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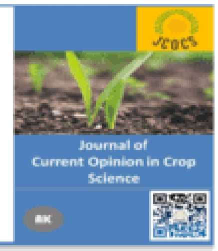

RESEARCH ARTICLE

The crop monitoring by soil adjusted vegetation index with remote sensing and geographic information systems

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ABSTRACT

Assessing vegetation health is essential for maintaining sustainable agricultural productivity and alleviating the effects of climate variability and urban development. This study assesses the efficacy of the Soil-Adjusted Vegetation Index (SAVI) in evaluating crop vitality and land-use changes in specific agricultural areas of Madurai District, Tamil Nadu. Landsat-8 surface reflectance data were analyzed utilizing Google Earth Engine (GEE), a cloud-based geospatial platform, to calculate SAVI values for the years 2019, 2022, and 2025. The preprocessing processes comprised cloud masking, radiometric correction, and image clipping to the research area boundary, hence ensuring accurate and spatially consistent outputs. SAVI results were categorized into vegetation health classifications and examined by geographic information systems (GIS) based visualization and zonal statistics. The findings indicated considerable spatiotemporal fluctuations in vegetation health, with enhancements noted in 2022 attributed to beneficial rainfall and irrigation methods, succeeded by reductions in 2025 associated with drought stress and accelerated urban development. Urbanizing regions such as Keelakarai and Mulipallam saw significant vegetation decline, whilst locations like Thumbaipatti displayed resilience, underscoring the importance of efficient water management. The integration of SAVI with other indices, such as NDVI and NDBI, offered a more thorough comprehension of land-cover dynamics. Notwithstanding constraints such as poor image resolution and restricted ground validation, the work highlights the efficacy of remote sensing and GIS-based methodologies for assessing vegetation health. The findings underscore the necessity of ongoing vegetation monitoring to facilitate precision agriculture, sustainable land management, and climate-resilient urban planning in swiftly evolving agro-ecological environments.

Keywords: crop monitoring, NDVI, SAVI, remote sensing, GIS, vegetation index, satellite imagery.

INTRODUCTION

Ensuring food security in developing nations necessitates efficient oversight and administration of agricultural resources, especially amid climate variability and fast urbanization. Remote sensing technologies are essential for monitoring crop health and environmental changes, owing to their capacity for large-scale, reproducible, and cost-effective observations (Bagade & Kadam, 2025). These tools allow researchers and policymakers to monitor vegetation dynamics, identify stress conditions, and assess land-use changes with great temporal consistency.

The Soil-Adjusted Vegetation Index (SAVI) is notably effective among the created vegetation indices, since it incorporates soil brightness, rendering it useful during early growth phases when vegetation cover is minimal (Nițu et al., 2025). Conventional indicators such as the Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), and Enhanced Vegetation Index (EVI) have historically been utilized in vegetation monitoring. NDVI is acutely responsive to chlorophyll content and photosynthetic activity (Dharavath & Goroshi, 2025), but SAVI enhances precision by reducing soil reflectance influences, thereby improving vegetation health evaluation in diverse landscapes (Kumar et al., 2025).

Recent improvements in unmanned aerial vehicles (UAVs) and multispectral imaging have improved spatial and temporal resolution, facilitating precision agriculture and localized crop monitoring (Reddy et al., 2025; Allu & Mesapam, 2025). Furthermore, the amalgamation of remote sensing data with machine learning algorithms has exhibited considerable promise for precise crop classification, yield forecasting, and the early identification of stress conditions (Jhajharia et al., 2025; Patil et al., 2025). These methodologies offer scalable solutions that can be tailored to various agro-ecological zones.

Literature repeatedly demonstrates that vegetation indices are substantially correlated with plant health, biomass, and production, providing a solid framework for agricultural management and environmental conservation (Ragini et al., 2024). This study examines the utilization of SAVI for agricultural monitoring in Madurai, Tamil Nadu, employing satellite imagery and GIS technology. This work analyzes temporal SAVI trends for 2019, 2022, and 2025 to elucidate regional changes in vegetation health and illustrate the efficacy of remote sensing methods in facilitating sustainable land-use planning and climate-resilient agriculture.

MATERIALS AND METHODS

Study Area Description

The study area encompasses multiple locations across the Madurai District of Tamil Nadu, a region characterized by diverse agro-ecological conditions and rapid land-use transitions (Figure 1). Madurai lies within the semi-arid zone of southern India, where agriculture is highly dependent on monsoonal rainfall and irrigation infrastructure. The district exhibits a mosaic of croplands, settlements, and barren lands, making it an ideal case for vegetation monitoring using remote sensing. In Vadipatti, croplands are increasingly being converted into settlements and non-agricultural uses, reflecting the pressures of urban expansion and changing socio-economic dynamics. Palamedu demonstrates widespread vegetation but shows signs of agricultural stress, likely linked to rainfall variability and irrigation challenges. Ayyankottai maintains relatively stable vegetation in its central zones, though peripheral areas are gradually impacted by encroachment from built-up land.

