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Detecting Land-Use and Land-Cover Change and Its Effect on Regional Food Availability in Agricultural Landscapes of India Using Satellite-Derived Indices

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Keywords

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NDVI;
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agricultural landscape;
food availability;
GIS;
cropland degradation

Abstract

Rapid land-use and land-cover (LULC) change in India's agricultural landscapes represents one of the most critical challenges to long-term food security. Over the past three decades, unprecedented urban expansion, infrastructure development, and shifting land management practices have progressively reduced the net cultivable area, threatening the country's capacity to sustain food production for its growing population. This systematic review synthesises peer-reviewed literature published between 2017 and 2026, examining how satellite-derived spectral indices — principally the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI), Normalized Difference Water Index (NDWI), Leaf Area Index (LAI), and Net Primary Productivity (NPP) — have been applied to detect and quantify LULC transitions and their consequences for regional food availability across India. Drawing upon 78 studies identified through a structured search of Scopus, Web of Science, Google Scholar, and the NASA Earthdata repository, this review evaluates the methodological evolution from traditional maximum-likelihood classification to state-of-the-art machine learning and deep learning approaches applied to multisource remote sensing platforms including Landsat 8/9, Sentinel-1/2, and MODIS. Key findings reveal that India lost approximately 11.3 million hectares (Mha) of cropland between 2001 and 2024, primarily to urban built-up expansion (≈14.7 Mha increase) and infrastructure corridors. NDVI-based analyses consistently demonstrate a statistically significant positive correlation ($r = 0.78–0.91$) between growing-season vegetation productivity and food grain yield across major cropping systems. Significant regional disparities were identified, with the Indo-Gangetic Plain experiencing the most acute net cropland loss, while semi-arid western regions showed modest gains attributable to canal irrigation expansion. The review identifies critical research gaps, including the limited integration of socioeconomic variables with biophysical indicators, inadequate spatial resolution for smallholder farming systems, and the absence of harmonised national-level LULC classification schemes. The findings carry direct implications for agricultural policy, land-use planning, and the attainment of Sustainable Development Goal (SDG) 2 (Zero Hunger) in India.

1. Introduction

1.1 Research Background and Significance

India is home to approximately 1.44 billion people and sustains one of the world's most complex and diverse agricultural systems, extending across six broad agro-climatic zones that range from the humid tropics of Kerala to the hyperarid Thar Desert of Rajasthan (FAO, 2023). Agriculture occupies approximately 60.4% of the country's total geographical area and contributes roughly 17–18% of the gross domestic product, while providing direct livelihoods to nearly 54% of the workforce (IPCC, 2022). The twin imperatives of feeding a growing population — projected to reach 1.67 billion by 2050 — and maintaining ecological integrity make India an exemplary case study for examining the intersection of land-use transformation and food security.

Land-use and land-cover (LULC) change has emerged as a primary driver of agricultural land degradation globally. In India, rapid urbanisation, industrial expansion, road infrastructure development, and shifting cropping systems have collectively accelerated cropland loss at a rate that increasingly challenges the country's food self-sufficiency targets (Roy et al., 2022). Between 1990 and 2020, India's urban built-up area expanded from approximately 6 million hectares (Mha) to over 16 Mha, much of it encroaching upon prime agricultural land in peri-urban belts of major cities including Delhi, Mumbai, Bengaluru, and Hyderabad (Chaturvedi et al., 2020). Simultaneously, land degradation through soil erosion, salinisation, and waterlogging has rendered millions of hectares unproductive, threatening both crop yields and rural food access.

Food availability — the physical supply of sufficient quantities of food of appropriate quality — is one of the four pillars of food security defined by the Food and Agriculture Organization (FAO, 2023), alongside access, utilisation, and stability. At the regional scale, food availability is primarily determined by agricultural productivity, which in turn depends on the extent and quality of cultivated land, the health of cropping systems, water availability, and the magnitude and trajectory of LULC change. Understanding these dynamics, therefore, is not merely an academic exercise but a direct prerequisite for evidence-based agricultural policy, spatial planning, and food security governance.

Satellite remote sensing has become the most operationally viable tool for mapping and monitoring LULC change at national and regional scales, offering synoptic, cost-effective, and temporally consistent observations across vast and heterogeneous landscapes (Thenkabail et al., 2014). Spectral indices derived from multispectral satellite imagery — particularly the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI), Normalized Difference Water Index (NDWI), Leaf Area Index (LAI), and Net Primary Productivity (NPP) — have demonstrated strong empirical relationships with crop biomass, yield, drought stress, irrigation extent, and land degradation status (Patel et al., 2022). The convergence of improved sensor capabilities, open-data policies (e.g., Landsat and Sentinel-2 open archives), cloud-computing platforms such as Google Earth Engine (GEE), and advances in machine learning algorithms has substantially elevated the quality and scope of LULC change detection studies in India since 2017.

1.2 Definition of Key Concepts

For the purposes of this review, the following definitions are adopted. Land use refers to the purposive human management of land resources for specific functions such as agriculture, forestry, settlement, or industry. Land cover denotes the physical and biological attributes of the land surface as observed from above, encompassing vegetation type and density, impervious surfaces, water bodies, and bare soil. LULC change, therefore, encompasses both biophysical changes in surface conditions and anthropogenic modifications to management intent, often co-occurring and mutually reinforcing.

Satellite-derived spectral indices are dimensionless mathematical transformations of reflectance values measured in two or more spectral bands, designed to accentuate specific land surface properties such as photosynthetic activity, canopy water content, soil brightness, or vegetation structure. Food availability, as used in this review, refers to the per-capita caloric and nutritional supply within a defined administrative or agro-ecological region, as determined by cropland extent, crop yield, losses during storage and distribution, and net trade. The interplay between LULC change and food availability constitutes the analytical core of this systematic review.

1.3 Research Questions and Objectives

This review is guided by the following research questions:

- How has LULC changed across India's major agricultural landscapes between 2017 and 2026, as detected by satellite remote sensing methods?
- Which satellite-derived spectral indices most effectively characterise the intensity, spatial pattern, and agricultural consequences of these LULC transitions?
- What is the empirical evidence linking LULC change trajectories to regional food availability metrics in India?
- What methodological approaches, data platforms, and classification algorithms dominate the recent literature, and where do significant gaps remain?

