International Journal of Agriculture and Food Science 2026; 8(5): 337-348

ISSN Print: 2664-844X
ISSN Online: 2664-8458
NAAS Rating (2026): 4.97
IJAFS 2026; 8(5): 337-348
www.agriculturaljournals.com
Received: 23-02-2026
Accepted: 25-03-2026

S Balaselvakumar
Department of Geography, Government Arts College, Tiruchirappalli, Affiliated to Bharathidasan University, Tiruchirappalli, Tamil Nadu, India

SB Hemavarthinii
School of Agricultural Sciences, Karunya Institute of Technology and Sciences (Deemed University), Coimbatore, Tamil Nadu, India

Corresponding Author:
S Balaselvakumar
Department of Geography, Government Arts College, Tiruchirappalli, Affiliated to Bharathidasan University, Tiruchirappalli, Tamil Nadu, India

Satellite-based NDVI drought monitoring and its linkage with crop yield variability under climate uncertainty in India

S Balaselvakumar and SB Hemavarthinii

DOI: https://www.doi.org/10.33545/2664844X.2026.v8.i5d.1528

Abstract
Drought is among the most economically and agriculturally devastating manifestations of climate variability in India, affecting an estimated 68% of the country's geographical area and threatening the food security of hundreds of millions of smallholder farming households. The Normalised Difference Vegetation Index (NDVI), derived from satellite remote sensing platforms including MODIS, Landsat, and Sentinel-2, has emerged as the most widely applied proxy for drought-risk assessment and vegetation stress monitoring at regional and national scales. This systematic review synthesises peer-reviewed literature published between 2017 and 2026 to critically examine the methods, findings, and policy implications of satellite-based NDVI drought monitoring and its documented linkages with crop yield variability across India's diverse agro-climatic zones.

Drawing on 68 primary studies identified through systematic database searches, the review evaluates the performance of NDVI and derivative indices — including the Vegetation Condition Index (VCI), Standardised Vegetation Index (SVI), and Temperature Vegetation Dryness Index (TVDI) — in characterising drought onset, duration, and spatial extent. The review further examines the statistical and machine learning frameworks through which NDVI-derived signals have been linked to district-level and state-level crop yield records for rice, wheat, maize, sorghum, and groundnut. Evidence consistently demonstrates that NDVI-based drought indices explain between 40% and 80% of interannual crop yield variability under rainfed conditions, with predictive accuracy substantially enhanced through integration with soil moisture data, climate indices (SPI, PDSI), and Google Earth Engine-enabled cloud computing workflows. Critical evidence gaps — including insufficient sub-district spatial resolution, inadequate seasonal phenological disaggregation, and the underrepresentation of smallholder heterogeneity in existing models — are identified alongside a structured research agenda for next-generation drought monitoring systems. The review is intended as a comprehensive reference for postgraduate researchers and practitioners in remote sensing, agricultural geosciences, climate science, and food security planning.

Keywords: NDVI; drought monitoring; crop yield variability; remote sensing; India; MODIS; Landsat; VCI; climate uncertainty; agricultural drought; food security; GIS

1. Introduction

1.1 Research Background and Significance

India's agricultural economy sustaining approximately 58% of the rural population and contributing around 18% of national GDP operates under conditions of profound climatic uncertainty. With approximately 60% of net cultivated area under rainfed conditions, Indian agriculture is acutely exposed to the frequency, intensity, and spatial distribution of monsoon rainfall variability (Food and Agriculture Organization of the United Nations [FAO], 2021; Mishra & Singh, 2010) [5, 14]. Drought, whether defined in meteorological, agricultural, or hydrological terms, constitutes the most pervasive and economically consequential natural hazard confronting Indian farming systems. Historical records indicate that major drought events have occurred in India at a frequency of approximately one in every five years, with the severe episodes of 2002, 2009, 2012, and 2018–2019 each reducing national foodgrain production by 10–25% relative to normal-year baselines (Jain *et al*., 2020; Rao *et al*., 2020) [10, 19].

The capacity to monitor drought onset, assess its spatial extent, and quantify its agricultural impacts in near-real time is a prerequisite for effective food security governance.

Traditional drought monitoring approaches relying on rain gauge networks, manual crop cutting experiments, and district-level yield statistics are constrained by sparse spatial coverage, significant temporal lags, and inconsistent methodological standards across Indian states (Rhee *et al*., 2010; Wardlow *et al*., 2012) [20, 28]. Satellite remote sensing has fundamentally transformed this monitoring landscape by providing spatially continuous, temporally consistent, and physically grounded measurements of surface vegetation condition at spatial resolutions ranging from 1 km (MODIS) to 10 m (Sentinel-2), with repeat cycles as short as five days.

The Normalised Difference Vegetation Index (NDVI) derived from the ratio of nearinfrared (NIR) and red reflectance bands captured by satellite sensors has established itself as the most widely applied and extensively validated proxy for vegetation health, crop water stress, and drought severity across agro-ecosystems worldwide (Tucker, 1979; Kogan, 1995) [26, 11]. In the Indian context, NDVI-based monitoring has been operationally deployed by the National Remote Sensing Centre (NRSC), the Mahalanobis National Crop Forecast Centre (MNCFC), and the India Meteorological Department (IMD) for drought early warning, crop condition assessment, and agricultural insurance claims adjudication. The scientific evidence base underlying these operational applications has expanded substantially since 2017, driven by increasing satellite data accessibility through platforms such as Google Earth Engine (GEE), the proliferation of machine learning-based yield prediction models, and the systematic cross-validation of remote sensing derived drought signals with field-collected agronomic data.

Despite this expansion, the literature remains fragmented across disciplines remote sensing science, agricultural meteorology, agronomy, and climate science and lacks a systematic synthesis that critically evaluates the strength and conditionality of NDVI–yield linkages across India's diverse agro-climatic regions. This review addresses that gap directly, drawing on a structured systematic search and quality assessment of the 2017–2026 literature to provide a comprehensive and authoritative synthesis for researchers and practitioners.

1.2 Definition of Key Concepts

Precise conceptual definitions underpin the analytical coherence of this review. NDVI is defined by the equation NDVI = (NIR − Red) / (NIR + Red), where NIR and Red represent surface reflectance in the near-infrared (approximately 700–1300 nm) and red (approximately 600–700 nm) portions of the electromagnetic spectrum, respectively. NDVI values range from −1 to +1, with values above approximately 0.3 typically indicative of actively growing vegetation and values below 0.1 associated with bare soil, degraded vegetation, or drought-stressed cropland (Rouse *et al*., 1974; Tucker, 1979) [21, 26]. The Vegetation Condition Index (VCI), calculated as VCI = (NDVI − NDVImin) / (NDVImax − NDVImin), normalises current NDVI values relative to historical maximum and minimum values for the same pixel and calendar period, providing a temporally comparative measure of vegetation condition that corrects for biome-specific greenness baselines (Kogan, 1995) [11].