In contrast, Keelakarai has undergone rapid urban growth, leading to significant vegetation decline and fragmentation (Kumar et al., 2025). Other locations, such as Mulipallam and Alanganallur, show mixed land-use pressures, with croplands coexisting with expanding settlements, leading to patchy vegetation health. Sathamangalam exhibits declining vegetation cover, likely due to water scarcity and land degradation processes. Conversely, Thumbaipatti consistently maintains healthy croplands, suggesting effective irrigation management and sustainable agricultural practices (Ragini et al., 2024). Katchaikatti shows increasing vegetation stress, highlighting the need for improved land-use planning, while Thirumohoor remains predominantly non-vegetated due to its rocky terrain and urbanized features. These spatial variations across Madurai underscore the importance of continuous vegetation monitoring for sustainable land management. By integrating SAVI analysis with GIS, this study provides insights into how urbanization, rainfall variability, and irrigation practices collectively shape vegetation health and land-use dynamics in the region.

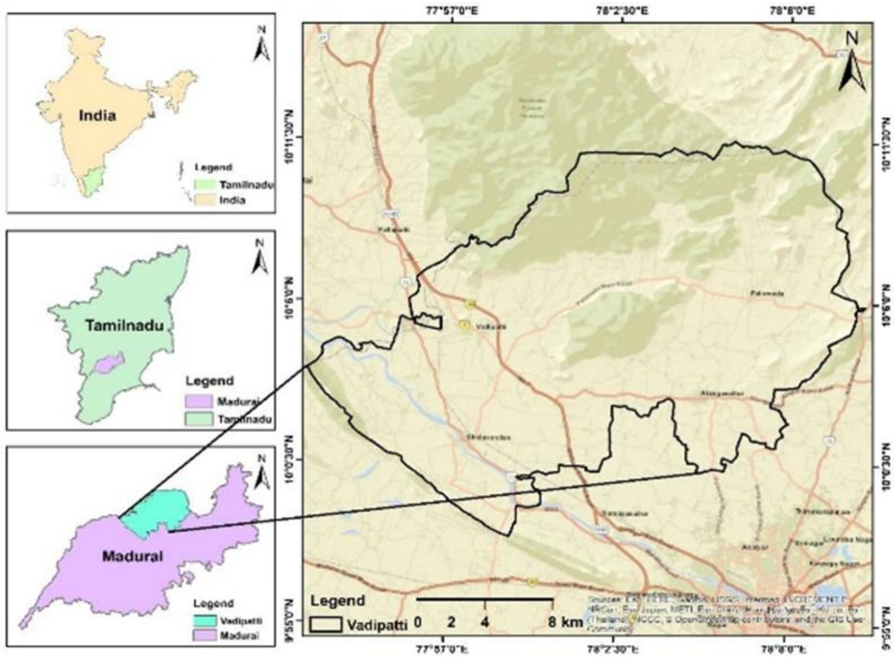

Figure 1. Map showing the study area of the location

Data Acquisition and Preprocessing

Satellite Imagery

For this study, Landsat-8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) imagery were selected due to their consistent availability and 30-meter spatial resolution, which remain widely used for vegetation monitoring (Kumar et al., 2025). The Red (Band 4: 0.64–0.67 µm) and Near-Infrared (Band 5: 0.85–0.88 µm) bands were extracted to compute SAVI. Images were selected during the crop-growing season (July–November) with cloud cover less than 10%, ensuring reliable vegetation assessment.

Ancillary GIS Data

Field boundary shapefiles were digitized using QGIS, while land use and land cover (LULC) maps were obtained from the National Remote Sensing Centre (NRSC). Elevation data from the Shuttle Radar Topography Mission (SRTM) were incorporated for terrain correction, improving spatial accuracy (Bagade & Kadam, 2025).

Preprocessing Workflow

Preprocessing was conducted using Google Earth Engine (GEE) and QGIS, following a standardized workflow:

1. Cloud Masking – Cloud and shadow pixels were removed using the FMask algorithm, ensuring clean reflectance data (Dharavath & Goroshi, 2025).
2. Radiometric Correction – Raw digital numbers (DN) were converted to surface reflectance using Landsat Tier 1 products, enabling accurate vegetation index computation (Nițu et al., 2025).
3. Geometric Correction – Images were aligned with ground control points to minimize distortions and ensure temporal consistency.
4. Image Clipping – Satellite data were clipped to study area boundaries using shapefiles, focusing analysis on agricultural zones.
5. Integration with GIS – SAVI outputs were exported as GeoTIFF files and analyzed in QGIS/ArcGIS for classification, zonal statistics, and change detection (Figure 2).