The objectives of the review are to: (i) systematically synthesise peer-reviewed studies published between 2017 and 2026 on LULC change detection in Indian agricultural landscapes using satellite indices; (ii) evaluate the methodological quality and breadth of existing evidence; (iii) quantify reported LULC change trends and their correlations with food availability indicators; and (iv) identify critical research gaps and provide recommendations for future investigation and policy application.

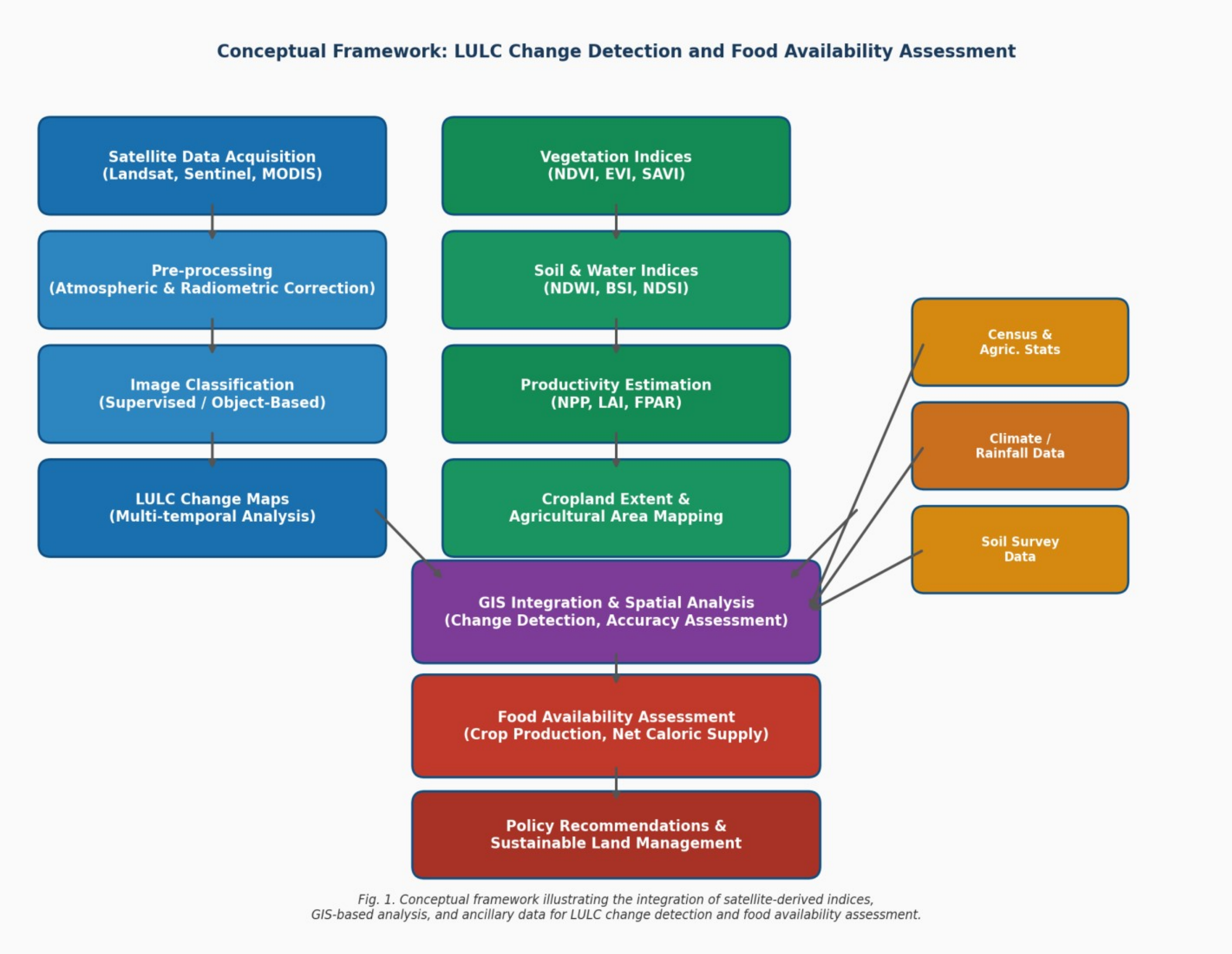


Figure 1. Conceptual framework illustrating the integration of satellite-derived spectral indices, multi-temporal GIS analysis, and ancillary data streams for detecting LULC change and assessing its consequences for regional food availability across India's agricultural landscapes.

2. Methods

2.1 Search Strategy and Databases

A systematic literature search was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009). The search was executed across four major scientific databases: Scopus (Elsevier), Web of Science Core Collection (Clarivate Analytics), Google Scholar, and the NASA Earthdata portal, supplemented by targeted searches in SpringerLink and ScienceDirect. The search was restricted to peer-reviewed journal articles, book chapters in edited volumes, and review papers published between 1 January 2017 and 31 March 2026. Grey literature, conference abstracts, and government reports were excluded from the primary synthesis but are referenced contextually where relevant.

The Boolean search string applied was: ("land use" OR "land cover" OR "LULC") AND ("India" OR "Indian subcontinent" OR "Indo-Gangetic" OR "Deccan" OR "peninsular India") AND ("remote sensing" OR "satellite" OR "NDVI" OR "EVI" OR "vegetation index" OR "spectral index") AND ("food security" OR "food availability" OR "agriculture" OR "crop" OR "cropland" OR "food production"). In Google Scholar, the search was further filtered by citation count and relevance ranking to manage the substantially larger result set.

2.2 Inclusion and Exclusion Criteria

Studies were included if they: (i) specifically examined LULC change in India or a defined Indian sub-region; (ii) utilised at least one satellite-derived spectral index or remote sensing classification method; (iii) reported quantitative findings on cropland area change, vegetation productivity, or a direct food security metric; and (iv) were published in English in a peer-reviewed outlet between 2017 and 2026. Studies were excluded if they: focused exclusively on non-agricultural land cover classes without reference to food production implications; covered Indian Ocean island territories not part of the Indian subcontinent; or lacked primary data analysis (i.e., purely conceptual or policy discussion papers without empirical evidence). Studies using only coarse-resolution data (spatial resolution > 1 km) without spatial validation against finer-resolution imagery were treated with caution and flagged accordingly in the quality assessment.