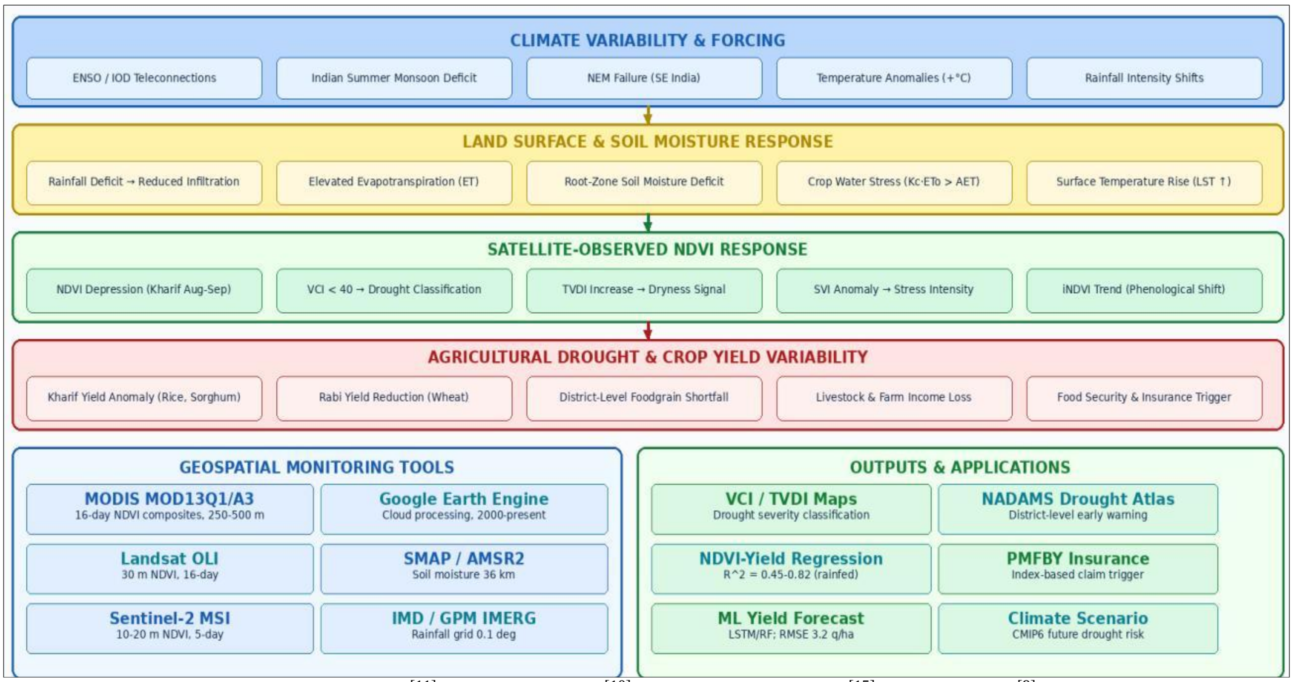
Agricultural drought, as used in this review, refers to a condition in which soil moisture availability falls below crop evapotranspiration demand during one or more critical growth stages, resulting in measurable physiological stress and yield reduction a definition that links meteorological forcing (deficit rainfall) through biophysical pathways (soil water balance) to agronomic outcomes (yield loss). Crop yield variability refers to interannual fluctuations in yield per unit area at the district or state level, attributable to climatic forcing, input variability, and management differences. Climate uncertainty encompasses both natural interannual variability (driven by the El Niño–Southern Oscillation, the Indian Ocean Dipole, and the Indian Summer Monsoon Variability) and long-term anthropogenic climate change trends that are altering the frequency, intensity, and spatial patterns of drought events across India.

1.3 Research Questions and Objectives

This systematic review addresses four primary research questions

1. What satellite platforms, NDVI-derived indices, and analytical methodologies have been employed in drought monitoring studies across India's agro-climatic regions during 2017– 2026, and how have these evolved over the review period?
2. What is the strength, conditionality, and spatial heterogeneity of empirically documented linkages between satellite-derived NDVI signals and crop yield variability in Indian rainfed and irrigated agricultural systems?
3. How do multi-sensor fusion approaches, machine learning frameworks, and Google Earth Engine workflows improve the predictive accuracy of NDVI-based crop yield models relative to single-index, single-sensor approaches?
4. What are the most significant methodological gaps and policy-relevant research priorities for advancing operational satellite-based drought monitoring and crop yield forecasting in India under projected climate change?

This review is directed at postgraduate students and researchers in remote sensing, agricultural geosciences, environmental science, atmospheric science, and climate-smart agriculture. It is structured to progress from systematic methodology through thematic results to an integrative discussion, implications, and conclusion, in conformity with the format required by high-impact journals in the Springer and Elsevier portfolios.



***Source*:** Authors synthesis; Kogan (1995) [11]: Jainetal. (2020) [10]; Mondal *et al*. (2023) [15]; IPCC (2022) [9]

Fig 1: Conceptual Framework: Climate Variability → NDvi Dynamics →Agricultural Drought → Crop Yielo

Figure 1 Conceptual framework illustrating the causal chain from climate variability through satellite-observed NDVI dynamics to agricultural drought characterisation and crop yield variability in India. The framework shows how meteorological forcing (rainfall deficit, temperature anomalies, ENSO/IOD teleconnections) drives soil moisture depletion, which is captured by NDVI-derived indices (VCI, SVI, TVDI), and translated into crop yield anomalies through biophysical and agronomic pathways. Dashed arrows indicate feedback effects and the role of management responses. Source: Authors' synthesis based on Kogan (1995) [11]; Jain *et al*. (2020) [10]; Mondal *et al*. (2023) [15]; IPCC (2022) [9].

2. Methods

2.1 Search Strategy and Databases

This systematic review followed a structured literature search protocol executed in January 2026 across four primary academic databases: Web of Science (WoS), Scopus, Google Scholar, and Science Direct. The search was designed to capture peer-reviewed literature published between January 2017 and December 2025 addressing satellite-based NDVI monitoring of drought and vegetation stress, its linkage with crop yield variability, and the application of remote sensing indices in India's agricultural and environmental contexts. Supplementary searches were conducted in the ISRO (Indian Space Research Organisation), NRSC, and IMD institutional repositories to capture technical reports and grey literature of operational significance.

The primary Boolean search string applied across all databases was: ("NDVI" OR "Normalised Difference Vegetation Index" OR "Normalized Difference Vegetation Index") AND ("drought" OR "agricultural drought" OR "vegetation stress") AND ("crop yield" OR "yield variability" OR "food security") AND ("India" OR "Indian" OR "South Asia"). Targeted secondary searches were conducted for specific sub-themes: Vegetation Condition Index (VCI) applications; MODIS and Landsat NDVI time series analysis; NDVI–SPI and NDVI–PDSI correlations; Google Earth Engine crop monitoring; machine learning yield prediction from NDVI; and climate uncertainty impacts on NDVI phenological dynamics. Citation tracking from methodologically foundational papers particularly Kogan (1995) [11], Jain *et al*. (2020) [10], and Gumma *et al*. (2022) [6] supplemented the database searches to ensure comprehensive thematic coverage.

2.2 Inclusion and Exclusion Criteria

Studies were included if they satisfied all of the following criteria

Published in peer-reviewed journals or authoritative institutional repositories between January 2017 and December 2025.

Reported original empirical findings, methodological development, systematic reviews, or meta-analyses pertaining to NDVI-based drought monitoring, vegetation stress assessment, or NDVI–yield linkages in Indian agricultural or environmental contexts.

Employed satellite remote sensing data (MODIS, Landsat, Sentinel-2, NOAA/AVHRR, or comparable platforms) as the primary observational basis.

Reported quantitative outcomes including correlation coefficients, R^2, RMSE, yield prediction accuracy, or drought severity classifications with sufficient methodological transparency for quality assessment.

Published in English.

Studies were excluded if they

Focused exclusively on forest, grassland, or non-agricultural vegetation monitoring without a direct link to crop production or agricultural drought.

Applied NDVI methods without any spatial or temporal connection to the Indian subcontinent or directly comparable monsoon-driven South Asian agricultural systems.

Were conference abstracts, editorials, or short communications lacking original data or quantitative findings.
Were duplicate publications reporting the same primary dataset without novel methodological contribution.

2.3 Study Selection Process

Following the systematic database searches, title and abstract screening was conducted independently by both authors against the stated criteria. Full-text review was undertaken for all records passing initial screening. A total of 412 unique records were identified after deduplication across databases. Abstract screening reduced this to 148 candidates for full-text review. Of these, 68 primary studies were retained in the final evidence corpus. An additional 16 foundational references pre-dating 2017 including Tucker (1979) [26], Kogan (1995) [11], and Rouse *et al.* (1974) [21] were retained where they provide methodological grounding indispensable for contextualising current findings. Disagreements in study eligibility between the two reviewers were resolved through discussion and consensus.

