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CLIMATE CHANGE, LAND USE TRANSFORMATION AND VEGETATION DYNAMICS IN INDIA A SPATIAL-TEMPORAL ASSESSMENT OF ECOSYSTEM VULNERABILITY USING GIS, REMOTE SENSING AND CLIMATE DATA

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Abstract:

India's vegetation systems are shaped by the interaction of climate variability, long-term warming, land-use and land-cover change (LULCC), disturbance regimes, and uneven adaptive capacity. These pressures differ sharply among the Himalaya, north-eastern forests, central Indian dry and moist deciduous landscapes, the Western Ghats, the Indo-Gangetic Plain, arid western India, and coastal/mangrove ecosystems. This paper synthesizes published national evidence and sets out a reproducible geospatial framework for assessing ecosystem vulnerability through multi-temporal satellite observations and climate datasets. The evidence base includes India's reported warming of approximately 0.7°C during 1901–2025; an approximately 75% rise in the frequency of daily precipitation extremes exceeding 150 mm during 1950–2025; the Forest Survey of India's 2023 estimate of 827,357 km² of forest and tree cover (25.17% of national geographical area); and a national remote-sensing study that mapped a decline in forest-class share from 23.25% in 1985 to 22.18% in 2005 alongside an increase in cropland and built-up land. These measures describe different periods and classification systems and must not be treated as a single continuous time series. The proposed workflow integrates Landsat surface reflectance, MODIS vegetation indices, ISRO/NRSC land-cover products, gridded rainfall, and ERA5-Land climate variables. It combines cloud-screened seasonal composites, supervised land-cover classification, NDVI/EVI/NDMI indicators, change-transition matrices, robust trend estimation, and a transparent vulnerability index based on exposure, sensitivity, and adaptive capacity. The paper argues that greenness trends alone are insufficient: a rise in tree cover or NDVI may coexist with native-forest loss, plantation expansion, fragmentation, altered seasonality, or biodiversity decline. Effective assessment therefore requires ecosystem-specific thresholds, independent validation, and explicit uncertainty reporting. The framework can support climate adaptation, landscape restoration, forest planning, and nature-based solutions, while clearly distinguishing published findings from analysis that remains to be performed.

Keywords: *climate change, land-use/land-cover change, vegetation dynamics, NDVI, GIS, remote sensing, ecosystem vulnerability, India, Landsat, climate datasets.*

1. Introduction:

Vegetation is both a responder to climatic conditions and an active component of the climate system. Through photosynthesis, transpiration, surface roughness, shading, litter inputs and soil protection, vegetation influences carbon storage, energy exchange, evapotranspiration, runoff, erosion and habitat availability. The amount, structure, composition and seasonal timing of vegetation therefore matter as much as the area mapped as green. Where climate change coincides with conversion or fragmentation of natural habitats, ecosystem resilience may decline even if a national tree-cover statistic appears stable or increases in some landscapes.

India is a particularly important setting for integrated vegetation assessment. Its environmental gradients extend from high-elevation Himalayan terrain to semi-arid and arid landscapes, humid tropical forests, monsoon-fed agricultural plains, coastal wetlands and islands. The annual monsoon controls water availability and plant phenology across much of the country, while temperature, elevation, soils, irrigation, fire, grazing, extraction, infrastructure and land management create strong local contrasts. Consequently, a single national average cannot adequately describe changes in ecosystem condition or vulnerability. The Ministry of Earth Sciences assessment led by Krishnan and colleagues reports that India's surface air temperature rose by about 0.7°C over 1901–2018. It also reports a substantial increase in the frequency of daily precipitation extremes above 150 mm during 1950–2015 and an increase in the frequency and spatial extent of droughts over 1951–2015 (Krishnan et al., 2020; Ministry of Earth Sciences, 2023). These pressures can alter soil moisture, evapotranspiration, disturbance and growing-season duration, but their ecological effect depends on ecosystem type and local land management.

Land-use transformation introduces a second, interacting pressure. Cropland expansion, settlement growth, road construction, mining, reservoirs, plantations, fire and other land-management practices can remove habitat, simplify vegetation structure or divide formerly connected landscapes. Nationally aggregated land-cover classes may hide such changes: an increase in planted trees is not necessarily equivalent to recovery of native forest, and stable class area does not guarantee stable biomass, species composition or ecological function. Remote sensing provides the repeated observations needed to examine these dimensions across space and time, but results remain dependent on resolution, seasonal timing, class definitions and validation. This article has two linked aims. First, it consolidates published evidence on climate and land-cover change in India, taking care not to conflate unlike datasets or definitions. Second, it specifies an auditable GIS and remote-sensing workflow for a subsequent spatio-temporal assessment of vegetation dynamics and ecosystem vulnerability. The distinction matters: a methodological framework can be rigorous without claiming that satellite scenes have already been classified. The workflow is designed to be implementable in Google Earth Engine, QGIS, Python or equivalent platforms.

2. Conceptual framework and literature synthesis:

2.1 Climate forcing and vegetation response:

Vegetation responses to climate are mediated by temperature, precipitation amount and timing, atmospheric dryness, soil moisture, radiation and disturbance. Warming may lengthen growing seasons in some cold regions, increase potential evapotranspiration, intensify heat stress, or raise fire risk in others. A shift in monsoon onset or rainfall concentration may affect crop calendars and forest regeneration even if annual rainfall changes little. Climatic effects may also operate with a lag: a dry year can reduce current-season greenness while repeated droughts affect recruitment, mortality and woody cover over several years.

Satellite vegetation indices are useful indicators of canopy greenness and seasonal dynamics. NDVI, defined as the normalised difference between near-infrared and red reflectance, has a long history in vegetation monitoring (Tucker, 1979). EVI can reduce some atmospheric and canopy-background influences, while NDMI-type metrics help characterise relative canopy moisture. Such indices are proxies derived from reflectance rather than direct measurements of biodiversity, net primary productivity or ecosystem health (Pettorelli et al., 2005). Dense canopies can cause NDVI saturation, bare soils can affect sparse-cover observations, and a greener signal can reflect irrigation, crop intensification or plantations rather than natural ecosystem recovery.

2.2 Land-use transformation and landscape pattern:

LULCC is not only a change in the quantity of each class; it is also a change in spatial arrangement. A forest patch can shrink, become elongated, acquire new edges or lose connectivity without a large national change in total forest area. Fragmentation can alter microclimates, seed dispersal, movement pathways, edge exposure and susceptibility to fire or invasive species. Change matrices are therefore more informative than comparing two maps independently: they identify transitions such as forest-to-cropland, forest-to-built-up, grassland-to-cropland, or degraded land-to-secondary vegetation.