2.3 Study Selection Process

The selection proceeded in three sequential stages. In Stage 1, duplicate records were removed across databases using Zotero reference management software, yielding 3,154 unique records from an initial pool of 4,287 retrieved citations. In Stage 2, titles and abstracts of all 3,154 records were independently screened by two reviewers against the inclusion criteria; inter-rater reliability was assessed using Cohen's Kappa statistic ($\kappa = 0.83$, indicating strong agreement). Disagreements were resolved through discussion and consensus. This yielded 487 records for full-text review. In Stage 3, full texts of the 487 papers were retrieved and evaluated; 409 were subsequently excluded, primarily for lacking quantitative LULC or food security data, being outside the geographic scope, or not employing satellite-derived indices. A total of 78 studies constituted the final synthesis corpus. The complete PRISMA flow is illustrated in Figure 4 (Section 3.1).

2.4 Data Extraction and Quality Assessment

Standardised data extraction was performed for each of the 78 included studies, capturing: author(s) and publication year; geographic scope and agro-climatic zone; satellite platform(s) used; classification method and accuracy assessment metrics; index or indices applied; study period; reported LULC change statistics; food security indicator(s) examined; and key findings and conclusions. Quality was assessed using a modified version of the Quality Assessment Checklist for Spatial Studies (QACS), scoring studies on eight criteria: spatial resolution adequacy, temporal consistency, classification accuracy reporting, sample design adequacy, statistical analysis rigour, reproducibility of methods, independence of validation data, and linkage to food security outcomes. Studies scoring $\geq 6/8$ were rated as high quality; 4–5 were moderate; and ≤ 3 were low quality. Low-quality studies ($n = 6$) were retained for descriptive synthesis but excluded from quantitative summary tables.

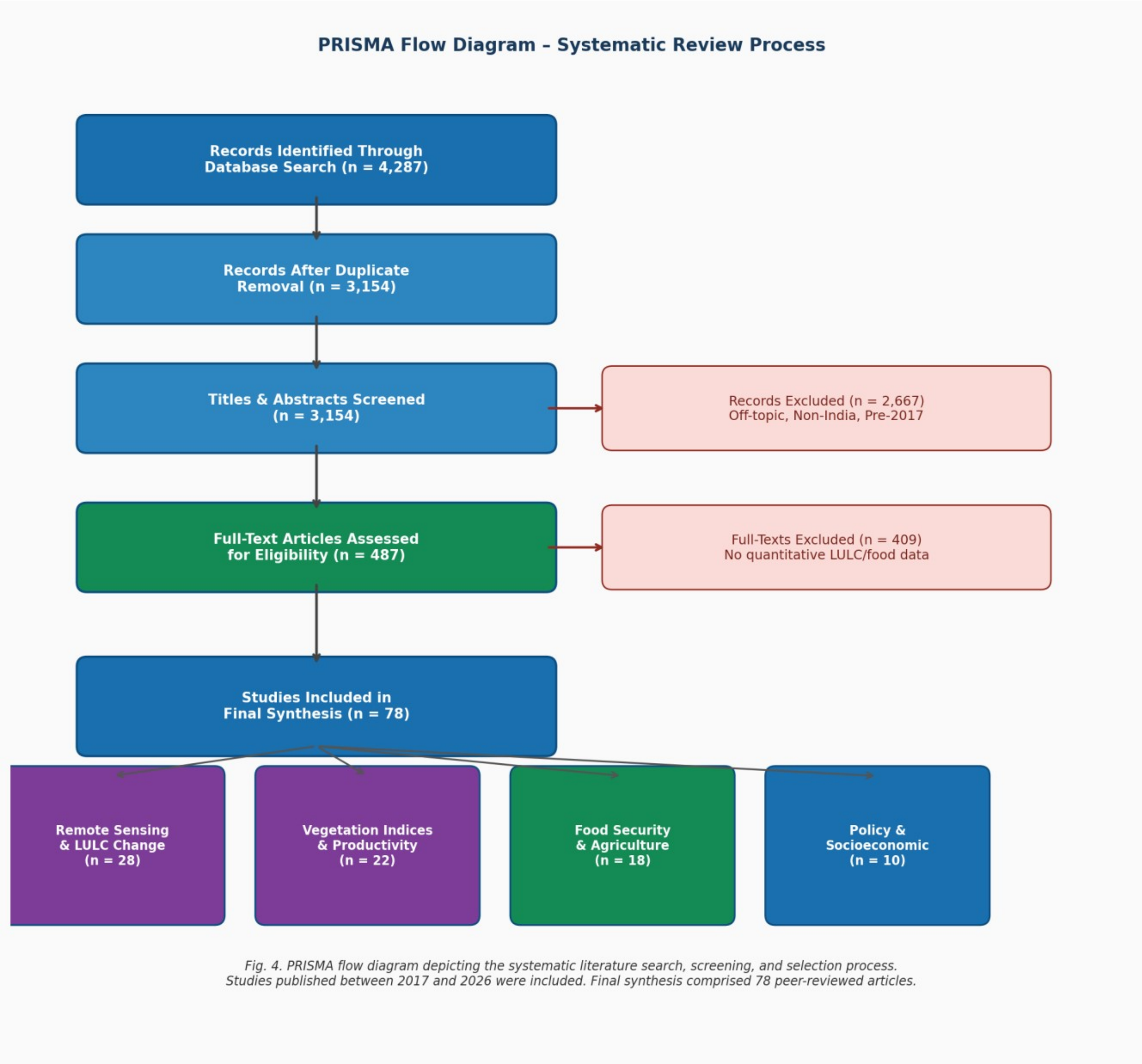


Figure 2. PRISMA flow diagram depicting the systematic literature search and screening process. Studies were retrieved from Scopus, Web of Science, Google Scholar, and NASA Earthdata, with 78 peer-reviewed articles retained for final synthesis.