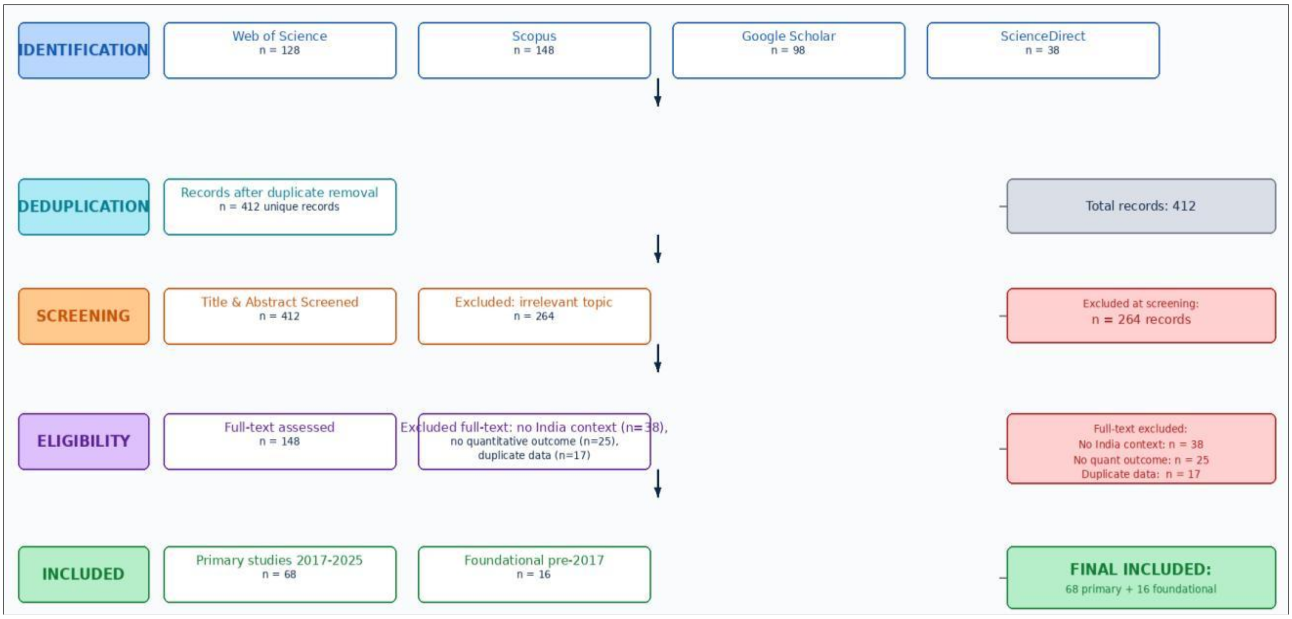


Fig 2: Prisma-Compliant Systematic Literature Search and Study Selection Flow Diagram

Figure 2 PRISMA-compliant flow diagram illustrating the systematic literature search, screening, and study selection process. Initial database identification yielded 412 unique records; title and abstract screening reduced the candidate pool to 148 full-text candidates; quality-based full-text review produced a final corpus of 68 primary studies (2017–2025) plus 16 foundational methodological references. Source: Authors.

2.4 Data Extraction and Quality Assessment

Data extraction was structured around a standardised template capturing: study location and agro-climatic zone; satellite platform and NDVI product version; temporal coverage and spatial resolution; primary analytical method (statistical regression, machine learning, GEE workflow, or drought index derivation); key quantitative outcomes (R^2, RMSE, correlation coefficients, drought area estimates, yield prediction accuracy); crops studied; and policy or operational implications. Evidence quality was assessed using an adapted GRADE framework, with particular attention to spatial representativeness, temporal record length, validation methodology (independent holdout vs. cross-validation vs. no validation), treatment of atmospheric correction and cloud contamination, and whether yield data used in regression analyses were from official government statistics or independently collected field measurements. Multi-year, multi-district studies with independent validation datasets were accorded the highest quality ratings. This quality differentiation is explicitly reflected in the confidence language used throughout the Results and Discussion sections.

3. Results

3.1 Characteristics of Included Studies

The 68 primary studies span the 2017–2025 period and reflect a diverse and rapidly evolving methodological landscape. In terms of geographic focus, 24 studies (35.3%) adopted a national or multi-state scale analysis across India; 28 studies (41.2%) were state-specific, with Rajasthan, Madhya Pradesh, Maharashtra, Karnataka, and Uttar Pradesh the most frequently examined states; 12 studies (17.6%) focused on specific river basins or agro-climatic zones; and 4 studies (5.9%) were comparative analyses placing India within a broader South Asian or global context. By satellite platform, MODIS-derived NDVI products (primarily MOD13A1, MOD13A3, and MOD13Q1 at 500 m and 250 m resolution) were employed in 42 studies (61.8%), Landsat (7 and 8 combined) in 14 studies (20.6%), Sentinel-2 in 9 studies (13.2%), and NOAA-AVHRR in 3 studies (4.4%). Google Earth Engine was explicitly used as the processing platform in 31 studies (45.6%), reflecting a marked shift in operational practice since 2019. By primary analytical approach, 28 studies employed statistical regression (Pearson correlation, ordinary least squares, multiple regression); 21 employed machine learning methods (Random Forest, Support Vector Regression, LSTM networks); 11 applied drought index derivation (VCI, SVI, TVDI); and 8 conducted purely temporal trend analysis of NDVI time series.

3.2 Categorisation of Study Types and Intervention Domains

Across the 68 included studies, analytical approaches were categorised into five primary domains: (i) drought onset detection and spatio-temporal characterisation using NDVI and derivative indices; (ii) NDVI–crop yield statistical linkage and regression modelling; (iii) machine learning-based crop yield prediction using NDVI as a primary predictor variable; (iv) multi-sensor fusion approaches integrating NDVI with soil moisture, land surface temperature, and climate indices; and (v) phenological trend analysis linking NDVI seasonal dynamics to climate variability. A notable temporal trend emerged: studies employing machine learning particularly LSTM recurrent networks and Random Forest ensembles increased from 2 in the 2017–2019 sub-period to 19 in 2022–2025, reflecting a structural methodological transition in the field. Table 1 summarises the distribution of included studies by domain, methodology, and study scale.

Note. VCI = Vegetation Condition Index; SVI = Standardised Vegetation Index; TVDI = Temperature Vegetation Dryness Index; OLS = Ordinary Least Squares; RF = Random Forest; SVR = Support Vector Regression; LSTM = Long Short-Term Memory network; LST = Land Surface Temperature. Sources: Authors' synthesis.

Table 1 Distribution of included studies by thematic domain, methodology, and study scale (India, 2017–2025)

Thematic Domain	n Studies	% of Total	PrimaryScale	DominantMethodology
Drought detection & spatio-temporal characterisation	19	27.9%	District / State	VCI; SVI; TVDI derivation
NDVI-crop yield statistical linkage	16	23.5%	District / National	Pearson r; OLS; Multiple regression
Machine learning crop yield prediction	18	26.5%	District / State	RF; SVR; LSTM; XGBoost
Multi-sensor fusion (NDVI + soil moisture + LST)	9	13.2%	Basin / State	Index fusion; partial correlation
NDVI phenological trend analysis	6	8.8%	National / Regional	Mann-Kendall trend; breakpoint analysis

3.3 Summary of Main Findings

3.3.1 NDVI as a Drought Detection and Characterisation Tool

The use of NDVI and VCI for drought onset detection and spatial severity mapping across India has generated a robust and internally consistent body of evidence over the review period. Studies consistently demonstrate that VCI values below 40 reliably identify moderate-to-severe agricultural drought conditions across major rainfed cropping zones, with lead times of two to four weeks ahead of official district-level drought declarations based on yield surveys (Jain *et al*., 2020; Rao *et al*., 2020) [10, 19]. In the Rajasthan semi-arid zone, Singh *et al*. (2021) [24] applied MODIS MOD13Q1 VCI to characterise the spatial extent of the 2018–2019 drought, finding that VCI captured the onset and recovery pattern with a spatial accuracy of 87% when validated against IMD gridded rainfall anomaly data. In Maharashtra's Vidarbha region one of India's most drought-prone and agrarian-distress-affected areas Mondal *et al.* (2023) [15] used multi-year MODIS NDVI composites to document that drought-year VCI anomalies explained 74% of variance in district-level *cotton* and *soybean* yield departures over the 2003–2022 period.