Roy et al. (2015) produced a decadal national land-use/land-cover database for 1985, 1995 and 2005 using multi-season satellite imagery and supporting information. Their mapped forest-class share declined from 23.25% to 22.18% between 1985 and 2005, while cropland share rose from 47.55% to 49.34% and built-up/urban share from 1.03% to 1.44%. This is strong evidence of historical land-cover transformation within that particular classification framework. It should not be compared directly with the Forest Survey of India's later forest-cover estimates without accounting for definitions, spatial resolution, mapping methods and reference dates.

2.3 National Forest statistics and comparability:

The India State of Forest Report 2023 (FSI, 2024) estimates total forest and tree cover at 827,357 km², or 25.17% of India's geographical area. It separates 715,343 km² of forest cover

(21.76%) from 112,014 km² of tree cover outside the forest-cover category (3.41%). Compared with 2021, the combined total increased by 1,445 km²; the report attributes 156 km² to the forest-cover component and 1,289 km² to tree cover. These are official assessment statistics under FSI's mapping definitions, not direct measures of primary-forest condition, habitat quality or native species richness. The rise in aggregate cover does not negate local degradation or fragmentation, and the difference in class definitions must be acknowledged when integrating FSI with Landsat-derived classes.

2.4 Emerging evidence on forest–savanna dynamics:

A recent study by Dubey, Chauhan and Ghosh (2026) examines tree-cover patterns and hydroclimatic controls across India. For 2001–2020, it reports a decline in the proportion of landscape grids with non-zero tree cover from about 30% to about 27%, alongside shifts in the composition of low-tree-cover, savanna-like and forest-like grid classes. The authors define savanna as 10–40% tree cover and forest as more than 40% for their statistical analysis. These thresholds are specific to the study and are not equivalent to FSI forest-cover definitions. Their future scenario analysis suggests a greater likelihood of forest-to-savanna-like shifts in some regions under strong warming, conditional on model assumptions. This finding illustrates the importance of analysing vegetation structure and climate relationships, rather than relying only on area totals.

2.5 Why an integrated assessment is needed:

The literature points to four methodological requirements. First, satellite data must be temporally harmonised and compared within comparable seasons. Second, climate and land use should be modelled jointly, because the same rainfall anomaly may produce different vegetation responses in intact forest, cropland, plantations or fragmented forest. Third, vulnerability should include exposure, sensitivity and adaptive capacity rather than equating low NDVI with high vulnerability. Fourth, any derived map must report classification accuracy, spatial scale and uncertainty. The conceptual interactions are summarised in Figure 1.

Conceptual model: coupled climate-land use-vegetation dynamics

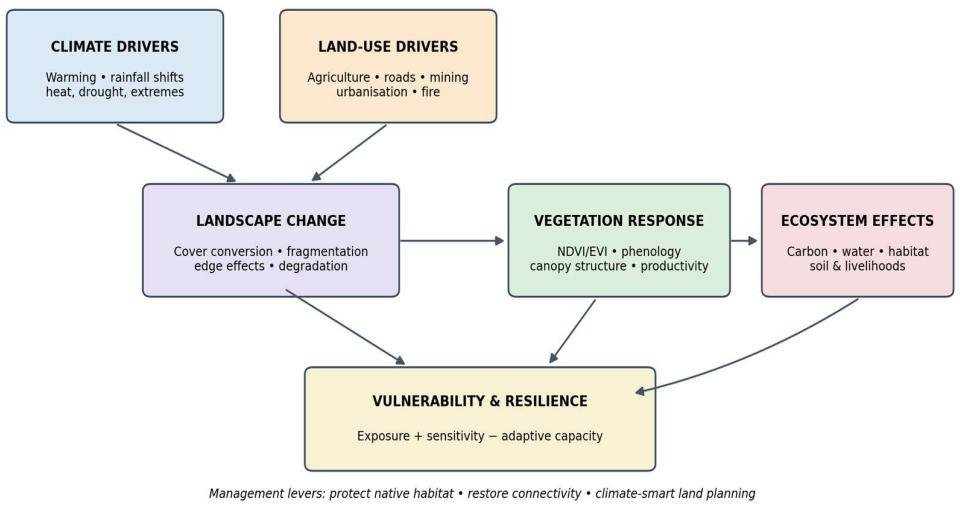

Figure 1. Conceptual relationships among climatic forcing, land-use drivers, vegetation response, ecosystem effects and vulnerability. The framework is conceptual rather than a fitted causal model.

3. Study area: India's eco-climatic diversity:

The proposed spatial extent is the Republic of India, including the mainland and island territories where consistent satellite and climate records are available. The study should use a single authoritative national boundary and should document how coastal buffers, open water and disputed/border areas are handled. For statistical summaries, India can be stratified by biogeographic zone, elevation, aridity, forest type, or a combination of these; state boundaries alone are not ecological units and should be used mainly for reporting and governance.

An operational assessment can begin with seven broad eco-climatic strata. (i) Himalayan and trans-Himalayan landscapes: elevation, snow and temperature gradients, slope aspect, landslides and treeline/phenology dynamics. (ii) North-eastern humid forests: high rainfall, diverse evergreen and semi-evergreen vegetation, shifting cultivation and infrastructure-related fragmentation. (iii) Central Indian Forest landscapes: dry and moist deciduous forests, mining, fire, grazing, agriculture and corridor fragmentation. (iv) Western Ghats: steep rainfall gradients, high endemism, plantation mosaics and road/settlement pressures. (v) Arid and semi-arid western India: sparse vegetation strongly controlled by rainfall pulses, soil texture, grazing and water availability. (vi) Indo-Gangetic and other intensively cultivated plains: crop phenology, irrigation, groundwater stress, wetlands and urban expansion. (vii) Coastal and island ecosystems: mangroves, tidal wetlands, dune systems and coastal forests exposed to sea-level rise, cyclones, sediment change and coastal conversion.

These strata are a practical analytical design, not an assertion that every pixel within a zone is uniformly vulnerable. For formal publication, researchers should cite the selected ecoregion boundary product, state its resolution and project it consistently with raster inputs. Analyses should be repeated at more than one spatial aggregation where feasible to test whether conclusions depend on boundary choice.

4. Research objectives, questions and hypotheses:

4.1 Objectives:

- Quantify the direction, magnitude and spatial distribution of vegetation-index and land-cover change across India over a consistent multi-decadal period.
- Distinguish climate-associated vegetation variability from changes associated with land conversion, fragmentation, irrigation, fire and other human pressures.
- Identify eco-climatic zones where exposure, ecological sensitivity and limited adaptive capacity combine to produce high potential vulnerability.
- Build a reproducible GIS/remote-sensing workflow with accuracy assessment, uncertainty reporting and clear data provenance.

- Translate the resulting evidence into ecosystem-specific conservation, restoration and climate-adaptation priorities.

4.2 Research questions:

- Where have forest, cropland, built-up land, shrubland and other vegetation classes expanded or contracted, and which transitions dominate?
- How do NDVI/EVI seasonal amplitude, peak greenness, start/end of season and moisture indicators vary across the selected periods?
- Are vegetation trends associated with temperature, rainfall totals, rainfall variability, drought indicators and land-cover transitions after controlling for seasonality?
- Which regions show the joint combination of high climatic exposure, high vegetation sensitivity and lower adaptive capacity?