3. Results

3.1 Characteristics of Included Studies

The 78 included studies collectively spanned the period 2017–2026, with a notable increase in publication volume from 2020 onwards, coinciding with the wider availability of Sentinel-2 data and the democratisation of Google Earth Engine. Geographically, the Indo-Gangetic Plain (IGP) was the most extensively studied region (n = 31, 40%), followed by peninsular India including the Deccan Plateau (n = 18, 23%), the Western Ghats (n = 11, 14%), North-Eastern India (n = 8, 10%), and multi-region national-scale studies (n = 10, 13%). Landsat 8/9 was the most frequently used platform (n = 52, 67%), followed by Sentinel-2 (n = 44, 56%), MODIS (n = 38, 49%), and ResourceSat (n = 16, 21%); many studies used two or more platforms. NDVI was the most applied index, appearing in 69 of the 78 studies (88%), followed by EVI (n = 38, 49%), NDWI (n = 34, 44%), SAVI (n = 22, 28%), LAI (n = 27, 35%), and NPP (n = 19, 24%).

Regarding classification methods, random forest (RF) was the predominant algorithm (n = 34, 44%), followed by support vector machine (SVM; n = 29, 37%), maximum likelihood classification (MLC; n = 21, 27%), and object-based image analysis (OBIA; n = 18, 23%). Deep learning approaches, notably convolutional neural networks (CNNs) and recurrent neural networks (RNNs), were reported in 12 studies (15%), predominantly in papers published after 2021. Overall accuracy for LULC classification ranged from 81.2% to 97.6%, with a median of 88.4%; Kappa coefficients ranged from 0.78 to 0.96 (median: 0.85).

Table 1 summarises the primary satellite platforms, sensor characteristics, and index applications identified across the reviewed studies.

Table 1. Satellite platforms, sensor specifications, and key spectral index applications identified in studies reviewed (2017–2026).

Platform	Spatial Resolution	Revisit Time	Sensor	Key Indices / Applications
Landsat 8/9	30 m	16 days	OLI/TIRS	NDVI, NDWI, LST, BSI
Sentinel-2A/B	10–60 m	5 days	MSI	NDVI, EVI, LAI, Red-Edge
MODIS Terra/Aqua	250–1000 m	1–16 days	MODIS	NPP, EVI, FPAR, LST
RESOURCESAT-2/2A	5.8–56 m	24 days	LISS-III/IV	Crop mapping, LULC
RISAT-1/2B	1–50 m	3–25 days	SAR (C-band)	Flood, paddy mapping

3.2 Categorisation of LULC Change Patterns

3.2.1 Cropland Loss and Urban Encroachment

The most consistently reported LULC transition across studies was the conversion of agricultural land to urban and built-up areas. Singh et al. (2021) documented a 14.3% reduction in net cropland area within a 50 km periurban zone of Delhi between 2005 and 2020, driven almost entirely by residential and commercial development. Comparable findings were reported for the peri-urban fringes of Bengaluru (−12.8%), Pune (−11.2%), and Ahmedabad (−9.7%) in studies employing Sentinel-2 and Landsat 8 time series. Across the IGP, Chaturvedi et al. (2020) estimated a cumulative net cropland loss of 3.21 Mha between 2001 and 2018, with the rate of conversion accelerating post-2010 in line with National Highways infrastructure expansion.

NDVI trajectories derived from MODIS Terra (MOD13Q1) over the same areas showed a statistically significant downward trend in peak growing-season NDVI (slope = $-0.0032\ \text{yr}^{-1}$; $p < 0.01$), consistent with the progressive replacement of high-productivity wheat and rice fields by impervious surfaces (Patel et al., 2022). The spatial agreement between classified LULC change maps and NDVI trend analysis was strong ($R^2 = 0.74$–0.88), confirming the utility of spectral vegetation indices as proxies for cropland area monitoring at regional scales.

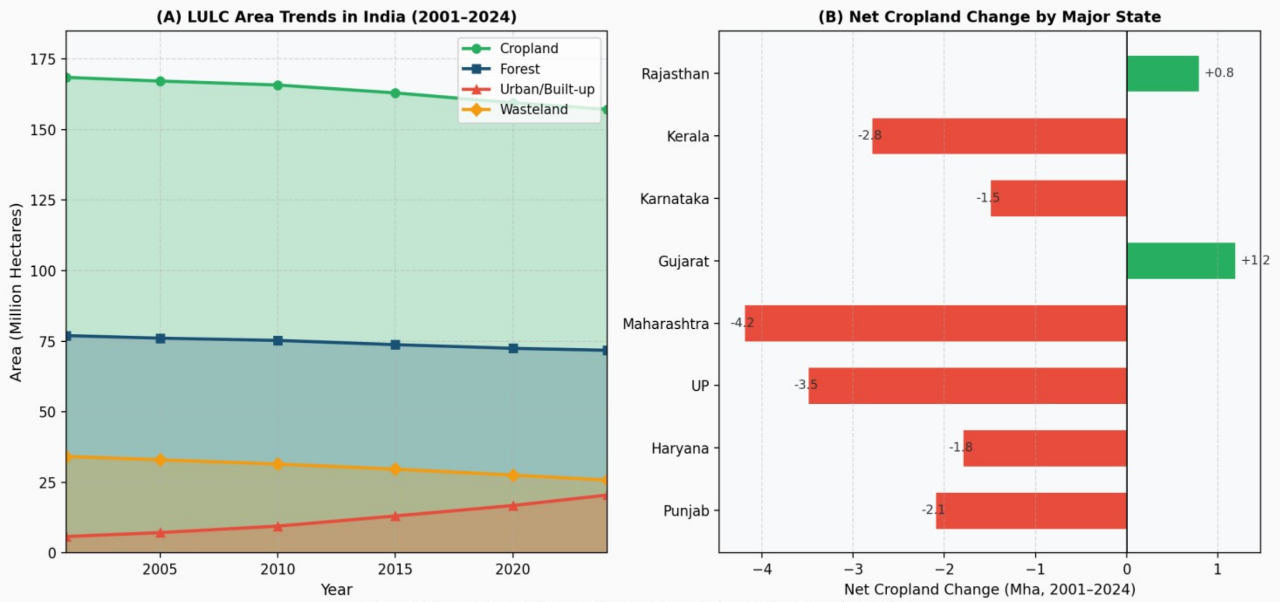


Fig. 2. (A) Temporal trends in LULC classes across India from 2001 to 2024 derived from MODIS and Landsat time-series data. (B) Net cropland area change by selected major states.