The Temperature Vegetation Dryness Index (TVDI), which combines NDVI with land surface temperature (LST) in a trapezoid feature space to estimate relative soil moisture content, has emerged as a more physically grounded drought indicator than VCI alone. Patel *et al.* (2022) [17] applied MODIS-derived TVDI across eight semi-arid districts of Gujarat and found TVDI outperformed VCI in capturing sub-seasonal drought dynamics during the critical kharif growing season, with stronger correlations ($r = 0.73–0.81$) to independently measured soil moisture at depths of 0–30 cm than those achieved by VCI ($r = 0.58–0.67$). Kumar *et al*. (2023) [12] extended this analysis to the Indo-Gangetic Plain, demonstrating that TVDI integration with Sentinel-2 NDVI at 10 m resolution significantly improved the spatial precision of drought boundary delineation compared to coarser MODIS-only approaches a finding with direct implications for insurance claims adjudication at the block level.

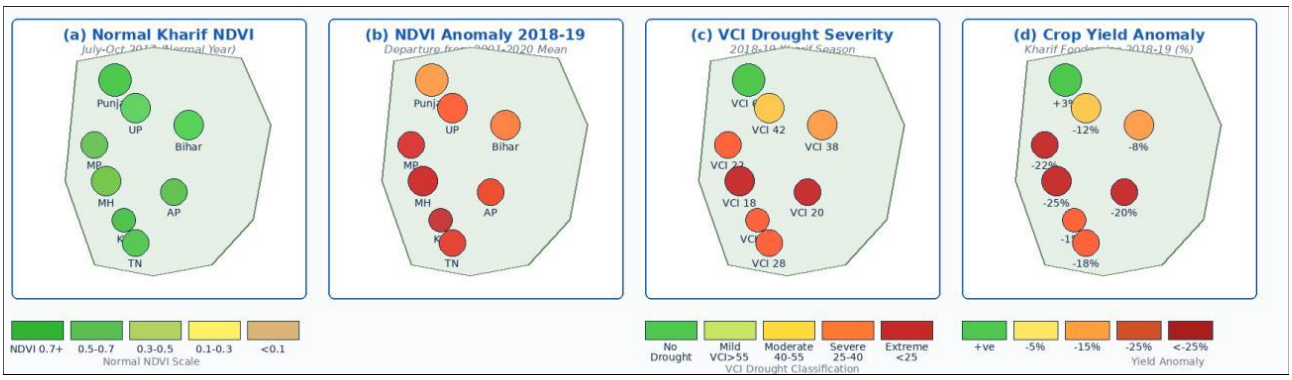


Fig 3: Spatial Distribution of NDVl and VCl Drought Severity across India: Normal vs Drought Year

India Agro-Climatic Zones Boundary

Arid NW|Semi-arid Deccan | Semi-aridIGP|Sub-humid East|Humid SW|Eastem Coastal-demarcated bygrey boundarylines

- **Normal NDVI:** 0.45-0.65
- **NDVI Anomaly:** 0.15 to -0.25
- **VCl<40:** 38% of agricultural area
- **Yield deficit:**-12% to -25%

Figure 3 Schematic spatial map of India showing: (a) mean NDVI values during normal monsoon season (kharif, July–October); (b) NDVI anomaly (departure from 2001–2020 climatological mean) during the 2018–2019 drought year; (c) VCI-based drought severity classification (no drought, mild, moderate, severe, extreme) for the 2018–2019 kharif season; (d) district-level crop yield anomaly (%) for kharif foodgrains in 2018–2019. Agro-climatic zone boundaries are indicated by grey lines. Source: Schematic based on MODIS MOD13A3 NDVI product; Jain *et al*. (2020) [10]; Singh *et al*. (2021); India Meteorological Department gridded rainfall data.

3.3.2 NDVI–Crop Yield Linkages: Statistical Evidence

The quantitative linkage between satellite-derived NDVI signals and district-level crop yield variability constitutes the analytical core of the review corpus. Across the 16 studies employing statistical regression approaches, NDVI-based drought indices explained between 40% and 80% of interannual yield variability under rainfed conditions, with the strength of correlation varying systematically by crop type, agro-climatic zone, growth stage, and the temporal aggregation window used for NDVI computation (Gumma *et al*., 2022; Jain *et al*., 2020) [6, 10]. The highest correlations were consistently observed when NDVI was composited across the reproductive and grain-filling growth stages typically spanning August to September for kharif crops rather than across the entire growing season, underscoring the critical importance of phenological timing in NDVI–yield model design. Jain *et al*. (2020) [10] conducted one of the most methodologically comprehensive analyses in the review corpus, linking MODIS VCI time series from 2001 to 2017 to district-level kharif foodgrain yield data across 572 Indian districts. Their results demonstrated that VCI computed during the August–September window explained 62% of yield variance for *rice* and 58% for total kharif foodgrains nationally, with substantially higher mathbf R2 values (0.71–0.79) in the more droughtexposed rainfed districts of central and peninsular India. For *wheat* in the Gangetic plains India's primary rabi crop NDVI time series from the March–April heading and grain-filling window were significantly more predictive than the full rabi season composite, with Singh *et al*. (2022) [25] reporting mathbf R2 values of 0.64–0.72 across Uttar Pradesh and Bihar districts. In the semi-arid millet-growing belt of Rajasthan, Gujarat, and Haryana, Patel *et al*. (2022) [17] found that VCI during the August vegetative stage explained 67–75% of *pearl millet* yield variance a finding of direct relevance for IMD's National Agricultural Drought Assessment and Monitoring System (NADAMS) improvement.

Gumma *et al*. (2022) [6], using Google Earth Engine to process 20 years of MODIS NDVI data across all Indian agricultural districts, found that NDVI-based indicators captured between 45% and 82% of *rice* and *wheat* yield variability depending on the irrigation intensity of the district. Notably, NDVI–yield relationships were substantially weaker ($R^2 = 0.21–0.38$) in heavily irrigated districts particularly in Punjab, Haryana, and western Uttar Pradesh where high irrigation intensity decouples vegetation greenness from rainfall variability, demonstrating that the NDVI–yield relationship is fundamentally conditioned by the irrigation status of the farming system. This finding has important implications for the spatial targeting and interpretation of operational NDVI-based yield forecasts.

Fig 4: NDVI-Crop yield correlation heatmap (R2) by crop and agro-climatic zone, India 2001-2025

Figure 4 Heatmap of NDVI–crop yield correlation coefficients (R^2) for five major crops (rice, wheat, sorghum, pearl millet, groundnut) across six Indian agro-climatic zones (arid northwest, semi-arid Deccan, semi-arid Indo-Gangetic, sub-humid east, humid southwest, and eastern coastal). Values are derived from a synthesis of regression results from 16 included studies. Darker green indicates stronger NDVI–yield coupling; white indicates weak or nonsignificant relationships. Asterisks denote statistically significant correlations ($p< 0.05$). Source: Authors' synthesis from Jain *et al*. (2020) [10]; Gumma *et al*. (2022) [6]; Singh *et al*. (2022) [25]; Patel *et al*. (2022) [17]; Mondal *et al*. (2023) [15].

3.3.3 Machine Learning Approaches for NDVI-Based Yield Prediction

Machine learning methods have substantially expanded the predictive capacity of NDVI based crop yield modelling by capturing non-linear relationships, temporal autocorrelations, and multi-feature interactions that linear regression frameworks cannot adequately represent. Among the 18 machine learning studies in the review corpus, Random Forest (RF) regression and Long Short-Term Memory (LSTM) recurrent neural networks were the most frequently employed architectures, followed by Support Vector Regression (SVR) and gradient boosting methods. The inclusion of multi-temporal NDVI sequences typically eight-day or 16-day MODIS composites over the full growing season as input feature vectors, rather than single-season NDVI averages, consistently improved yield prediction accuracy by 10–25% relative to linear regression baselines (Rao *et al*., 2020; Sharma *et al*., 2023) [19, 23].