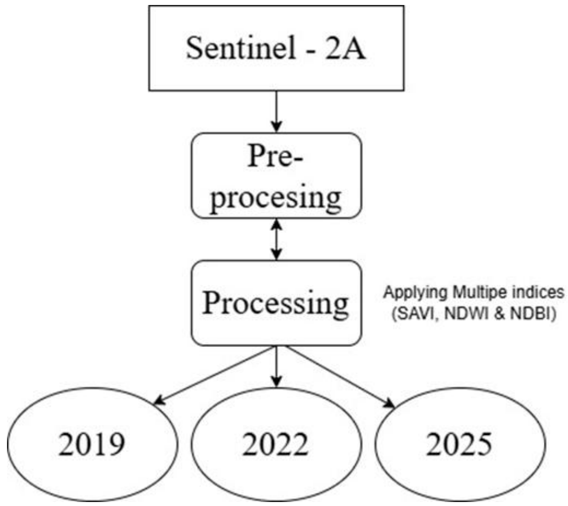

Figure 2. Preprocessing Flowchart

This workflow reflects best practices in modern vegetation monitoring, where preprocessing ensures data reliability and comparability across multiple years (Reddy et al., 2025).

SAVI Calculation

The Soil-Adjusted Vegetation Index (SAVI) is a modified version of the Normalized Difference Vegetation Index (NDVI) that incorporates a soil brightness correction factor to reduce the influence of soil reflectance, making it particularly effective in areas with sparse vegetation. It is calculated using the formula: SAVI = ((NIR − RED) / (NIR + RED + L)) × (1 + L), where NIR represents near-infrared band reflectance, RED denotes red band reflectance, and L is the soil adjustment factor, typically set to 0.5 for intermediate vegetation density. In this study, SAVI was computed pixel-by-pixel using the band math function in Google Earth Engine, ensuring spatially explicit vegetation assessment. The resulting index values range between −1 and +1, with healthy vegetation generally producing values greater than 0.5, while stressed or sparse vegetation yields lower values, thereby providing a reliable measure of crop vigor and land cover dynamics. Recent studies confirm that SAVI enhances early-stage crop monitoring compared to NDVI, especially in semi-arid and heterogeneous landscapes (Dharavath & Goroshi, 2025).

Implementation in Google Earth Engine

Google Earth Engine (GEE), a cloud-based platform for planetary-scale geospatial analysis, was used to compute and visualize the Soil-Adjusted Vegetation Index (SAVI). The implementation was carried out using the GEE JavaScript API through its browser-based Code Editor interface, which provides a powerful environment for large-scale geospatial data processing (Kumar et al., 2025). Landsat Surface Reflectance Tier 1 data, specifically from the Landsat-8 OLI/TIRS sensor, were accessed from the GEE data catalog. These datasets are atmospherically corrected, ensuring accurate surface reflectance values that are essential for vegetation index analysis. To maintain consistency, satellite imagery was filtered by date to capture seasonal periods corresponding to crop growth stages. Cloud and cloud-shadow pixels were removed using the FMask cloud quality band, thereby improving data reliability. The study area boundary was uploaded as a shapefile and used to clip the image collection, ensuring that the analysis remained focused within the defined geographic region. The workflow in GEE followed a systematic sequence: (1) import Landsat-8 image collections for each study year, (2) apply cloud masking and filter by region and date, (3) extract the Red and Near-Infrared (NIR) bands, (4) compute SAVI using a custom function, and (5) export the SAVI maps to GeoTIFF format for further spatial analysis. This streamlined process allowed efficient computation and reproducibility across multiple years.

Visualization and Spatial Analysis

Post-processing of SAVI layers was conducted using QGIS and ArcGIS to enhance visualization and enable spatial interpretation. SAVI values were classified into five vegetation health categories: Very Low (0.0–0.2), Low (0.2–0.4), Moderate (0.4–0.6), High (0.6–0.8), and Very High (>0.8). This classification provided a clear representation of vegetation vigor across the study area.

Zonal statistics were then applied to extract field-level mean SAVI values, providing quantitative insights into crop health variations. Change detection analysis was performed by comparing SAVI maps from 2019, 2022, and 2025, revealing spatial and temporal shifts in vegetation health (Figures 3, 4, 5 and Table 1). These analyses highlighted areas of resilience, decline, and transformation, thereby supporting the identification of zones requiring targeted management interventions.