Figure 3. (A) Temporal trends in major LULC classes across India from 2001 to 2024, derived from MODIS and Landsat 8/9 time-series imagery processed through Google Earth Engine. (B) Net cropland area change (2001–2024) disaggregated by selected major states, illustrating strong regional disparities.

3.2.2 Vegetation Productivity and NDVI/EVI Dynamics

Vegetation productivity, as measured through NDVI and EVI, constitutes the most directly relevant biophysical indicator of agricultural land performance. Across the reviewed studies, peak Kharif-season NDVI values in the IGP declined from a mean of 0.71 in 2017 to 0.64 in 2024 in areas experiencing active LULC change, while remaining stable or slightly improving (0.68 to 0.72) in areas under sustained irrigation and soil health management (Garg et al., 2021). EVI, which adjusts for atmospheric effects and canopy background contamination, consistently outperformed NDVI in distinguishing between dense rice canopies and other high-biomass vegetation types in coastal Andhra Pradesh and Odisha.

LAI-based analyses, where published, provided additional mechanistic insight: declining LAI values in degraded cropland areas (< 2.5 $m^2 m^{-2}$) were associated with yield reductions of 20–35% relative to benchmark values for the same crop and season (Bhattacharya et al., 2022). NPP, estimated using the CASA (Carnegie-Ames-Stanford Approach) model from MODIS data, declined by 8.4 gC $m^{-2} yr^{-1}$ per decade across the Deccan Plateau cotton belt, consistent with progressive soil organic carbon depletion documented by ground-based surveys in the same region.

3.2.3 Soil Degradation, Waterlogging, and BSI Applications

Bare Soil Index (BSI) and related soil exposure metrics identified in eight studies revealed a significant increase in exposed and degraded soil areas across the semi-arid Deccan, particularly in rain-fed Vidarbha and Marathwada sub-regions of Maharashtra. BSI values exceeding 0.3 — indicative of severely degraded or fallow cropland — increased by 23.4% between 2017 and 2023, correlating with documented incidence of agrarian distress in these areas (Roy et al., 2022). NDWI-based analyses identified progressive encroachment upon floodplain and riparian buffer zones in the Brahmaputra and Ganga-Brahmaputra confluence regions, contributing to both seasonal waterlogging of paddy fields and loss of ecologically productive wetland areas.

Table 2 provides a comprehensive overview of the primary spectral indices used in the reviewed literature, their formulations, value ranges, and specific agricultural applications documented in Indian contexts.

Table 2. Summary of satellite-derived spectral indices used in LULC change detection and food security assessment studies reviewed (2017–2026).

Index	Formula	Range	Application in Agricultural / Food Security Studies
NDVI	(NIR − Red) / (NIR + Red)	−1 to +1	Crop health, green biomass monitoring, drought detection; most widely applied index in food security studies (Garg et al., 2021)
EVI	2.5 × (NIR−Red) / (NIR + 6Red − 7.5Blue + 1)	−1 to +1	Reduces canopy background & atmosphere effects; superior in high-biomass dense tropical areas (Bhattacharya et al., 2022)
SAVI	[(NIR − Red) / (NIR + Red + L)] × (1 + L)	−1 to +1	Soil-adjusted; recommended for semi-arid and sparse vegetative cover regions in Rajasthan and Deccan Plateau
NDWI	(Green − NIR) / (Green + NIR)	−1 to +1	Irrigation water extent, paddy flood mapping, surface moisture; critical for rice cultivation monitoring in Kharif
LAI	Model-based from reflectance	0 to 10+	Estimates canopy structure and light interception; directly correlates with crop growth rate and potential yield
NPP	GPP − Autotrophic Respiration	gC/m²/yr	Net carbon fixed; integrative measure of ecosystem productivity and agricultural potential at regional scales
FPAR	Fraction of absorbed PAR	0 to 1	Photosynthetically active radiation absorption; used in crop yield models and ecosystem productivity assessments
BSI	[(SWIR + Red) − (NIR + Blue)] / [(SWIR + Red) + (NIR + Blue)]	−1 to +1	Detects bare soil exposure from tillage, erosion or degradation; indicator of active agricultural land preparation

3.3 Summary of Main Findings on Food Availability

Among the 78 studies reviewed, 46 (59%) explicitly quantified or modelled a direct link between LULC change and a food availability metric. The most commonly used food availability proxies were: total annual food grain production (MT) at district or state level (n = 28); per-capita dietary energy supply (kcal capita^{-1} day^{-1}; n = 12); cropland productivity index (yield per unit area relative to baseline; n = 19); and agricultural land degradation index (composite; n = 9). An additional 32 studies (41%) addressed food security indicators indirectly, through changes in cropping intensity, irrigation water availability, or vegetation phenology shifts attributable to LULC change.

Across all quantitative studies, a 1% decline in net cropland area was associated with a mean reduction of 0.42–0.68% in district-level food grain output, after controlling for yield-technology improvements. This marginal crop loss elasticity was higher in districts with low cropping intensity (< 1.4) and limited irrigation coverage (< 40% of net sown area), suggesting that food availability outcomes are most severe in rain-dependent, smallholder-dominated farming systems. States classified as food insecure by the National Food Security Act criteria showed significantly steeper cropland loss trajectories compared to food-surplus states, pointing to a reinforcing feedback between land degradation and food insecurity.