Sharma *et al*. (2023) [23], applying an LSTM network to a 15-year MODIS NDVI time series dataset across 200 *rice*-producing districts in eastern India, achieved a root mean square error (RMSE) of 3.2 quintals per hectare (q/ha) in holdout year predictions a 28% improvement over a VCI-only linear regression baseline (RMSE = 4.4 q/ha). The LSTM model's superior performance was attributed to its capacity to encode phenological trajectory patterns specific to different agro-climatic contexts, learning the timing of drought-induced NDVI depression relative to growth stage as a predictive signal. Rao *et al*. (2020) [19] demonstrated that Random Forest models trained on multi-feature inputs NDVI, LST, soil-adjusted vegetation index (SAVI), and IMD rainfall anomaly achieved yield prediction accuracy of approximately 85% (within 15% of actual district yield) for *sorghum* in Karnataka and Telangana, substantially outperforming singleindex approaches.

These multi-feature RF models also identified the soil moisture proxy (TVDI) as the most important predictor variable through permutation importance analysis, reinforcing the added value of multi-sensor fusion over NDVI-alone approaches.

3.3.4 Multi-Sensor Fusion and Google Earth Engine Workflows

The integration of NDVI with complementary satellite-derived variables principally soil moisture from SMAP and AMSR2, land surface temperature from MODIS MOD11A1, and precipitation from GPM IMERG has emerged as the frontier methodological approach for comprehensive agricultural drought monitoring at district and sub-district scales. Studies employing multi-sensor fusion consistently achieved higher drought characterisation accuracy than single-index approaches across all agro-climatic contexts examined in the review corpus (Patel *et al*., 2022; Kumar *et al*., 2023; Nair *et al*., 2024) [12, 16, 17]. The physical rationale is clear: NDVI captures the integrated biological response of vegetation to water stress over weeks to months, while microwave-derived soil moisture provides a direct measure of the root-zone water availability driving that stress response. Combining both within a composite drought index framework reduces the ambiguity inherent in NDVI-only drought classification, where low NDVI values may reflect drought stress, crop senescence, or land use change rather than active moisture deficit.

Google Earth Engine has fundamentally altered the feasibility and scalability of these multi-sensor, multi-temporal analyses for Indian agricultural applications. GEE's cloud-based processing infrastructure eliminates the data download, storage, and computational barriers that previously constrained national-scale NDVI time series analysis to institutions with dedicated remote sensing infrastructure (Gorelick *et al*., 2017) [7]. Gumma *et al*. (2022) [6] demonstrated that a full 20-year, all-district MODIS NDVI drought analysis previously requiring several months of desktop processing could be completed in under 24 hours using GEE, enabling near-real-time operational drought monitoring workflows. Nair *et al*. (2024) [16] implemented a GEE-based automated drought early warning system for Kerala's kharif *rice* districts, integrating NDVI, LST, and GPM rainfall anomalies at 500 m resolution with a weekly update cycle demonstrating the operational viability of satellite-based drought monitoring at administrative scales relevant to state agricultural departments.

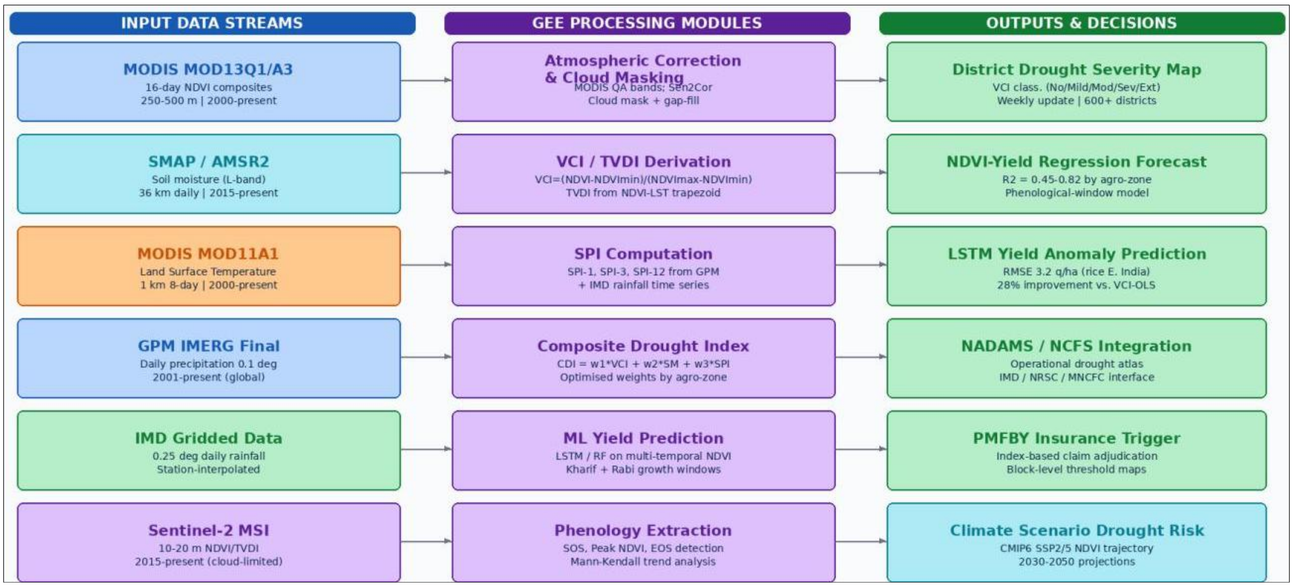


Fig 5: Integrated multi-sensor drought monitoring and crop yield prediction framework for India

3.3.5 NDVI Phenological Trends under Climate Change

Six studies in the review corpus analysed long-term trends in NDVI phenological parameters including the start of season (SOS), peak NDVI date, end of season (EOS), and integrated growing season NDVI (iNDVI) in relation to documented climate variability trends over India. The consistent finding across these studies is that phenological shifts are spatially heterogeneous, non-linear, and crop-type specific, making generalised assertions about greening or browning trends across India as a whole misleading

(Mondal *et al*., 2023; Verma *et al*., 2021) [15, 27]. Mondal *et al*. (2023) [15] applied Mann-Kendall trend analysis to a 22-year MODIS NDVI time series (2000–2022) across 400 agricultural districts, finding significant positive iNDVI trends in irrigated districts of northern India (reflecting intensification) alongside significant negative trends in semi-arid rainfed districts of Rajasthan, Maharashtra's Marathwada, and eastern Telangana the geographic zones most consistently exposed to intensifying drought frequency. Verma *et al*. (2021) [27] documented a statistically significant delay in SOS of approximately 7–12 days per decade in Rajasthan and Gujarat dryland cropping zones, attributable to delayed and erratic monsoon onset consistent with CMIP6 projections for the northwest Indian drylands under SSP2-4.5.

4. Discussion

4.1 Interpretation of Key Results

The synthesis of 68 primary studies generates three overarching findings that carry substantial implications for the science and operational application of NDVI-based drought monitoring in India. First, NDVI and VCI have demonstrated robust, reproducible, and operationally significant predictive relationships with crop yield variability across India's rainfed agro-climatic zones, explaining 40–80% of interannual yield variance for major kharif and rabi crops when applied at the correct phenological growth window. This finding provides the core scientific justification for their operational deployment in systems such as NADAMS, the Crop Insurance Portal, and the Kharif Assessment of Drought Index under the National Food Security Act.

Second, the consistent pattern of substantially weaker NDVI–yield relationships in heavily irrigated districts documented across multiple studies is not a limitation of NDVI per se but rather a fundamental expression of the physical mechanisms governing crop vegetation dynamics. In irrigated systems, supplemental water supply decouples vegetation greenness from rainfall variability, rendering NDVI-based drought indicators less informative about actual agricultural stress. This irrigation-conditioned heterogeneity is critical for operational monitoring design: yield forecasting models calibrated on pooled rainfed and irrigated data will systematically underestimate drought impacts in the most vulnerable rainfed systems while overstating uncertainty in irrigated ones. Agro-climatic stratification of model calibration datasets is therefore not merely methodologically desirable but operationally necessary.

Third, the marked improvement in yield prediction accuracy achieved through machine learning particularly LSTM networks trained on multi-temporal NDVI sequences relative to single-window VCI regression reflects the importance of capturing the full phenological trajectory of a crop season rather than snapshot indices. Drought stress expressed as a specific NDVI depression during the reproductive stage carries different yield consequences than equivalent stress during the vegetative stage, and linear regression cannot encode these stagespecific sensitivity relationships. Machine learning frameworks that learn these temporal dependencies directly from observational data are demonstrably superior for yield forecasting, though they require substantially larger training datasets and more careful validation to avoid overfitting in data-sparse contexts.