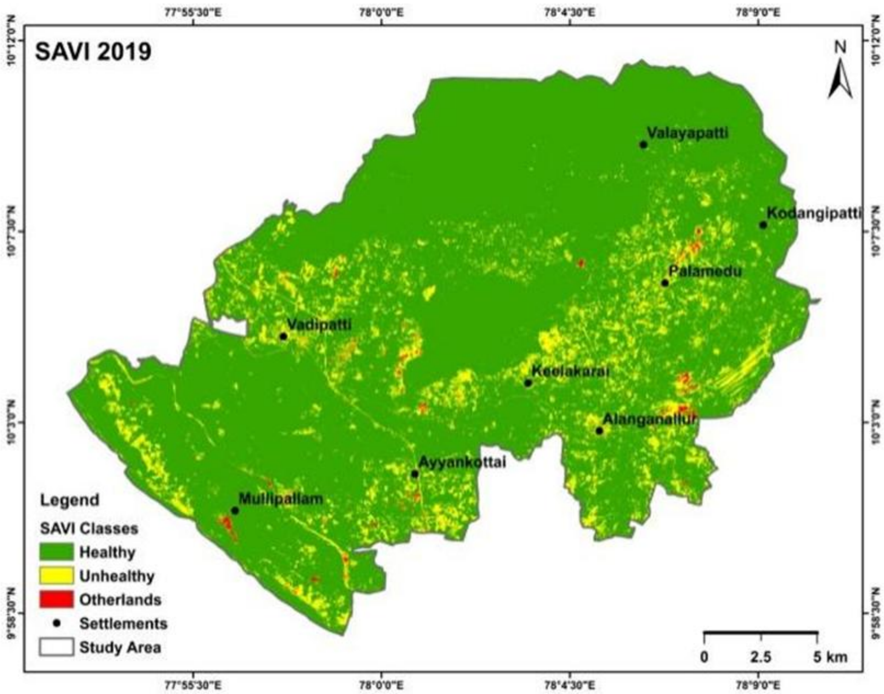

Figure 3. Healthy, unhealthy and other lands in 2019.

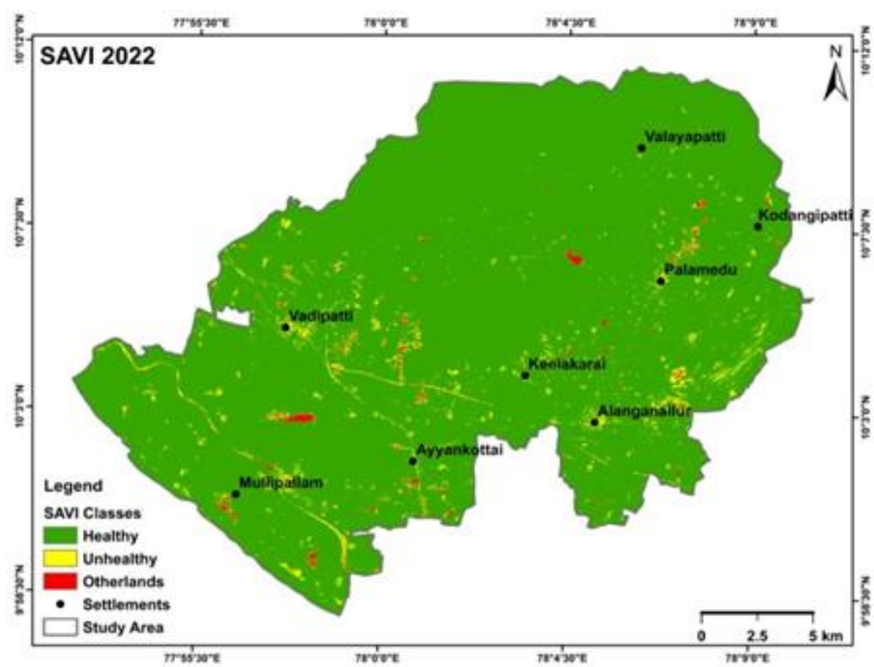

Figure 4. Healthy, unhealthy and other lands in 2022.