4.3 Testable hypotheses:

H1: Regions with persistent warming and greater rainfall variability will show stronger negative vegetation or moisture trends where water limitation is already high, with the relationship differing by ecosystem and land management.

H2: Forest-to-built-up or forest-to-cropland conversion will be associated with increased fragmentation and reduced core habitat, even where regional mean greenness is stable.

H3: Climate–vegetation relationships will be stronger in water-limited ecosystems than in intensively irrigated areas, where human water management can decouple vegetation from rainfall.

H4: vulnerability rankings based on exposure alone will differ materially from rankings that include sensitivity, landscape connectivity and adaptive capacity. These hypotheses require testing; they are not treated as confirmed results in this synthesis.

5. Data sources, variables and temporal design:

A defensible national study should define a common reference period before downloading data. A practical design is 2001–2024 for MODIS time series and annual land cover, with a longer Landsat-based analysis (for example, 1985–2024) where sensor continuity, cloud coverage and classification consistency permit. Climate records can extend further back, but comparisons should be made over matched periods. The most recent year should be excluded if its annual composite is incomplete or if the data product is not yet final.

Data layer	Candidate product / provider	Nominal scale or resolution	Role in analysis / cautions
Land cover	ISRO/NRSC Bhuvan LULC; Landsat Collection 2 Level-2	Bhuvan LULC at 1:250,000; Landsat 30 m	LULC transition and regional reporting. Product class definitions differ; do not merge without crosswalk.

Data layer	Candidate product / provider	Nominal scale or resolution	Role in analysis / cautions
Surface reflectance	Landsat 5/7/8/9 Collection 2 Level-2, USGS	30 m; multiple revisit intervals	Long-term seasonal composites, LULC classification, NDVI/EVI/NDMI. Requires cloud/shadow/snow masking and sensor harmonisation.
Vegetation indices	MODIS MOD13Q1 / MOD13A1, NASA LP DAAC	250 m or 500 m; 16-day products	Consistent long time series since 2000; coarser than Landsat and may mix land-cover classes.
Forest reference	India State of Forest Report 2023, Forest Survey of India	National/state statistics and mapped products	Benchmark for interpretation; forest and tree-cover definitions must be retained.
Rainfall	India Meteorological Department gridded precipitation; optional CHIRPS for sensitivity test	Common IMD daily grid about 0.25° (product dependent); CHIRPS 0.05°	Rainfall totals, anomalies, monsoon timing, variability and drought metrics. Verify product version and period.
Temperature / land climate	ERA5-Land, Copernicus Climate Change Service	About 9 km native grid; hourly/monthly variables	Temperature, soil moisture and energy/water variables. Reanalysis estimates have uncertainty and are coarser than Landsat.
Topography	SRTM or another documented DEM	Typically 30 m	Elevation, slope, aspect and terrain controls; avoid treating DEM-derived factors as climate data.
Human pressure / protection	Roads, settlements, mining, fire, protected areas, population datasets	Dataset-specific	Sensitivity/adaptive-capacity context; years and positional accuracy must match study period.

Source notes: ISRO/NRSC describes national LULC products at 1:250,000 scale and multi-cycle 1:50,000 products; USGS distributes Landsat surface-reflectance products at 30 m; Copernicus describes ERA5-Land as a land reanalysis with approximately 9 km native resolution from 1950 onward (NRSC, n.d.; USGS, n.d.; C3S, n.d.). Product access, version, collection date and citation should be recorded in a data inventory.

5.1 Temporal harmonization:

Landsat observations should be grouped into comparable seasonal windows, ideally including a pre-monsoon/dry-season composite and a post-monsoon/peak-growing-season composite where

regional phenology supports such choices. A single month is not suitable for all of India. In agriculture, kharif and rabi calendars can cause strong NDVI differences unrelated to long-term ecosystem degradation. In the Himalaya, snow cover and phenological timing must be addressed explicitly; in arid regions, a post-rainfall composite can be dominated by short-lived annual plants. Each ecoregion therefore needs an a priori seasonal calendar and a documented sensitivity test.

Climate variables should be aggregated to the period and spatial support relevant to the vegetation response. Annual rainfall alone may conceal onset, dry-spell duration and intensity. Candidate metrics include monsoon rainfall anomaly, coefficient of variation, consecutive dry days, hot-day frequency, vapour-pressure deficit if available, and soil-moisture anomaly. When combining 30 m Landsat with 9 km ERA5-Land, the fine-scale vegetation data should be summarised to the climate grid or to ecologically meaningful polygons; resampling a coarse climate grid to 30 m does not create new climate information.

6. Methods: reproducible GIS and remote-sensing workflow:

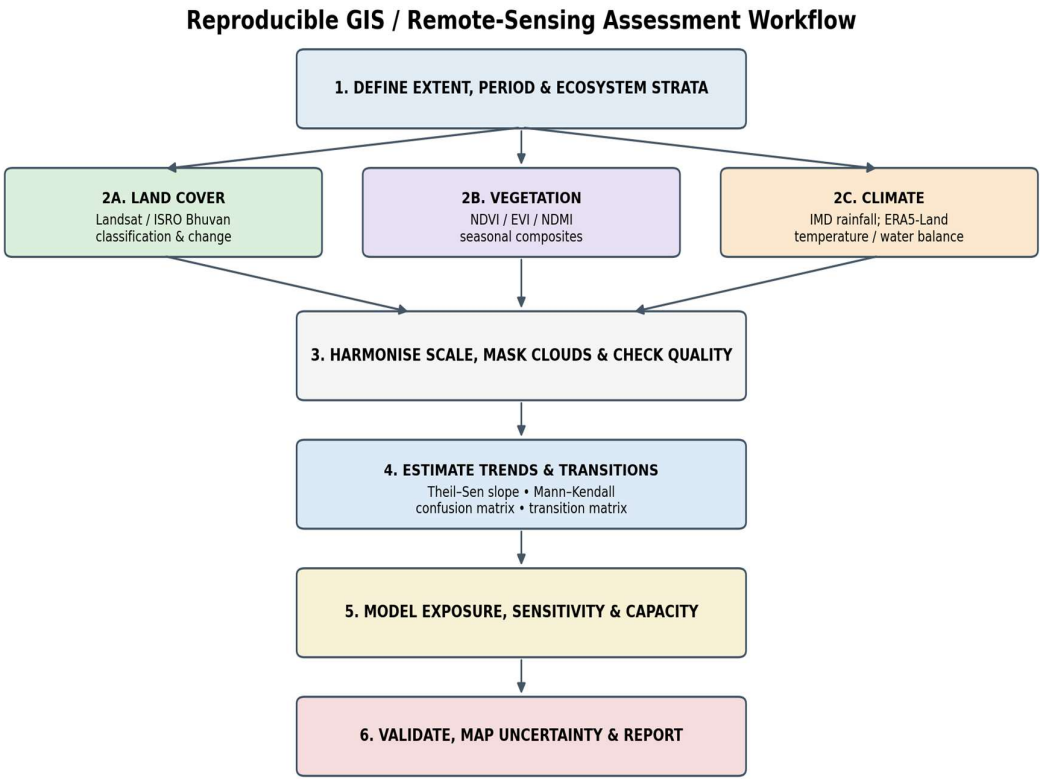

Figure 2. Data-processing and inference workflow. The workflow is proposed for implementation and validation; it is not a report of completed national raster processing.