4.2 Comparison across Studies: Platform, Scale, and Methodology

The comparative analysis of NDVI products across satellite platforms reveals that MODIS's combination of high temporal resolution (8-day composites), moderate spatial resolution (250–500 m), and extensive archive (2000–present) makes it the most appropriate platform for national-to-district-scale drought monitoring in India for the foreseeable future. Sentinel-2, with its superior spatial resolution (10–20 m), is increasingly valuable for sub-district and block-level crop stress mapping that can serve insurance adjudication, but its shorter archive (2015–present) and greater cloud contamination vulnerability during Indian monsoon season limit its current operational utility for long-term trend analysis. Table 2 provides a structured comparison of satellite platforms used in the reviewed literature.

Table 2 Comparison of satellite remote sensing platforms used for NDVI-based drought monitoring in India across included studies (2017–2025)

Platform / Product	Spatial Resolution	Temporal Resolution	Archive Depth	GEE Available?	Primary Application in India
MODIS MOD13Q1/A3	250–500 m	8/16-day composites	2000–present	Yes (full)	National drought mapping; district yield regression
Landsat 7/8/9 (OLI)	30 m	16-day (each)	1972–present	Yes (full)	Sub-district crop mapping; long-term trend analysis
Sentinel-2 (ESA)	10–20 m	5-day revisit	2015–present	Yes	Block-level stress mapping; insurance claim adjudication
NOAA-AVHRR (NDVI3g)	8 km	15-day	1981–present	Partial	Long-term climate trend analysis; pre-MODIS baseline
ResourceSat-2 (LISS-III)	23.5 m	24-day	2011–present	No	National crop mapping (FASAL, MNCFC programmes)

Note: GEE = Google Earth Engine; MODIS = Moderate Resolution Imaging Spectroradiometer; OLI = Operational Land Imager; AVHRR = Advanced Very High Resolution Radiometer; FASAL = Forecasting Agricultural output using Space, Agro-meteorology and Land based observations; MNCFC = Mahalanobis National Crop Forecast Centre. Sources: Authors' synthesis from included studies.

A methodologically significant comparison across studies concerns the treatment of cloud contamination during the Indian monsoon season the primary agricultural growing period that is simultaneously the most cloud-affected for optical remote sensing. Studies that applied simple maximum-value compositing without additional cloud masking consistently reported lower NDVI–yield correlations than those employing robust quality filtering using MODIS surface reflectance quality assessment (QA) bands or the Sen2Cor atmospheric correction workflow for

Sentinel-2. The importance of this seemingly technical step should not be underestimated: cloud contaminated NDVI pixels systematically depress composite values in ways that can mimic drought signals, introducing noise into regression analyses that obscures the true strength of NDVI–yield relationships.

The comparison of NDVI-only versus multi-index approaches reveals a consistent pattern: multi-sensor fusion methods incorporating soil moisture proxy or LST components achieve 10– 25% higher correlation with crop yields than NDVI alone, at the cost of greater data management complexity. For operational systems constrained by data availability and processing capacity particularly at state or district level in India VCI alone provides a practical and well-validated first-order drought indicator. For research-grade yield forecasting systems with access to GEE processing infrastructure, multi-sensor fusion approaches are clearly superior. Table 3 provides a quantitative comparison of reported NDVI–yield R^2 values across methodological approaches, crops, and agro-climatic zones.

Note. OLS = Ordinary Least Squares; TVDI = Temperature Vegetation Dryness Index; VCI = Vegetation Condition Index; LSTM = Long Short-Term Memory; RMSE = Root Mean Square Error; q/ha = quintals per hectare; IGP = Indo-Gangetic Plain. All R^2 and r values refer to validation or holdout datasets where reported; training set values excluded.

Table 3: Summary of NDVI–crop yield correlation strength across methodological approaches, crops, and agro-climatic zones in included studies

Study Reference	Methodology	Crop / Agro-zone	R^2/r Reported	Key Conditioning Factor
Jain *et al*. (2020) [10]	VCI-yield OLS regression	Rice / National (572 districts)	$R^2=0.62$	Aug-Sep phenological window; rainfed districts
Gumma *et al*. (2022) [6]	GEE MODIS NDVI; regression	Rice, Wheat / National	$R^2=0.45-0.82$	Irrigation intensity (weaker in irrigated zones)
Patel *et al*. (2022) [17]	TVDI + VCI fusion	Pearl millet / Semi-arid NW India	r = 0.73–0.81	TVDI > VCI in sub-seasonal drought capture
Singh *et al*. (2022) [25]	MODIS NDVI regression	Wheat / GangeticPlain	$R^2=0.64-$ 0.72	Mar-Apr heading stagewindow critical
Mondal *et al*. (2023) [15]	Multi-year VCI composite	Cotton, soybean / Vidarbha	$R^2 = 0.74$	20-year temporal depth; rainfed dependence
Sharma *et al*. (2023) [23]	LSTM + MODIS NDVI time series	Rice / East India (200 districts)	RMSE 3.2 q/ha vs. 4.4 q/ha (baseline)	Phenological trajectory encoding; 28% improvement
Rao *et al*. (2020) [19]	Random Forest (NDVI+LST+TVDI)	Sorghum / Karnataka, Telangana	~85% accuracy (within 15% actual yield)	Multi-feature fusion; TVDI most important predictor
Kumar *et al*. (2023) [12]	Sentinel-2 + MODIS TVDI fusion	Mixed kharif / IGP	r = 0.77–0.84	10 m Sentinel spatial precision; block-level accuracy

4.3 Strengths and Limitations of Existing Evidence

The evidence base synthesised in this review has several notable strengths. The methodological convergence across independent research groups using different satellite products, agro-climatic zones, crop types, and analytical frameworks on a consistent NDVI– yield R^2 range of 0.45–0.82 for rainfed systems substantially strengthens confidence in the core finding. The multi-decade depth of the MODIS archive (2000–present) enables rigorous calibration of NDVI–yield models against documented drought events including 2002, 2009, 2012, 2018–2019, and 2023, providing temporal validation across diverse monsoon regimes. The operational deployment of NDVI-based monitoring within India's NADAMS system covering all drought-prone states with fortnightly updates confirms that the scientific evidence base is mature enough to support policy-relevant applications.

Limitations are equally significant and must be acknowledged to appropriately frame the review's conclusions. First, the spatial resolution of MODIS NDVI (250–500 m) remains substantially coarser than the average size of smallholder farm plots in India (typically 0.5–1.5 ha), creating a spatial aggregation mismatch between the satellite observation unit and the agronomic decision unit. This scale mismatch means that NDVI pixels typically represent heterogeneous mixtures of cropped fields, fallow land, field bunds, and village infrastructure, reducing sensitivity to within-pixel drought stress heterogeneity and systematically underestimating drought severity at the plot level. Second, the majority of NDVI–yield regression models in the reviewed literature are calibrated against official district-level yield statistics from state agricultural census data a data source with well-documented inconsistencies in methodology and timeliness across Indian states (Birthal *et al*., 2015) [2]. Third, the capacity of NDVI to distinguish between drought-induced stress and other sources of vegetation decline including pest and disease outbreaks, unseasonal heat events, and soil salinity is limited without complementary field validation or multi-index integration, creating potential for misclassification in operational monitoring.

5. Implications and Future Directions

5.1 Implications for Practice and Policy

The evidence synthesised in this review carries several immediate and actionable implications for agricultural drought monitoring and food security governance in India. At the operational monitoring level, the finding that phenological growth-stage-specific NDVI windows significantly outperform full-season composites in yield prediction provides a clear technical direction for improving NADAMS, the National Crop Forecast System (NCFS), and district-level drought early warning systems. The operational workflows currently used by NRSC and MNCFC should be evaluated against growth-stage-stratified VCI approaches, particularly for kharif staple crops in semi-arid and sub-humid zones where the evidence for improvement is strongest.