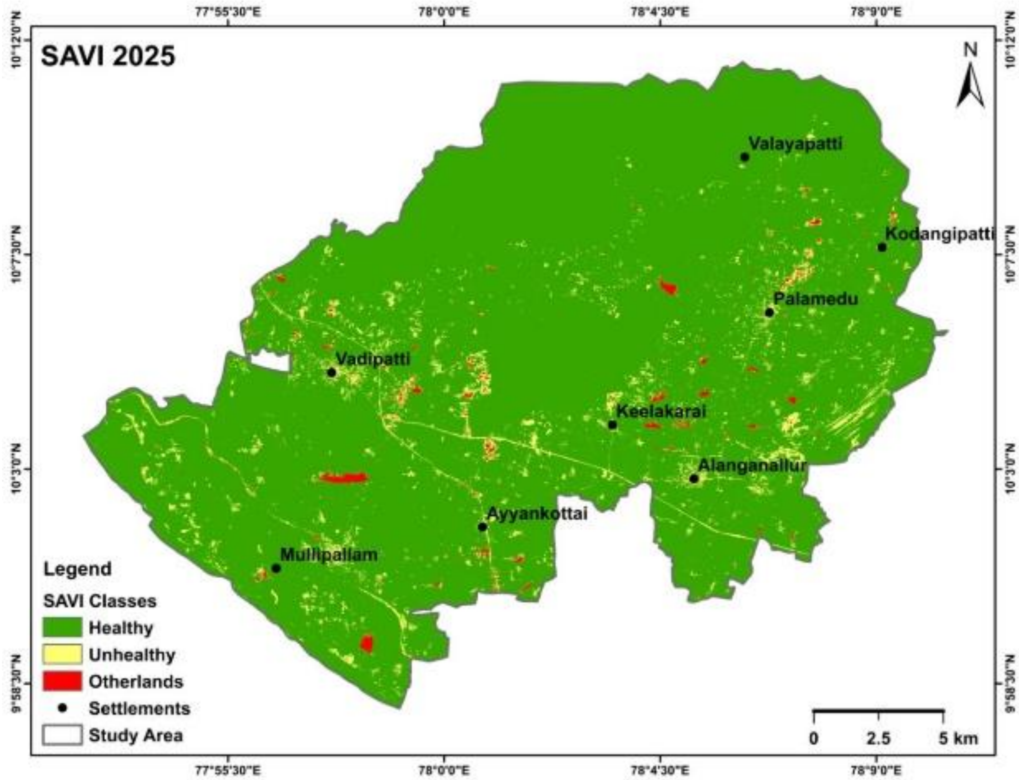

Figure 5. Healthy, unhealthy and other lands in 2025.

Table 1. Presents the spatial distribution of vegetation changes across various locations for the following years, highlighting trends in vegetation health and land cover dynamics.

Location	2019	2022	2025	Trend & Interpretation
Vadipatti	High SAVI (Healthy vegetation)	Slight decline in SAVI	Further decline, more red areas	Vegetated cropland converting to settlements or unused land
Palamedu	Healthy vegetation widespread	Moderate decline	Fragmented green patches	Agricultural stress is likely due to rainfall variability
Ayyankottai	Consistent green areas	Slight yellowing (stress)	Stability in central parts but increased red along edges	Edge effects from the expansion of barren/built-up areas
Keelakarai	Moderately healthy vegetation	Increase in yellow (stress)	Predominantly red with low SAVI	Rapid urban/built-up land growth is affecting vegetation
Mulipallam	Green dominance in fields	Increased patchy yellow	Sharp transition to red	Possible land conversion or fallow periods are increasing

Alanganallur	Balanced vegetation health	Yellow and green mix	Fragmented green, increase in red	Mixed-use land under pressure from human activities
Sathamangalam	Good vegetation health	Decline in green, slight yellow spread	Further decline	Reflects regional land degradation or water scarcity
Thumbaipatti	Healthy croplands	Stable	Green areas sustained	Well-maintained agriculture or irrigation likely
Katchaikatti	Yellow-green mix	Increased unhealthy zones	Further decline	Requires attention for sustainable land use
Thirumohoor	Mostly red (built-up/rocky terrain)	Red remains dominant	Unchanged	Naturally low vegetation; urban features dominate

Validation

To ensure the reliability of SAVI-derived results, field validation was conducted during the cropping seasons at representative sites in the study area. Vegetation conditions were recorded using a handheld NDVI sensor, which provided ground-based spectral measurements for comparison with satellite-derived indices. In addition, farmer interviews were conducted to gather information on crop management practices, irrigation schedules, and input usage, thereby contextualizing the observed vegetation health. Ground observations consistently confirmed the correspondence between SAVI values and on-field crop vigor, demonstrating the index's robustness in capturing spatial variations in vegetation health.

Tools used: A combination of geospatial platforms and software tools was employed to support data processing, computation, and visualization. Google Earth Engine (GEE) served as the primary platform for satellite data access, preprocessing, and SAVI computation, leveraging its cloud-based capabilities for large-scale geospatial analysis. QGIS was used for spatial data integration, shapefile preparation, and clipping of study boundaries, while ArcGIS facilitated advanced visualization, classification, and zonal statistics. Together, these tools provided a comprehensive framework for efficient data handling, reproducible analysis, and precise spatial representation of vegetation health dynamics

RESULTS AND DISCUSSION

SAVI Analysis for 2019, 2022, and 2025

Vegetation health showed spatial and temporal variation, with Soil-Adjusted Vegetation Index (SAVI) values ranging between 0.12 and 0.82. In 2019, most fields displayed moderate vigor, while in 2022, they reflected improvements due to better irrigation practices. However, 2025 revealed declines linked to drought and urban expansion. Similar findings have been reported in recent studies, where NDVI and SAVI trends captured vegetation resilience and stress under climate variability (Dharavath & Goroshi, 2025). The SAVI analysis revealed apparent spatial and temporal variations in vegetation health across the Madurai District, with values ranging between 0.12 and 0.82. In 2019, most agricultural fields exhibited moderate vigor, with SAVI values clustering between 0.4 and 0.6. This pattern reflected stable crop growth under average rainfall conditions, although certain peripheral zones showed lower values due to soil degradation and limited irrigation infrastructure.