6.1 Pre-processing and quality control:

All raster inputs should be clipped to a single study boundary, transformed to a documented coordinate reference system and aligned to a defined analysis grid. Landsat Level-2 surface reflectance must be converted using the scaling factors specified by USGS for the relevant sensor and collection.

Cloud, cloud-shadow, saturation and snow pixels should be masked using quality-assurance bands; Landsat 7 scan-line gaps must be handled through multi-date compositing rather than silently imputed. Median or medoid composites reduce transient cloud and outlier effects, but should be accompanied by valid-observation counts. Radiometric or cross-sensor consistency should be checked before interpreting trends across Landsat sensor transitions.

6.2 Vegetation indices and phenological metrics:

The primary greenness indicator is NDVI:

NDVI = (NIR − Red) / (NIR + Red)

EVI may be calculated where blue-band information and product-specific coefficients are available; a common form is EVI = 2.5 × (NIR − Red) / (NIR + 6 × Red − 7.5 × Blue + 1). NDMI-type moisture indices use near-infrared and short-wave infrared reflectance, commonly (NIR − SWIR) / (NIR + SWIR), subject to sensor bands and the chosen product definition. These indices should be computed from surface reflectance or a documented science product, not from raw digital numbers.

For each pixel or reporting polygon, useful summaries include seasonal median NDVI, annual maximum, seasonal amplitude, number of valid observations, interannual variability, start/end of season and anomaly from a fixed baseline. A negative trend in seasonal peak greenness may indicate stress or land change, while a change in amplitude or timing can reveal altered crop calendars or rainfall seasonality. If indices are aggregated across all land-cover classes, changes in the proportion of each class may drive apparent trends; class-stratified trends should therefore be reported as well as all-land averages.

6.3 Land-cover classification and change detection:

A supervised classifier such as Random Forest can classify a defined legend using multi-season surface reflectance, vegetation indices, terrain features and ancillary data. A practical Level-I legend could include: (1) forest/woodland, (2) shrub/grassland, (3) cropland, (4) built-up/bare surfaces, (5) water/wetland, and (6) snow/ice where relevant. Further classes should be introduced only when the available reference labels support reliable separation. Forest plantations should be separated from native forests when reference data permit; otherwise the merged class must be acknowledged as a limitation.

Training and validation samples must be independent and stratified across classes, ecological zones and change/no-change strata. Random splitting of neighbouring pixels can inflate apparent accuracy because spatially adjacent samples are not independent; spatially separated folds or block cross-validation are preferable. Report an error/confusion matrix, overall accuracy, class-level producer's and user's accuracy, F1 score, and area-adjusted class estimates with confidence intervals where possible. Kappa can be reported as a supplementary measure but should not replace class-specific errors (Congalton & Green, 2019).

For two maps, a transition matrix T should report the area moving from class i at time t1 to class j at time t2. Diagonal entries represent persistence; off-diagonal entries reveal conversion. The analysis should distinguish gross loss, gross gain and net change because similar net area can conceal substantial two-way turnover. Patch metrics—largest patch index, edge density, core area and a selected connectivity measure—can complement class area where landscape fragmentation is a primary question.

6.4 Trend detection and climate association:

For a time, series of annual or seasonal vegetation indicators, the Theil–Sen estimator provides a robust slope estimate based on the median of pairwise slopes. The Mann–Kendall test can assess monotonic trend, but serial autocorrelation and seasonality must be considered; modified tests, pre-whitening or block-bootstrap confidence intervals may be warranted. Trend magnitude, confidence interval and effective sample size should be reported, not only a p-value. Multiple testing across thousands of pixels requires false-discovery control or aggregation to avoid over-interpreting scattered significant cells.

Climate associations can be assessed with ecoregion-level regression, partial correlation, generalised additive models or mixed-effects models, depending on sample size and the question. Candidate predictors include temperature anomaly, rainfall anomaly, rainfall variability, soil moisture, fire incidence and LULC transition. Models should include seasonal terms and account for spatial dependence where feasible. A statistical association does not establish causation: land management, irrigation, grazing, fires and changes in sensor sampling can confound climate–vegetation relationships. Analyses should compare the full sample, stable land-cover pixels and changed pixels separately.

6.5 Ecosystem vulnerability index:

A transparent screening index may combine three dimensions, each normalised to 0–1: exposure (E), sensitivity (S) and inverse adaptive capacity (1−AC). With equal weights as an initial, explicitly provisional choice:

$V_i = wE \cdot E_i + wS \cdot S_i + wA \cdot (1 - AC_i)$, where $wE + wS + wA = 1$

If equal weights are used, $wE = wS = wA = 1/3$. Exposure indicators may include warming trend, heat extremes and rainfall/drought variability. Sensitivity indicators may include negative vegetation trend, high interannual variability, fragmentation, low habitat redundancy and fire/drought exposure. Adaptive-capacity proxies may include landscape connectivity, protected-area or community-conservation coverage, ecological corridors, restoration potential and locally available monitoring/governance capacity. Proxy choice depends on scale and data availability; protected-area coverage alone does not measure effective management or social capacity.

Each indicator should be oriented so that larger values consistently mean greater vulnerability,

normalised with an interpretable method, and checked for outliers. Correlated inputs should be screened to avoid counting the same signal several times. The resulting index is a relative prioritisation tool, not a direct probability of ecosystem collapse. Sensitivity analysis should compare equal weighting with alternative plausible weights and publish the component layers alongside the composite. Regions that remain high priority under multiple reasonable settings are more defensible candidates for intervention.

6.6 Reproducibility, validation and uncertainty:

An auditable project should archive the code, dataset identifiers, acquisition dates, masks, class legend, training/validation locations, random seeds, software versions, projection, resampling rule and all parameter settings. It should preserve intermediate cloud-free composites and observation-count layers, and export tables of area estimates and trend statistics. Uncertainty has several sources: mixed pixels, atmospheric contamination, class confusion, spatial resolution mismatch, non-stationary seasonality, climate reanalysis error, uncertain management data and sensitivity to thresholds. Reporting only a coloured vulnerability map is insufficient; uncertainty and data-quality layers are part of the result.