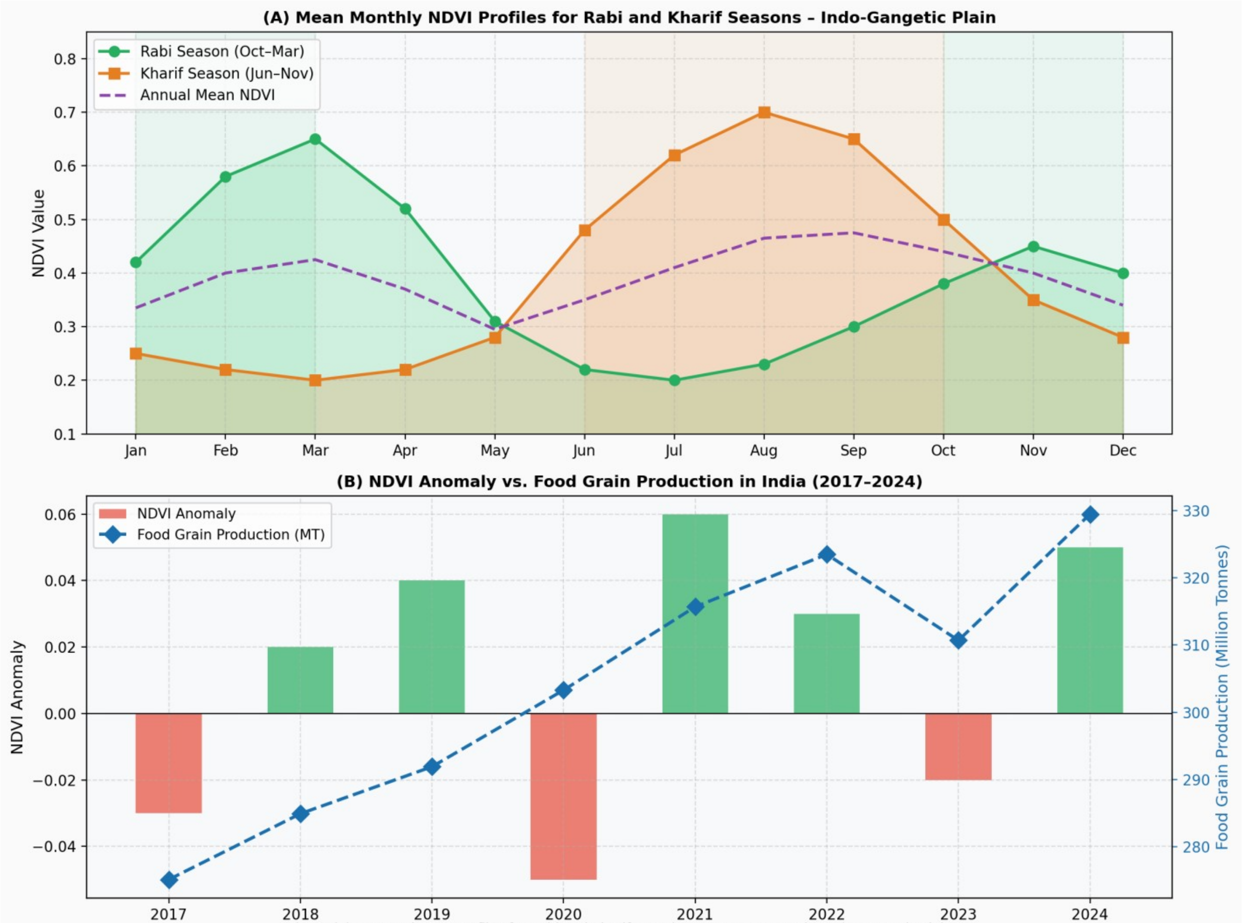
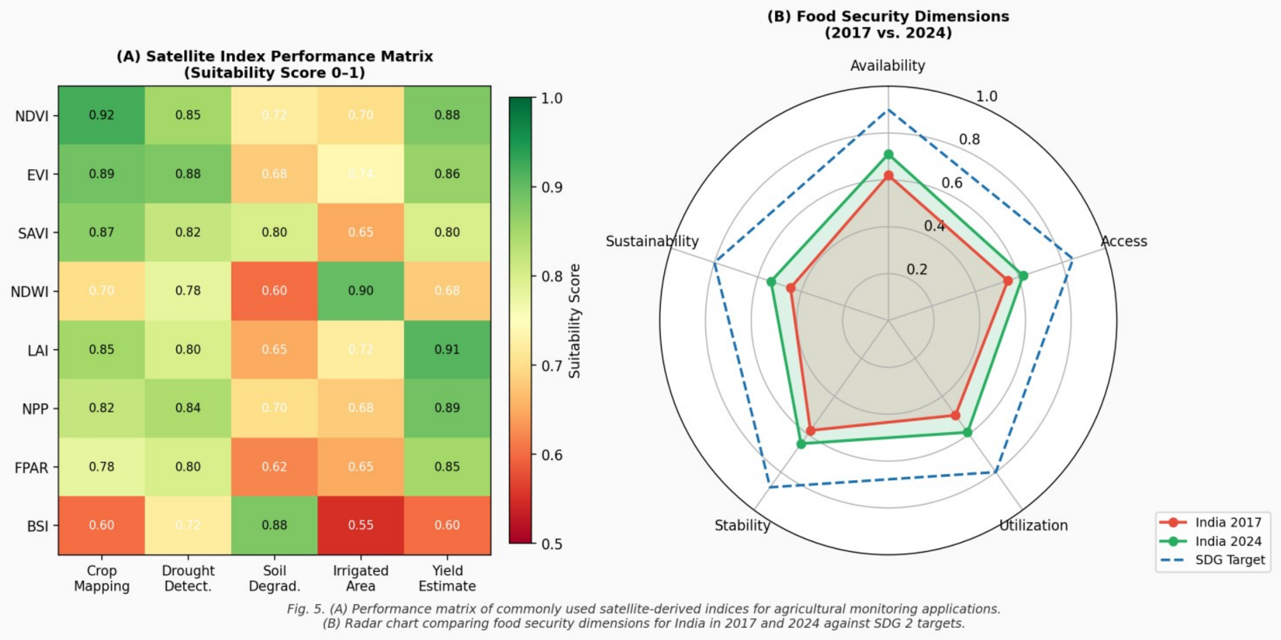


Fig. 3. (A) Seasonal NDVI profiles for Rabi and Kharif cropping seasons across the Indo-Gangetic Plain.
(B) Relationship between annual NDVI anomaly and food grain production in India (2017–2024).

