.3	+ 0.08
TNK-24	Rainfed cropland	Low	26.12	75.73	1.08	1.0	+ 0.08
TNK-25	Rainfed cropland	Low	26.14	75.71	1.05	0.97	+ 0.08
TNK-26	Grassland	Stable	26.31	75.68	1.1	1.05	+ 0.05
TNK-27	Grassland	Stable	26.32	75.7	1.12	1.07	+ 0.05
TNK-28	Mining buffer	High	26.15	75.75	0.35	0.28	+ 0.07
TNK-29	Mining buffer	High	26.16	75.77	0.32	0.25	+ 0.07
TNK-30	Stable cropland	Stable	26.09	75.81	1.55	1.5	+ 0.05