7. Evidence synthesis and reported national patterns:

7.1 Historical land-cover trends:

The national LULC database of Roy et al. (2015) provides one of the most explicit published benchmarks in the evidence base for this manuscript. From 1985 to 2005, the study's forest class declined by 34,881 km² (about 4.6% of its 1985 mapped area) and its share of national area decreased by 1.07 percentage points. Cropland increased by 56,209 km² (about 3.6% of its 1985 area), while built-up/urban land increased by 13,220 km² (about 38.9% of its 1985 area). These are calculations from the study's published table, not a newly generated classification. Differences in mapped areas and definitions mean they should be cited as results of that mapping exercise rather than treated as current estimates.

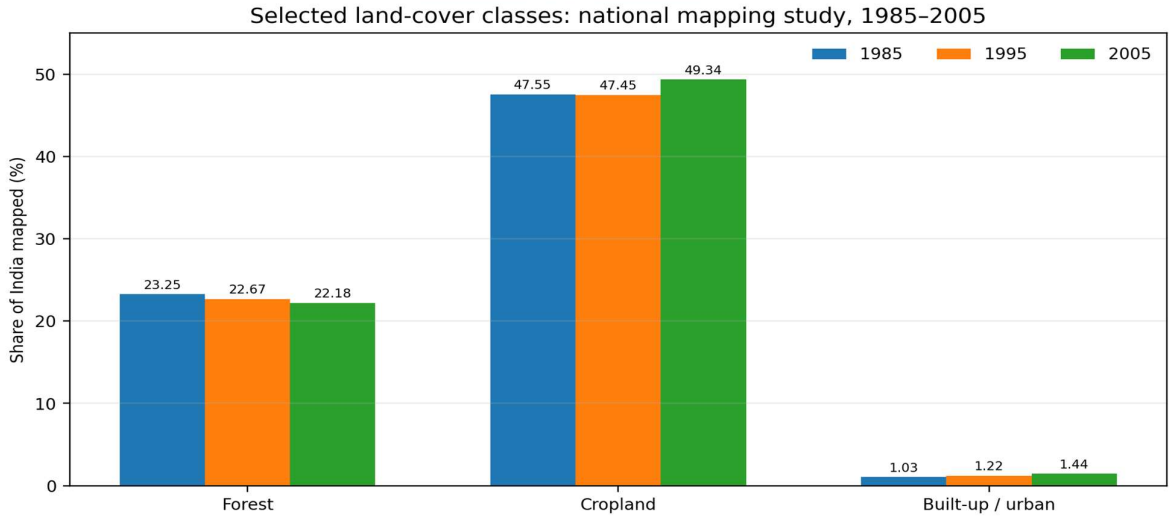

Figure 3. Selected class shares from Roy et al. (2015), based on their national 1985, 1995 and 2005 LULC maps. The classification is study-specific and should not be merged directly with FSI forest-cover statistics.

The direction of change reported in the 1985–2005 database is consistent with concern about agricultural intensification and built-up expansion, but it does not by itself attribute each transition to a specific driver. Attribution requires transition locations, time-matched socio-economic and infrastructure data, and spatial modelling. Nor should the national result be read as implying that every Indian region lost forest: aggregate decline can coexist with local regrowth, plantation expansion and gains in some classes.

7.2 Official forest and tree-cover estimates:

FSI's 2023 assessment estimates 715,343 km² of forest cover and 112,014 km² of tree cover, for a combined 827,357 km² or 25.17% of national geographical area. Between the 2021 and 2023 assessments, the combined total rose by 1,445 km². Tree cover outside the forest-cover category accounted for most of this increment. Such statistics are valuable national reporting benchmarks; nevertheless, the distinction between forest-cover and tree-cover classes is important. The indicator does not alone disclose native species composition, patch connectivity, plantation share, degradation, age structure or the degree to which ecosystems withstand climate extremes.

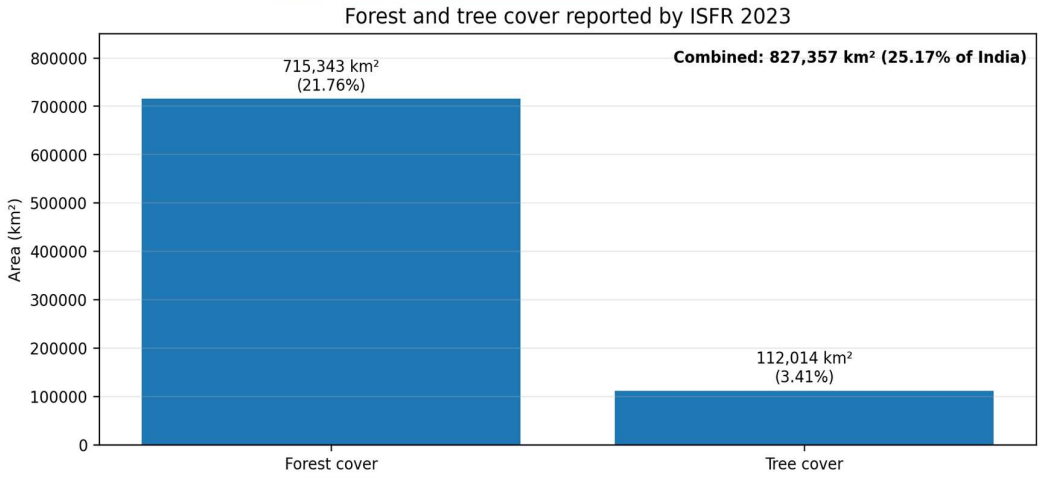

Figure 4. Forest cover and tree cover components reported in India State of Forest Report 2023. Source: Forest Survey of India (2024).

7.3 Climate indicators relevant to vegetation:

The MoES regional climate assessment documents long-term warming and changes in extremes with direct relevance to vegetation water balance. It reports approximately 0.7°C warming in India during 1901–2018, about a 75% rise in the frequency of daily precipitation extremes above 150 mm during 1950–2015, and a significant increase in drought frequency and spatial extent during 1951–2015. It also reports North Indian Ocean sea-level rise of roughly 3.3 mm per year over 1993–

2017. The metrics have different periods, domains and units and are shown as separate indicators in Figure 5, not as directly comparable values.

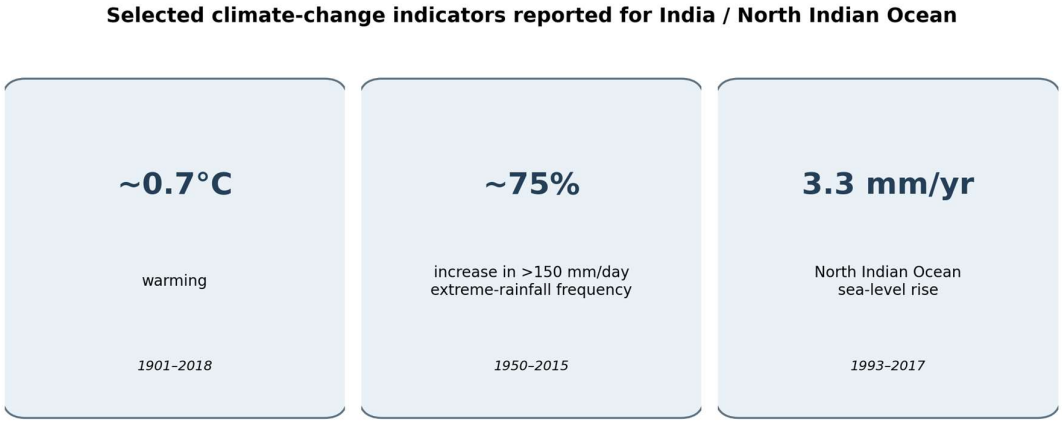

Figure 5. Selected reported climate-change metrics for India and the North Indian Ocean. Each panel retains its own unit and reference period; the values are not directly comparable as a common scale.