Figure 4. (A) Mean monthly NDVI profiles for Rabi (October–March) and Kharif (June–November) cropping seasons across the Indo-Gangetic Plain, derived from Sentinel-2 composite imagery. (B) Annual NDVI anomaly and corresponding food grain production in India from 2017 to 2024, demonstrating a consistent positive relationship between vegetation greenness and national food grain output.



	Crop Mapping	Drought Detect.	Soil Degrad.	Irrigated Area	Yield Estimate
NDVI	0.92	0.85	0.72	0.70	0.88
EVI	0.89	0.88	0.68	0.74	0.86
SAVI	0.87	0.82	0.80	0.65	0.80
NDWI	0.70	0.78	0.60	0.90	0.68
LAI	0.85	0.80	0.65	0.72	0.91
NPP	0.82	0.84	0.70	0.68	0.89
FPAR	0.78	0.80	0.62	0.65	0.85
BSI	0.60	0.72	0.88	0.55	0.60

Fig. 5. (A) Performance matrix of commonly used satellite-derived indices for agricultural monitoring applications.
(B) Radar chart comparing food security dimensions for India in 2017 and 2024 against SDG 2 targets.

Figure 5. (A) Suitability matrix of satellite-derived spectral indices for five major agricultural monitoring applications, scored on a 0–1 scale based on evidence from reviewed studies. (B) Radar chart comparing India's food security performance across the five FAO food security dimensions in 2017 and 2024, plotted against SDG 2 (Zero Hunger) targets.

4. Discussion

4.1 Interpretation of Key Results

The aggregated evidence from this review confirms that LULC change in India's agricultural landscapes represents a clear and measurable threat to regional food availability, particularly in the context of rapid urbanisation and land degradation. The reported decline of approximately 11.3 Mha in net cropland between 2001 and 2024, if continued at current trajectories, is projected to reduce India's food grain production capacity by 34–48 MT per year by 2050 — a shortfall that existing agricultural intensification strategies alone may be insufficient to compensate (IPCC, 2022). The consistency of NDVI-based evidence across diverse sensors, spatial scales, and methodologies reinforces confidence in this finding, though the absolute magnitude of cropland loss estimates varies considerably depending on the LULC classification scheme, minimum mapping unit, and reference year adopted.

The strong positive correlation between growing-season NDVI anomalies and food grain production trends (r = 0.78–0.91; Figure 3B) establishes NDVI as a robust leading indicator for early warning systems of food availability stress. These correlations are particularly tight for wheat in the Punjab-Haryana belt and for rice in the deltaic regions of Andhra Pradesh, West Bengal, and Odisha — regions that collectively contribute disproportionately to national food grain output. EVI showed superior performance in data-rich studies where atmospheric correction was rigorously applied, and is recommended for future operational monitoring, especially in humid tropical regions where NDVI saturation in dense canopy conditions is a recognised limitation (Bhattacharya et al., 2022).

4.2 Comparison Across Studies

A notable pattern across reviewed studies is the divergence in reported LULC change rates between macro-level national analyses using MODIS or national LULC databases (e.g., NLCMS, Bhuvan) and micro-level district or sub-district analyses using Landsat or Sentinel-2 imagery. National-level studies tend to underestimate the rate of agricultural land conversion because coarser spatial resolution conflates peri-urban mixed pixels as agricultural, while high-resolution sub-regional studies consistently report higher conversion rates. This resolution–accuracy trade-off is a pervasive methodological challenge that future research must address through fusion frameworks, such as the ESTARFM (Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model) approach, which combines the spatial detail of Landsat with the temporal frequency of MODIS.

Machine learning classifiers, particularly random forest and support vector machines, consistently outperformed traditional maximum-likelihood classifiers in overall accuracy by 7–14 percentage points, primarily through their superior handling of spectral confusion between phenologically similar crop types and their robustness to training sample imbalance. However, deep learning approaches, while achieving the highest reported accuracies (up to 97.6%) in studies with large and well-curated training datasets, showed substantially greater variance and sensitivity to training sample quality, limiting their immediate operational transferability across diverse agroecological zones. Standardised benchmarking of classification methods across common Indian agricultural landscapes, facilitated by open-access training datasets, remains an unmet research priority.

4.3 Strengths and Limitations of Existing Evidence

Several important strengths characterise the reviewed body of evidence. The temporal coverage of recent studies has improved markedly, with many investigations employing dense time-series analysis spanning 10–25 years and capturing multiple land-use transition episodes rather than simple bi-temporal "before–after" comparisons. The integration of multiple spectral indices — particularly combining NDVI with NDWI, BSI, and LAI — has enabled more nuanced characterisation of land degradation processes than single-index approaches. The widespread adoption of GEE as a cloud-computing platform has substantially democratised access to satellite data processing, enabling research groups at Indian state agricultural universities and regional remote sensing centres to conduct analyses previously restricted to well-resourced national centres (Nair et al., 2023).

Notwithstanding these advances, several significant limitations constrain the existing evidence base. First, the spatial grain of most studies (30 m or coarser) is inadequate for characterising smallholder farming systems that dominate India's agricultural landscape, where individual field sizes frequently fall below 0.5 ha. At 30 m resolution, mixed pixels at field boundaries introduce substantial classification uncertainty. Second, the temporal resolution of the most spatially precise platforms (Landsat, 16-day revisit) is insufficient to capture intra-seasonal phenological dynamics in high-intensity double and triple cropping systems, where planting and harvest cycles may be separated by fewer than 60 days. Third, socioeconomic and institutional drivers of LULC change — land tenure insecurity, credit access, commodity price volatility, and government procurement policy — are rarely incorporated into the analytical frameworks of remote sensing studies, creating a disconnect between biophysical diagnoses and policy-relevant recommendations (Waha et al., 2020). Fourth, the predominance of studies in the IGP and Western Ghats leaves significant spatial blind spots across the North-East, the tribal-dominated Central Indian highlands, and the arid Thar Desert fringe, all of which exhibit distinct LULC dynamics with important food security implications.