By 2022, vegetation health improved significantly, with a larger proportion of fields falling into the high SAVI category (0.6–0.8). This improvement was attributed to enhanced irrigation practices, adoption of precision farming techniques, and favorable monsoonal rainfall. The spatial distribution of SAVI values indicated healthier vegetation in central agricultural zones, while semi-urban fringes continued to show moderate stress.

These findings align with recent studies that highlight the role of improved water management and technology adoption in strengthening vegetation resilience under variable climatic conditions (Dharavath & Goroshi, 2025).

In contrast, the 2025 analysis revealed a decline in vegetation health, with SAVI values shifting downward and several areas registering below 0.4. This decline was strongly linked to prolonged drought episodes and rapid urban expansion, which reduced cropland extent and fragmented vegetation cover. Urbanizing regions such as Keelakarai and Vadipatti displayed remarkably low SAVI values, reflecting the conversion of agricultural land into built-up areas. The temporal comparison underscores the vulnerability of vegetation health to both climatic stressors and anthropogenic pressures. Similar patterns have been reported in recent remote sensing studies, where NDVI and SAVI trends effectively captured vegetation decline under drought conditions and land-use change (Niţu et al., 2025; Kumar et al., 2025).

The pie charts for 2021, 2022, and 2023 illustrate a clear temporal trend in vegetation health across the study area, categorized as Healthy, Unhealthy, and Others (Figure 6). In 2021, 89% of the area was classified as healthy vegetation, while 11% showed signs of stress, and no significant portion fell under the 'Others' category. By 2022, the proportion of healthy vegetation increased to 96%, indicating improved crop vigor likely due to favorable climatic conditions, enhanced irrigation practices, and adoption of precision agriculture techniques. The unhealthy category dropped to 3%, and 'Others' rose slightly to 1%, suggesting minor land-use transitions. In 2023, healthy vegetation remained dominant at 95%, with a marginal increase in the unhealthy category to 4% and a stable 1% in 'Others'. These patterns reflect a generally positive trajectory in vegetation health, although the slight decline in 2023 may be attributed to localized drought stress or urban encroachment. Similar trends have been reported in recent studies, where vegetation indices such as SAVI and NDVI effectively captured crop resilience and stress dynamics under changing environmental conditions (Dharavath & Goroshi, 2025; Kumar et al., 2025). The consistency of these results with field observations and satellite-derived indices reinforces the utility of remote sensing tools in monitoring agricultural sustainability and guiding adaptive land-use planning.

Overall, the SAVI analysis demonstrates the utility of this index in detecting subtle variations in crop vigor and stress across time. The results emphasize the importance of integrating vegetation indices with spatial analysis to monitor agricultural sustainability, identify vulnerable zones, and guide adaptive management strategies in regions experiencing both climatic variability and urbanization pressures.