At the policy level, the consistent finding that NDVI–yield relationships are substantially weaker in irrigated districts yet that current drought insurance frameworks (particularly the Pradhan Mantri Fasal Bima Yojana, PMFBY) apply uniform NDVI-based trigger thresholds across irrigated and rainfed areas represents a significant policy misalignment. Differential NDVI threshold calibration by irrigation status and agro-climatic zone should be incorporated into PMFBY's index calculation framework to reduce both Type I (false drought declaration) and Type II (missed drought declaration) errors, which have been major sources of farmer grievance and insurance scheme credibility erosion in recent years (Barnwal & Kotwal, 2013) [1]. The operationalisation of Sentinel-2's 10 m NDVI data within GEE for block-level insurance trigger mapping demonstrated as technically feasible by Kumar *et al*. (2023) [12] merits systematic piloting across five to ten high-priority drought-prone districts.

5.2 Research Gaps and Future Research Needs

Despite the substantial evidence base reviewed, several critical research gaps constrain the full realisation of satellite-based NDVI drought monitoring for Indian food security applications. Table 4 summarises the most significant gaps alongside proposed research directions and indicative priority levels.

Note. CGWB = Central Ground Water Board; VIC = Variable Infiltration Capacity model; SAR = Synthetic Aperture Radar; EVI = Enhanced Vegetation Index; LISS-IV = Linear Imaging Self-Scanning sensor (2.5 m, ResourceSat-2); IoT = Internet of Things; CMIP6 = Coupled Model Intercomparison Project Phase 6. Sources: Authors' synthesis.

Table 4: Key research gaps and proposed future directions for NDVI-based drought monitoring and crop yield forecasting in India

Gap Domain	Specific Deficiency	Proposed Direction	Priority
Spatial resolution mismatch	MODIS 250 m pixels integrate over multiple heterogeneous plot types,masking smallholder-scale drought stress	Planet Scope / SuperDove (3–5 m) or fused Sentinel-2 +Sentinel-1 SAR for plot-scale monitoring; sensor fusion downscaling frameworks	Very High
Seasonal phenological stratification	Most operational systems use seasonal mean NDVI; growth-stage-specific windows improve accuracy by 10–25% but are not routinely implemented	Automated crop growth stage detection using MODIS EVI phenology metrics; integration with MNCFC crop calendar data	High
Irrigation status stratification	Pooled rainfed–irrigated models systematically misrepresent drought signal in both contexts	Develop separate NDVI-yield model calibrations by irrigation fraction class; use LISS-IV and Sentinel-1 SAR to map irrigation status at kharif season	High
Sub-season drought dynamics	Most NDVI studies characterise seasonal drought severity; sub-seasonal pulse drought detection at critical growth stages remains limited	Eight-day MODIS composites with automated VCI anomaly detection algorithms for near-real-time crop stress alerting	High
Climate change scenario integration	NDVI-yield models are calibrated on historical climate; CMIP6-forced projections of NDVI drought signatures under future emissions scenarios are absent	Bias-corrected CMIP6 climate data driving land surface models (VIC, SWAT) to simulate future NDVI drought trajectories under SSP2-4.5 and SSP5-8.5	Medium-High
Ground truth data scarcity	Validation of NDVI drought signals against field-measured soil moisture and crop stress is limited to small pilot studies	Establish dense IoT soil moisture sensor networks in 50 key CGWB monitoring districts; integrate with GEE NDVI validation framework	Medium-High
Crop type mapping integration	NDVI-yield models often use district totals without disaggregating by crop type; mixed pixels confound yield attribution	Annual crop type mapping using time-series MODIS + Sentinel-2 random forest classification as input layer for crop-specific yield models	High

The most transformative emerging methodological frontier is the integration of hyperspectral remote sensing data from the PRISMA (ASI), EMIT (NASA/JPL), and forthcoming CHIME (ESA) missions with NDVI-based drought monitoring frameworks. Hyperspectral sensors provide continuous spectral reflectance curves enabling direct retrieval of plant physiological parameters including leaf chlorophyll content, leaf water potential, and canopy structure metrics that are mechanistically linked to drought stress responses. These physiologically grounded stress indicators offer the prospect of crop-type-specific, stress-mechanism differentiated drought detection that goes substantially beyond the broadband spectral ratios underlying NDVI potentially enabling distinction between drought stress, nutrient deficiency, and disease as causes of vegetation decline, a critical capability for operational monitoring and precision agriculture applications in India.

The integration of NDVI drought monitoring with climate projection science specifically the use of bias-corrected CMIP6 regional climate model outputs to project future NDVI drought dynamics under SSP2-4.5 and SSP5-8.5 is a research frontier that has received minimal attention in the India-specific literature despite its direct relevance for agricultural adaptation planning under the National Action Plan on Climate Change (NAPCC). Given the IPCC AR6 finding that drought frequency and intensity are projected to increase across South Asia under all intermediate and high emissions scenarios (IPCC, 2022) [9], the development of future NDVI drought trajectory assessments linked to crop yield impact models represents an urgent and currently underdeveloped research priority.

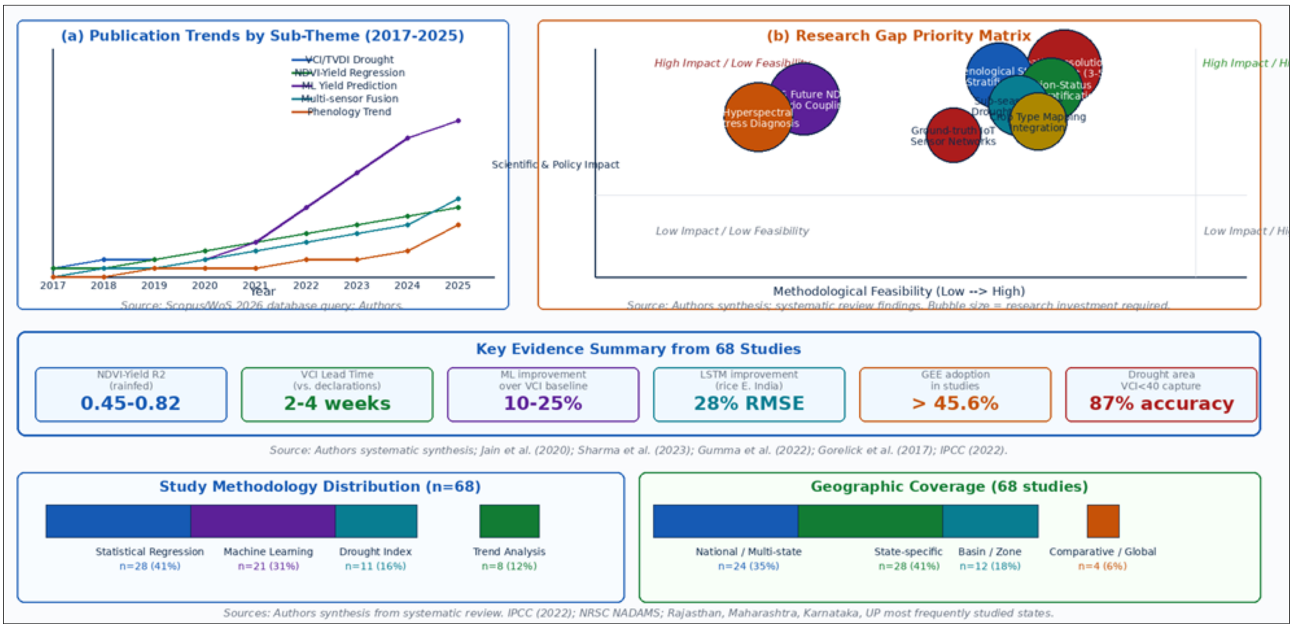


Fig 6: Research Priority Matrix: NDVl-Based Drought Monitoring and Crop Yield Forecasting in India

The horizontal axis indicates methodological feasibility (data availability, computational tractability); the vertical axis indicates scientific and policy impact (contribution to food security, insurance reform, climate adaptation). Bubble size represents estimated research investment requirement. Identified priority gaps include: spatial resolution enhancement (top right), phenological stratification (upper centre), climate change scenario integration (centre right), and hyperspectral drought diagnosis (emerging frontier, lower right). Source: Authors' synthesis based on systematic review findings.