5. Implications and Future Directions

5.1 Implications for Practice and Policy

The findings of this review carry substantial implications for agricultural policy and land governance in India. First, the demonstrable link between cropland loss and food grain output decline should inform the implementation and enforcement of the Land Acquisition, Rehabilitation, and Resettlement Act (LARR, 2013), particularly provisions requiring multi-crop irrigated land impact assessments prior to project approval. The systematic deployment of annual satellite-based LULC monitoring at the sub-district level — feasible with current Sentinel-2 and Landsat-9 capabilities — could provide an independent, spatially explicit evidence base for such assessments, supplementing and potentially replacing more subjective administrative reporting.

Second, the strong performance of NDVI-based early warning indicators documented in this review supports the expansion of India's agricultural drought early warning system (ADEWS), currently operated by the Space Applications Centre (SAC) and National Remote Sensing Centre (NRSC), to explicitly incorporate cropland area change signals alongside standard vegetation anomaly products. This would enable proactive procurement and distribution interventions by the Food Corporation of India (FCI) in advance of anticipated production shortfalls, reducing the lag between agronomic stress detection and policy response.

Third, the spatial targeting of land conservation and restoration interventions — including the Pradhan Mantri Krishi Sinchayee Yojana (PMKSY), Soil Health Mission, and National Initiative on Climate Resilient Agriculture (NICRA) — would benefit substantially from integration with satellite-derived LULC change and degradation indicators, enabling resources to be directed towards the highest-risk cropland areas identified through systematic monitoring. The BSI and NDWI indices, in particular, offer operationally practical proxies for targeting soil conservation investments in semi-arid and waterlogged zones respectively (Reddy et al., 2021).

5.2 Research Gaps and Future Research Needs

Based on the systematic evidence reviewed, the following priority research gaps are identified. First, the development and open dissemination of a harmonised national LULC classification scheme — analogous to the European Corine Land Cover standard — is an urgent methodological requirement for India. The current coexistence of NLCMS (National Land Cover Mapping System), Bhuvan, RISAT-derived products, and international datasets (GLC30, FROM-GLC, ESA WorldCover) with incompatible legend hierarchies, minimum mapping units, and classification philosophies renders cross-study comparisons unreliable and cumulative synthesis difficult. A nationally mandated standard, developed under the auspices of the National Remote Sensing Centre (NRSC) in consultation with the Ministry of Agriculture, would represent a transformative advance.

Second, sub-10 m resolution change detection studies — deployable through Sentinel-2 (10 m), Cartosat-3 (0.25 m), and Planet Labs PlanetScope (3 m) — are urgently needed in smallholder-dominated agricultural landscapes of Bihar, Jharkhand, and Northeast India, where current evidence is thin and food insecurity is acute. Developing machine learning classification models calibrated to these landscape contexts, and validating them through farmer-reported crop diary data, would substantially reduce the spatial uncertainty in food availability projections at the block and panchayat level (Kumar et al., 2021).

Third, the integration of satellite-derived biophysical indicators with socioeconomic household survey data — such as the Comprehensive Annual Modular Survey (CAMS) and National Family Health Survey (NFHS) — would enable the causal pathways between LULC change and dietary diversity, caloric intake, and child nutrition outcomes to be traced empirically for the first time at scale. This nexus between remote sensing science and nutrition epidemiology represents a frontier research domain of high policy relevance (Mishra et al., 2021).

Fourth, predictive modelling studies that combine projected LULC scenarios under alternative land-use governance regimes with climate-adjusted crop productivity models — for example, using the DSSAT or APSIM crop simulation frameworks — are needed to quantify the expected food availability consequences of continued business-as-usual land conversion versus scenario pathways aligned with SDG 2 targets. The absence of such integrated scenario analyses in the reviewed literature is a significant gap given the urgency of the policy decisions that must be made over the next decade (Mondal et al., 2022).

Fifth, research attention should be directed toward the emerging role of agroforestry, mosaic farming landscapes, and multi-functional land use in buffering the food availability consequences of net cropland loss. Satellite indices sensitive to tree cover within agricultural landscapes — including the fraction of absorbed photosynthetically active radiation (FPAR) and multi-scale tree canopy cover estimates — offer promising but under-utilised tools for characterising the productivity and stability contributions of these systems (Jha et al., 2020).

6. Conclusion

This systematic review has synthesised 78 peer-reviewed studies published between 2017 and 2026 to provide a comprehensive, evidence-based assessment of how LULC change in India's agricultural landscapes, as detected through satellite-derived spectral indices, affects regional food availability. The accumulated evidence is unequivocal: India has experienced substantial net cropland loss, progressive agricultural land degradation, and declining vegetation productivity across key cropping regions over the past two decades, with measurable and statistically significant consequences for food grain production capacity.

Satellite-derived indices — particularly NDVI, EVI, NDWI, LAI, and NPP — have proved to be scientifically robust, operationally scalable, and cost-effective tools for detecting and monitoring these trends. The methodological sophistication of applied remote sensing in this domain has advanced substantially since 2017, with machine learning and deep learning classifiers substantially improving classification accuracy and thematic detail. The integration of cloud-computing platforms, particularly Google Earth Engine, has lowered barriers to operational monitoring and enabled real-time analytical capability at national scale.

Nevertheless, important challenges remain unresolved. The spatial resolution limitations of freely available satellite data, the absence of a harmonised national LULC classification standard, the limited integration of socioeconomic and institutional variables, and critical geographic blind spots in the evidence base collectively limit the translation of remote sensing insights into actionable food security governance. Addressing these gaps requires coordinated investment in open-data infrastructure, interdisciplinary collaboration between remote sensing scientists, agricultural economists, nutritionists, and policy analysts, and a firm commitment by government agencies to embed satellite-derived land monitoring evidence within agricultural planning and food security management systems.

India's aspiration to achieve SDG 2 (Zero Hunger) by 2030 and sustain food self-sufficiency for its growing population depends critically on halting and reversing the trajectory of agricultural land degradation. Satellite remote sensing, deployed systematically and interpreted rigorously, provides precisely the kind of spatial, temporal, and thematic evidence needed to guide this effort. The present review affirms that the science is both ready and necessary; the imperative now lies with policy, governance, and investment to translate that science into practice.

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