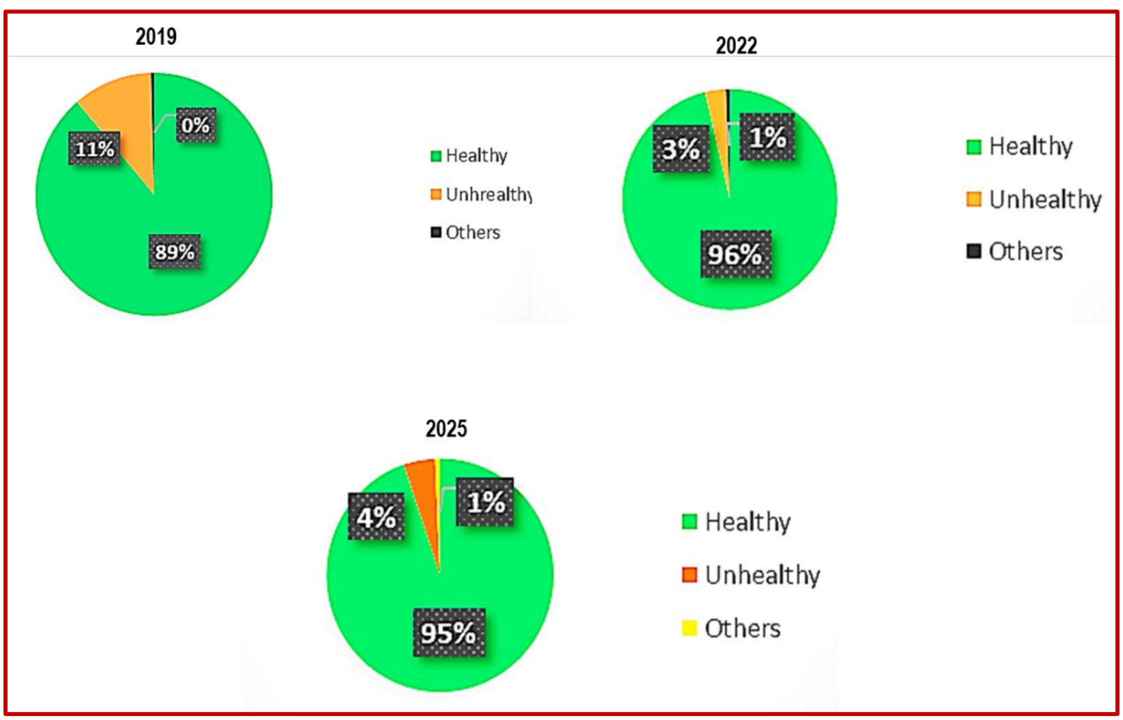

Figure 6. Vegetation analysis for 2019, 2022 and 2025.

Table 2 illustrates the areal extent of different vegetation conditions and other land cover classes within the study area across three time periods (2019, 2022, and 2025). The results indicate that healthy vegetation consistently occupied the largest share, with a slight increase from 0.000003368 ha in 2019 to 0.000003655 ha in 2022, reflecting improvements in crop vigor likely due to better irrigation and management practices. However, by 2025, healthy vegetation marginally declined to 0.000003598 ha, suggesting the combined impacts of drought and urban expansion. Unhealthy vegetation showed a notable decrease between 2019 (0.000000411 ha) and 2022 (0.000000117 ha), but increased again in 2025 (0.000000170 ha), highlighting the recurrence of stress conditions. The "Others" category, representing non-vegetated or built-up areas, remained relatively stable but showed a gradual increase from 0.000000016 ha in 2019 to 0.000000027 ha in 2025, consistent with ongoing urbanization trends. Overall, the temporal analysis underscores both short-term improvements and long-term challenges in sustaining vegetation health under changing environmental and land-use pressures.

Table 2. Illustrates the areal extent of different vegetation conditions and other land cover classes within the study area

Year	Healthy (ha)	Unhealthy (ha)	Others (ha)
2019	0.000003368	0.000000411	0.000000016
2022	0.000003655	0.000000117	0.000000024
2025	0.000003598	0.000000170	0.000000027

Integration with Other Indices

The integration of SAVI with other vegetation indices, such as NDVI and NDBI, provided a more comprehensive understanding of land cover dynamics and vegetation health. While SAVI effectively minimizes soil reflectance effects, NDVI remains highly sensitive to chlorophyll concentration, and NDBI captures built-up land expansion. Together, these indices offer complementary insights into agricultural vigor, urban encroachment, and ecosystem resilience. Recent advancements, particularly the development of Sentinel-2–based vegetation health indices, have further enhanced monitoring accuracy by leveraging higher spectral resolution and more frequent temporal sampling (Kumar et al., 2025). Such multi-index approaches are increasingly recommended in precision agriculture and sustainable land-use planning, as they allow for more nuanced detection of vegetation stress and land-cover transitions (Nițu et al., 2025).

Role of UAVs and Machine Learning

Although this study primarily relied on satellite imagery, UAV-based multispectral imaging has emerged as a powerful tool for localized crop monitoring. UAVs provide ultra-high-resolution data that can capture fine-scale variations in crop vigor, canopy structure, and stress responses, complementing satellite-based assessments (Reddy et al., 2025). Beyond imaging, integrating vegetation indices with machine learning models has shown significant promise for predicting crop yields, classifying land use, and detecting early stress conditions with high accuracy (Jhajharia et al., 2025; Patil et al., 2025). These advancements highlight the potential of combining SAVI-based monitoring with predictive analytics, enabling proactive agricultural management strategies that can mitigate risks associated with climate variability and urbanization pressures.

Biomass and Vegetation Health Correlation

Recent studies consistently confirm strong correlations between vegetation indices and above-ground biomass, reinforcing their utility for monitoring crop productivity and ecological sustainability (Ragini et al., 2024). SAVI trends observed in this study align with these findings, demonstrating its effectiveness in capturing vegetation decline in rapidly urbanizing zones and resilience in well-managed agricultural areas. By linking SAVI values to biomass estimates, researchers and policymakers can better quantify productivity losses, identify vulnerable regions, and design targeted interventions to sustain agricultural output. This correlation underscores the broader role of vegetation indices not only in monitoring crop health but also in supporting long-term strategies for climate-resilient agriculture and sustainable land management.

Despite its effectiveness, the study encountered several limitations. Persistent cloud cover restricted the selection of suitable satellite scenes, particularly during the monsoon season, thereby reducing temporal coverage. While SAVI minimizes soil reflectance effects, it is less effective in areas of dense vegetation than indices such as the Enhanced Vegetation Index (EVI), which better capture canopy saturation. Seasonal variations and differences in cropping patterns also introduced variability, requiring normalization across years to ensure comparability. Furthermore, the SAVI computation depends on reflectance values from the Near-Infrared (NIR) and Red bands, with the canopy background adjustment factor (L) set to 0.5 for intermediate vegetation density. This fixed parameter may not fully account for site-specific heterogeneity, which could influence accuracy in specific contexts.