These climatic signals establish a plausible pressure context but do not prove that a specific vegetation trend was caused by climate change. Attribution requires consistent vegetation and climate time series, controls for land-cover conversion and management, and an explicit uncertainty model. A useful follow-on analysis would test whether vegetation response varies with rainfall anomalies, temperature, soil moisture and land-cover persistence within each ecological stratum.

7.4 Evidence from vegetation structure and forest–savanna transitions:

The 2026 Communications Earth & Environment study by Dubey et al. underlines that "tree cover" can represent multiple structural states. Its analysis reports that the proportion of grid cells with non-zero tree cover fell between 2001 and 2020, even as the within-tree-cover composition shifted away from low-cover classes toward its statistical forest and savanna classes. In that article, the 10–40% and above-40% canopy thresholds were analytical definitions, not legal or FSI classes. The results therefore demonstrate why a single national aggregate can hide divergent structural transitions. For field-based ecology, the relevant test is whether such shifts correspond to native forest condition, woody encroachment, degradation, regeneration or a different ecosystem state.

Evidence summary Table

Evidence stream	Reported result	What it supports	What it does not establish
India climate assessment	~0.7°C surface-air warming, 1901–2018	National exposure context for vegetation monitoring	A causal effect on an individual forest pixel
Extreme precipitation / drought	~75% rise in >150 mm/day daily extreme frequency, 1950–2015; drought	Need to examine rainfall variability, dry spells and disturbance	Uniform wetting or drying across all of India

	frequency and extent increased 1951–2015		
National LULC map, 1985–2005	Forest class share 23.25% to 22.18%; cropland 47.55% to 49.34%; built-up 1.03% to 1.44%	Historical mapped transition pressure	Direct comparison with FSI classes without harmonisation
ISFR 2023	Forest + tree cover 827,357 km² (25.17%); +1,445 km² relative to 2021	Official reference for national forest/tree-cover reporting	Complete measure of native-forest quality, connectivity or resilience
Forest–savanna tree-cover study, 2001–2020	Tree-cover-grid share with non-zero cover about 30% to 27%; structural classes shifted under the study's thresholds	Need for canopy-structure analysis and climate interactions	A direct substitute for national FSI forest-cover statistics

8.Regional ecosystem vulnerability: a screening synthesis-

A national assessment must allow ecological mechanisms to differ by region. The following matrix is a qualitative screening framework based on known eco-climatic exposure pathways and the cited national climate/LULC evidence. It is not a spatially validated vulnerability ranking. Formal rankings should be derived only after indicators are calculated, normalised and checked against independent ecological evidence.

Eco-climatic stratum	Potential exposure / pressure	Vegetation response to monitor	Priority validation / management focus
Himalaya and trans-Himalaya	Warming; snow/soil-moisture shifts; extreme rainfall; slope disturbance	Phenology, treeline/upper-elevation shifts, NDVI/EVI seasonality, landslide/fire scars	Elevation-stratified ground plots; protect elevational connectivity and native regeneration
North-east humid forests	Rainfall variability; roads/settlements; extraction; shifting cultivation mosaics	Forest fragmentation, evergreen canopy moisture, edge effects, secondary growth	Independent forest-type samples; retain corridors and community-managed native forest
Central Indian forests	Heat/drought; fire; mining; agricultural expansion; grazing	Dry-season greenness, canopy moisture, patch size/core area, post-fire recovery	Fire history and mining overlays; restore links between large habitat blocks
Western Ghats	Rainfall/temperature change; road/plantation expansion; slope and edge effects	Evergreen/deciduous phenology, NDMI, native-forest fragmentation	Separate plantations from native forest; field checks at elevation/rainfall gradients

Eco-climatic stratum	Potential exposure / pressure	Vegetation response to monitor	Priority validation / management focus
Arid / semi-arid west	High heat; rainfall pulses; drought; grazing pressure	Rainfall-response lag, seasonal NDVI amplitude, soil moisture, bare-ground fraction	Use rainfall-adjusted baselines; avoid interpreting annual NDVI alone as degradation
Indo-Gangetic / intensive agriculture	Heat extremes; irrigation and groundwater pressure; urban growth	Crop phenology, crop calendars, wetland change, urban tree cover	Separate cropped from natural vegetation; incorporate irrigation and urban-growth data
Coasts, mangroves and islands	Sea-level rise; cyclone; salinity; aquaculture and embankments	Mangrove extent/condition, shoreline migration, inundation and post-cyclone recovery	Tidal-season consistency, sediment/context data and field verification

8.1 Interpreting vegetation signals by ecosystem:

In arid and semi-arid landscapes, vegetation indices may rise sharply after episodic rain and fall during long dry intervals. A trend estimated from a short period can be misleading if it begins or ends with an exceptional monsoon. Rainfall-normalized residuals or models with lagged precipitation can help distinguish climate sensitivity from persistent cover change. In irrigated plains, greenness may remain high despite falling groundwater levels, so vegetation indices need interpretation alongside water-use and crop-intensity data. In tropical forests, spectral saturation and cloud cover can reduce the sensitivity of NDVI to dense-canopy structural change, making radar, canopy-height or field data valuable complements.

For mangroves and other coastal wetlands, imagery must be compared at similar tidal stage or with tidal and inundation information where possible. A change in spectral index may reflect water level or sediment rather than mortality. In high mountains, snow and topographic illumination need explicit treatment, and apparent upward vegetation shifts should be tested with elevation, aspect, land use and repeated field observations. These ecosystem-specific checks are essential before assigning a vulnerability category.