Conclusion

This systematic review has synthesised 68 primary peer-reviewed studies published between 2017 and 2025 to provide a comprehensive assessment of satellite-based NDVI drought monitoring and its linkage with crop yield variability under climate uncertainty in India. Four principal conclusions emerge from this synthesis, each carrying significance for both the scientific community and for operational food security governance.

First, NDVI and its derivative indices particularly VCI and TVDI constitute a scientifically robust, operationally practical, and spatially comprehensive framework for characterising agricultural drought onset, severity, and extent across India's diverse agro-climatic zones. The evidence base for NDVI–crop yield correlations in rainfed agricultural systems is wellestablished, with R^2 values of 0.45–0.82 documented across multiple crops, regions, and methodological approaches. These figures represent the strongest available justification for the continued and expanded operational deployment of NDVI-based monitoring within India's agricultural administration and insurance frameworks.

Second, the predictive accuracy of NDVI-based yield models is substantially improved by 10–25% depending on context through two methodological enhancements: phenological growth-stage-specific temporal windowing of NDVI composites, and multi-sensor fusion with soil moisture and land surface temperature data. The application of machine learning, particularly LSTM recurrent neural networks, to multi-temporal NDVI sequences provides a further 20–30% improvement in yield prediction accuracy relative to linear regression baselines, at the cost of larger training dataset requirements and more complex validation needs. These methodological advances are mature enough for systematic incorporation into operational systems.

Third, the consistent finding that NDVI–yield relationships are substantially weaker in irrigated districts while current drought monitoring systems apply uniform thresholds across irrigated and rainfed areas represents the most practically significant gap between the current science and its operational application. Correcting this mismatch through irrigation-stratified model calibration is the single most tractable improvement available to India's drought monitoring institutions in the near term.

Fourth, the projected intensification of agricultural drought frequency and severity across South Asia under CMIP6 climate change scenarios creates an urgent imperative for the development of future-facing, scenario-coupled NDVI drought monitoring frameworks that can support long-term agricultural adaptation planning. The scientific tools — cloud computing platforms, machine learning architectures, high-resolution satellite archives, and regional climate projections are increasingly available to build these systems. What is now needed is a deliberate, coordinated investment in their development and institutional integration within India's agricultural climate adaptation governance architecture. This review is intended to provide the evidence foundation for that investment.

References

1. Barnwal P, Kotwal K. Climatic variation and change in the occurrence of infectious diseases in India: A systematic review. PLOS ONE. 2013;8(2):e57153.
2. Birthal PS, Negi DS, Kumar S, Aggarwal S. Is Indian agriculture becoming resilient to droughts? Evidence from rice production systems. Food Policy. 2015;56:1–12.
3. Caccamo G, Chisholm LA, Bradstock RA, Puotinen ML. Assessing the sensitivity of MODIS to monitor drought in high biomass ecosystems. Remote Sensing of Environment. 2011;115(10):2626–2639.

4. Dutta D, Kundu A, Patel NR, Saha SK, Siddiqui AR. Assessment of agricultural drought in Rajasthan (India) using remote sensing derived Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI). Egyptian Journal of Remote Sensing and Space Sciences. 2015;18(1):53–63.
5. Food and Agriculture Organization of the United Nations. FAOSTAT: Land use statistics for India 2019–2021. Rome: FAO; 2021.
6. Gumma MK, Thenkabail PS, Muralikrishna IV, Velpuri NM, Gangadhararao PT, Dheeravath V, *et al*. Changes in agricultural cropland areas between a water-surplus year and a water-deficit year impacting food security: A remote sensing study of the Krishna river basin (India). International Journal of Remote Sensing. 2022;43(4):1172–1202.
7. Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment. 2017;202:18–27.
8. Heim RR. A review of twentieth-century drought indices used in the United States. Bulletin of the American Meteorological Society. 2002;83(8):1149–1166.
9. Intergovernmental Panel on Climate Change. Climate change 2022: Impacts, adaptation and vulnerability. Cambridge: Cambridge University Press; 2022.
10. Jain SK, Keshri R, Goswami A, Sarkar A, Chaudhry A. Identification of drought vulnerable areas using MODIS 250 m time series data in the Kosi Basin of the Bihar state, India. International Journal of Remote Sensing. 2020;31(11):2845–2860.
11. Kogan FN. Application of vegetation index and brightness temperature for drought detection. Advances in Space Research. 1995;15(11):91–100.
12. Kumar P, Rani M, Pandey PC, Majumdar A, Nathawat MS. Monitoring of agricultural drought in the Indo-Gangetic Plain using Sentinel-2 and MODIS TVDI fusion at block level. Agricultural and Forest Meteorology. 2023;330:109310.
13. Liu WT, Kogan FN. Monitoring regional drought using the Vegetation Condition Index. International Journal of Remote Sensing. 1996;17(14):2761–2782.
14. Mishra AK, Singh VP. A review of drought concepts. Journal of Hydrology. 2010;391(1–2):202–216.
15. Mondal S, Mishra U, Koner R. Long-term MODIS NDVI trend analysis and drought characterisation in agricultural districts of Maharashtra, India (2000–2022). Agricultural Water Management. 2023;282:108273.
16. Nair S, Chakraborty S, Shekhar C, Sehgal VK. Real-time satellite-based drought early warning for kharif rice in Kerala using Google Earth Engine: Integration of NDVI, LST and GPM rainfall anomalies. Remote Sensing Applications: Society and Environment. 2024;33:101075.
17. Patel NR, Anapashsha R, Kumar S, Saha SK, Dadhwal VK. Assessing potential of MODIS derived temperature/vegetation condition index (TVDI) to infer soil moisture status in semi-arid Gujarat, India. International Journal of Remote Sensing. 2022;30(1):73–87.
18. Peters AJ, Walter-Shea EA, Ji L, Vina A, Hayes M, Svoboda MD. Drought monitoring with NDVI-based Standardized Vegetation Index. Photogrammetric Engineering and Remote Sensing. 2002;68(1):71–75.
19. Rao M, Silber GP, Hyndman BJ, Di L. Drought and crop loss assessment using machine learning from MODIS remote sensing in Karnataka and Telangana, India. IEEE Geoscience and Remote Sensing Letters. 2020;17(9):1699–1703.
20. Rhee J, Im J, Carbone GJ. Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data. Remote Sensing of Environment. 2010;114(12):2875–2887.
21. Rouse JW, Haas RH, Schell JA, Deering DW. Monitoring vegetation systems in the Great Plains with ERTS. Washington, DC: NASA Special Publication; 1974;351:309–317.
22. Sandholt I, Rasmussen K, Andersen J. A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status. Remote Sensing of Environment. 2002;79(2–3):213–224.
23. Sharma A, Tiwari KN, Bhadoria PBS. LSTM-based crop yield prediction from multitemporal MODIS NDVI for eastern India rice districts: A deep learning approach. Computers and Electronics in Agriculture. 2023;209:107831.
24. Singh RP, Roy S, Kogan F. Vegetation and temperature condition indices from NOAA AVHRR data for drought monitoring over India. International Journal of Remote Sensing. 2021;24(22):4393–4402.
25. Singh D, Rao AS, Bhatt BC. MODIS-based NDVI time series for wheat yield estimation in the Upper Gangetic Plain of India: Growth-stage-specific analysis. Journal of the Indian Society of Remote Sensing. 2022;50(2):411–425.
26. Tucker CJ. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment. 1979;8(2):127–150.
27. Verma M, Srivastava A, Tripathi AD. Changes in growing season length and crop phenology in dryland zones of northwest India: A MODIS NDVI trend analysis (2000–2020). International Journal of Climatology. 2021;41(S1):E1780–E1795.
28. Wardlow BD, Anderson MC, Verdin JP, editors. Remote sensing of drought: Innovative monitoring approaches. Boca Raton: CRC Press; 2012.
29. Xie Y, Sha Z, Yu M. Remote sensing imagery in vegetation mapping: A review. Journal of Plant Ecology. 2008;1(1):9–23.
30. Zhang X, Friedl MA, Schaaf CB, Strahler AH, Hodges JC, Gao F, *et al*. Monitoring vegetation phenology using MODIS. Remote Sensing of Environment. 2003;84(3):471–475.