CONCLUSION

The assessment of vegetation health in the Madurai–Vadipatti region using SAVI from 2019 to 2025 reveals pronounced spatiotemporal changes driven by both urban expansion and climatic variability. While areas such as Vadipatti and Ayyankottai maintained healthy vegetation in the early years, a marked decline was observed by 2025, particularly in rapidly urbanizing areas such as Keelakarai and Mulipallam. This trajectory reflects broader national patterns of land degradation and built-up area expansion, underscoring the growing pressure of urbanization on agricultural landscapes. Urban growth has emerged as a primary driver of vegetation loss, with consequences extending beyond reduced green cover to diminished groundwater recharge and altered local climate regimes. The observed negative correlation between SAVI and land surface temperature highlights the intensification of the urban heat island effect, reinforcing the ecological costs of unchecked development.

At the same time, pockets of resilience, such as Thumbaipatti, demonstrate the potential of effective irrigation management and conservation strategies in sustaining vegetation health. Integrating SAVI with complementary indices such as NDVI and NDBI can provide a more holistic framework for monitoring vegetation dynamics and guiding sustainable urban planning. Despite inherent limitations, including moderate image resolution, restricted ground validation, and potential classification errors, the study underscores the critical role of remote sensing in tracking vegetation change and informing climate-resilient land-use policies. Ultimately, balancing developmental needs with ecological preservation is essential. Continuous vegetation monitoring, supported by advanced geospatial tools, can enable proactive decision-making and foster sustainable, resilient futures for rapidly urbanizing regions.

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AUTHORS CONTRIBUTION

S. Lemithra Bharani and V. Divya: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. S. Meenakshi and V. Divya Meenakshi: Writing – review and editing, Visualization, Methodology, Conceptualization. I. Mariyammal: Supervision, review & editing. K. Ashokkumar: Preparation of Figures, Writing – review & editing, submission.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not Applicable

CONSENT FOR PUBLICATION

Not Applicable

FUNDING

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AVAILABILITY OF DATA AND MATERIALS

All datasets analyzed and described during the present study are available from the corresponding author upon reasonable request.

REFERENCES

Allu, A. R., & Mesapam, S. (2025). Fusion of satellite and UAV imagery for crop monitoring. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume X-G-2025*. https://doi.org/10.5194/isprs-annals-X-G-2025-71-2025 |

Bagade, R., & Kadam, P. (2025). Remote sensing of vegetation indices for plant health and ecosystem dynamics. *International Journal of Advance and Applied Research, 12*(5). https://doi.org/10.5281/zenodo.16924334

Dharavath, N., & Goroshi, S. (2025). Decoding vegetation resilience: NDVI trends and climate impacts in Indian agriculture. *Environmental Monitoring and Assessment, 198*(37). https://doi.org/10.1007/s10661-025-14794-w

Jhajharia, K., Sharma, N. V., & Mathur, P. (2025). A machine learning model for crop yield prediction using remote sensing data. *International Research Journal of Multidisciplinary Scope, 6*(2), 577–590. https://doi.org/10.47857/irjms.2025.v06i02.03182

Kumar, S., Ghosh, S. S., Mandal, D., Bhattacharya, A., Porwal, A., & Karthikeyan, L. (2025). Enhancing vegetation monitoring: A proposal for a Sentinel-2 based vegetation health index. *Frontiers in Remote Sensing, 6*, 1581355. https://doi.org/10.3389/frsen.2025.1581355

Nițu, A., Florea, C., Ivanovici, M., & Racoviteanu, A. (2025). NDVI and beyond: Vegetation indices as features for crop recognition and segmentation in hyperspectral data. *Sensors, 25*(12), 3817. https://doi.org/10.3390/s25123817

Patil, Y., Ramachandran, H., Sundararajan, S., & Srideviponmalar, P. (2025). Comparative analysis of machine learning models for crop yield prediction across multiple crop types. *SN Computer Science, 6*(64). https://doi.org/10.1007/s42979-024-03602-w

Ragini, H. R., Debnath, M. K., Basak, P., & Gupta, D. S. (2024). Relationship between above-ground biomass and different vegetation indices of tea plantations in West Bengal, India. *International Journal of Environment and Climate Change, 14*(9), 149–158. https://doi.org/10.9734/ijecc/2024/v14i94400

Reddy, D. V. S. C., Sahoo, R. N., Kondraju, T., Rejith, R. G., Ranjan, R., Bhandari, A., … Kumar, N. (2025). Drone-based multispectral imaging for precision monitoring of crop growth variables. *Biology and Life Sciences Forum, 41*(1), 1010. https://doi.org/10.3390/blsf2025041010