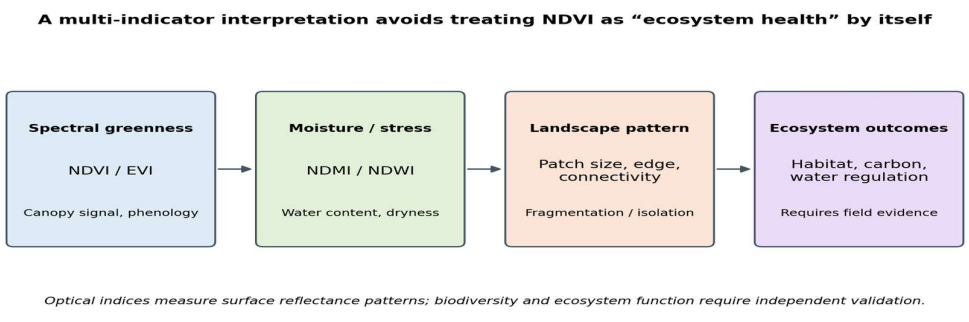

Figure 6. Multi-indicator interpretation ladder: spectral metrics, moisture signals, landscape pattern and ecosystem outcomes should be combined rather than assuming that one vegetation index measures ecosystem health.

9. Discussion:

9.1 National cover statistics and ecosystem condition answer different questions:

A central implication of the evidence is that national area totals, satellite greenness and ecosystem vulnerability are related but non-equivalent. The FSI's rise in combined forest and tree cover between 2021 and 2023 is a valid finding under its reporting method. The historic Roy et al. classification, by contrast, shows a decline in its forest class between 1985 and 2005. There is no necessary contradiction: the periods, sensor products, definitions and classes differ, and gains in some forms of tree cover can coexist with losses or degradation in other places. A rigorous synthesis must retain metadata rather than forcing disparate measurements into one line chart.

Likewise, the increase in NDVI can be associated with more leaf area, higher crop intensity, afforestation, plantation growth or rainfall timing; it does not automatically mean improved biodiversity or restored native forest. Conversely, lower seasonal NDVI can be caused by drought, fire, harvesting, deciduous phenology or a shift in cropping date. Ecosystem interpretation should combine land-cover transitions, seasonal curves, canopy-moisture signals, spatial pattern and independent reference data. Strong inference comes from convergent evidence, not from a single index.

9.2 Climate and land use interact rather than act separately:

Climate pressure can amplify the effects of land-use change. Fragmented forest edges are exposed to hotter and drier microclimates; drought can increase susceptibility to fire and mortality; and habitat loss can reduce options for species to move along elevation or moisture gradients. Conversely, land management can buffer climate effects through riparian vegetation, native-forest connectivity, soil-water conservation and reduced degradation. A climate-only model risks attributing human-driven changes to climate, while a land-cover-only model misses climate-driven variation within apparently stable classes. Joint models and explicit land-cover stratification are therefore central to the research design.

9.3 Vulnerability mapping should support decisions, not disguise uncertainty:

Composite vulnerability maps can help prioritise investigation and resources, but they are sensitive to indicator choice, normalisation, weighting and spatial unit. Equal weighting is transparent but not inherently correct. A high-exposure region may have strong ecological connectivity or effective local conservation, while a less exposed region may be highly sensitive because its habitat is fragmented or geographically restricted. Publishing the three dimensions separately makes the trade-offs visible. Robustness maps showing areas that remain high priority under alternative weights can guide targeted ground verification and monitoring.

9.4 Methodological contribution:

The principal contribution of the framework is to integrate multiple evidence levels into a single workflow. Landsat supports long-duration change mapping at relatively fine spatial scale; MODIS supports dense seasonal time series; national LULC and forest reports provide independent context; climate grids quantify exposure; and field or high-resolution references validate ecological meaning. The recommended analysis distinguishes stable vegetation from pixels undergoing conversion, estimates both trend magnitude and uncertainty, and keeps an explicit audit trail. That combination is more useful for ecosystem planning than an unvalidated national NDVI map.

10. Policy and management implications:

- Protect remaining native forest and high-connectivity patches, not only aggregate tree-cover area. Landscape corridors and riparian strips can maintain dispersal and microclimatic refugia.
- Prioritise restoration that matches native vegetation, local hydrology and soil conditions. Tree planting should not replace natural grasslands, savannas, wetlands or other non-forest ecosystems.
- Use climate-informed fire management in fire-prone forest landscapes and develop post-fire monitoring that separates temporary spectral recovery from durable structural recovery.
- Integrate LULC planning with roads, mining, urban growth, irrigation and groundwater policy. These pressures can shape vegetation patterns independently of climate trends.
- Develop repeatable monitoring dashboards that show class area, transitions, phenology, climate anomalies, fragmentation and uncertainty side by side.
- Combine satellite indicators with local ecological knowledge, forest inventories and community monitoring. Remote sensing locates change; field data help explain its cause and ecological significance.

The national and state-level use case is adaptive prioritisation: identify places where climatic exposure is intensifying, natural habitat is fragmented, and vegetation trends are persistently negative; verify those signals on the ground; then select interventions suited to the ecosystem and the communities who depend on it. Monitoring should evaluate outcomes over several years rather than treating hectares planted or annual NDVI as sufficient evidence of success.

11. Limitations and recommended next steps:

This document is a synthesis and methods framework, not a completed geospatial experiment. No India-wide Landsat image stack was processed for this paper; no classification accuracy, trend p-value, regional vulnerability score or original vulnerability map is reported. Figure 1–2 and Figure 6 are author-created conceptual diagrams; Figures 3–5 visualise published statistics identified in their captions. This separation is deliberate and should be retained in any adaptation of the manuscript.

The national data sources themselves have limitations. Land-cover products differ in spatial resolution, legend and interpretation rules. Climate reanalysis is spatially coarser than satellite imagery

and includes model uncertainty. Optical reflectance is affected by cloud, haze, terrain shadow, soil background, canopy saturation and the timing of observations. NDVI cannot independently separate native forests from plantations or measure biodiversity. A composite vulnerability score can conceal these weaknesses if inputs and weights are not disclosed.

12. Conclusion:

India's vegetation systems are increasingly shaped by the joint effects of warming, precipitation extremes, drought, land conversion and landscape fragmentation. Published evidence documents substantial changes in climate indicators, historical national land cover and current forest/tree-cover estimates; however, these indicators use different periods and classification systems and should not be collapsed into a single trend without harmonisation. In particular, the increase in the latest aggregate forest-and-tree-cover estimate does not by itself demonstrate improvement in native-forest condition, spatial connectivity or climate resilience.

A reliable spatio-temporal assessment should combine multi-season Landsat and MODIS observations, compatible land-cover classes, gridded climate variables, change-transition analysis, robust trend statistics and explicit uncertainty assessment. It should separate spectral greenness from moisture, landscape structure and ecosystem outcomes, and it should account for ecosystem-specific seasonality and human management. An exposure–sensitivity–adaptive-capacity framework can support prioritisation only when its indicators, weights and validation are transparent.

The practical conclusion is methodological as well as ecological: monitor not just how much vegetation exists, but where it is changing, what it is changing into, how climate and land use jointly shape those changes, and how certain the inference is. With reproducible processing and independent validation, the proposed workflow can provide useful evidence for climate adaptation, ecological restoration, forest conservation and sustainable land-use planning across India.

References:

1. Copernicus Climate Change Service (C3S). (n.d.). ERA5-Land hourly data from 1950 to present. Climate Data Store.
2. Congalton, R. G., & Green, K. (2019). Assessing the Accuracy of Remotely Sensed Data: Principles and Practices (3rd ed.). CRC Press.
3. Dubey, N., Chauhan, T. A., & Ghosh, S. (2026). Forest-savanna stability in India under human interventions and changing climate. Communications Earth & Environment, 7, Article 58. https://doi.org/10.1038/s43247-025-03076-5
4. Forest Survey of India (FSI). (2024). India State of Forest Report 2023 (Vol. I). Ministry of Environment, Forest and Climate Change, Government of India, Dehradun. https://fsi.nic.in/uploads/isfr2023/isfr_book_eng-vol-1_2023.pdf
5. Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google

Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

6. Krishnan, R., Sanjay, J., Gnanaseelan, C., Mujumdar, M., Kulkarni, A., & Chakraborty, S. (Eds.). (2020). Assessment of Climate Change over the Indian Region: A Report of the Ministry of Earth Sciences (MoES), Government of India. Springer. https://doi.org/10.1007/978-981-15-4327-2
7. Mann, H. B. (1945). Nonparametric tests against trend. Econometrica, 13(3), 245–259. https://doi.org/10.2307/1907187
8. Ministry of Earth Sciences, Government of India. (2023, August 2). Impact of climate change upon the Indian subcontinent. Press Information Bureau. https://www.pib.gov.in/PressReleasePage.aspx?PRID=1945036
9. National Remote Sensing Centre (NRSC), ISRO. (n.d.). Land Use-Land Cover applications. https://www.nrsc.gov.in/nrscnew/Apps_LULC.php
10. Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J.-M., Tucker, C. J., & Stenseth, N. C. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. Trends in Ecology & Evolution, 20(9), 503–510. https://doi.org/10.1016/j.tree.2005.05.011
11. Roy, P. S., Roy, A., Joshi, P. K., Kale, M. P., Srivastava, V. K., Srivastava, S. K., Dwevidi, R. S., Joshi, C., Behera, M. D., Meiyappan, P., Sharma, Y., Jain, A. K., Singh, J. S., & Kushwaha, D. (2015). Development of decadal (1985–1995–2005) land use and land cover database for India. Remote Sensing, 7(3), 2401–2430. https://doi.org/10.3390/rs70302401
12. Sen, P. K. (1968). Estimates of the regression coefficient based on Kendall's tau. Journal of the American Statistical Association, 63(324), 1379–1389. https://doi.org/10.1080/01621459.1968.10480934
13. Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment, 8(2), 127–150. https://doi.org/10.1016/0034-4257(79)90013-0
14. U.S. Geological Survey (USGS). (n.d.). Landsat Collection 2 surface reflectance. https://www.usgs.gov/landsat-missions/landsat-collection-2-surface-reflectance
15. Forest Survey of India (FSI). (n.d.). India State of Forest Report: Volume I / report portal. https://fsi.nic.in/isfr-volume-i
16. Breiman, L. (2001). Random forests. Machine Learning, 45, 5–32. https://doi.org/10.1023/A:1010933404324
17. Wulder, M. A., et al. (2019). Current status of Landsat program, science, and applications. Remote Sensing of Environment, 225, 127–147. https://doi.org/10.1016/j.rse.2019.02.015

18. Agarwal, V., Singh, B. V. R., Marsh, S., Qin, Z., Sen, A., & Kulhari, K. (2025). Integrated remote sensing for enhanced drought assessment: A multi-index approach in Rajasthan, India. Earth and Space Science, 12(2), e2024EA003639. https://doi.org/10.1029/2024EA003639
19. Didan, K. (2021). MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V061 [Data set]. NASA Land Processes Distributed Active Archive Center. https://doi.org/10.5067/MODIS/MOD13Q1.061
20. Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P., Martimort, P., Meygret, A., Spoto, F., Sy, O., Marchese, F., & Bargellini, P. (2012). Sentinel-2: ESA's optical high-resolution mission for GMES operational services. Remote Sensing of Environment, 120, 25–36. https://doi.org/10.1016/j.rse.2011.11.026
21. Fensholt, R., & Proud, S. R. (2012). Evaluation of Earth observation-based global long-term vegetation trends—Comparing GIMMS and MODIS global NDVI time series. Remote Sensing of Environment, 119, 131–147. https://doi.org/10.1016/j.rse.2011.12.015
22. Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Scientific Data, 2, Article 150066. https://doi.org/10.1038/sdata.2015.66
23. Friedl, M. A., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A., & Huang, X. (2010). MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. Remote Sensing of Environment, 114(1), 168–182. https://doi.org/10.1016/j.rse.2009.08.016
24. Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2013). High-resolution global maps of 21st-century forest cover change. Science, 342(6160), 850–853. https://doi.org/10.1126/science.1244693
25. Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment, 83(1–2), 195–213. https://doi.org/10.1016/S0034-4257(02)00096-2
26. Intergovernmental Panel on Climate Change (IPCC). (2021). Climate change 2021: The physical science basis. Cambridge University Press. https://doi.org/10.1017/9781009157896
27. Intergovernmental Panel on Climate Change (IPCC). (2022). Climate change 2022: Impacts, adaptation and vulnerability. Cambridge University Press. https://doi.org/10.1017/9781009325844
28. Lambin, E. F., Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Bruce, J. W., Coomes, O. T., Dirzo, R., Fischer, G., Folke, C., George, P. S., Homewood, K., Imbernon, J., Leemans,

R., Li, X., Moran, E. F., Mortimore, M., Ramakrishnan, P. S., Richards, J. F., . . . Xu, J. (2001). The causes of land-use and land-cover change: Moving beyond the myths. Global Environmental Change, 11(4), 261–269. https://doi.org/10.1016/S0959-3780(01)00007-3

29. Meiyappan, P., Roy, P. S., Sharma, Y., Ramachandran, R. M., Joshi, P. K., DeFries, R. S., & Jain, A. K. (2017). Dynamics and determinants of land change in India: Integrating satellite data with village socioeconomics. Regional Environmental Change, 17, 753–766. https://doi.org/10.1007/s10113-016-1068-2
30. Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., & Thépaut, J.-N. (2021). ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. Earth System Science Data, 13, 4349–4383. https://doi.org/10.5194/essd-13-4349-2021
31. Roxy, M. K., Kapoor, R., Terray, P., Murtugudde, R., Ashok, K., & Goswami, B. N. (2015). Drying of Indian subcontinent by rapid Indian Ocean warming and a weakening land–sea thermal gradient. Nature Communications, 6, Article 7423. https://doi.org/10.1038/ncomms8423
32. Roxy, M. K., Ghosh, S., Pathak, A., Athulya, R., Mujumdar, M., Murtugudde, R., Terray, P., & Rajeevan, M. (2017). A threefold rise in widespread extreme rain events over central India. Nature Communications, 8, Article 708. https://doi.org/10.1038/s41467-017-00744-9