Collection of Time-Series Datasets from Sentinel and Landsat

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Abstract
Satellite time series data plays a critical role in the monitoring of forest and vegetation changes in India's diverse forest landscape. This review is based on the processing of Sentinel, Landsat and Global Forest Watch-derived datasets and their availability for forest monitoring in India, specifically for Maharashtra and central Indian landscapes. The process of data set collection is described through the methodological steps of sensor selection, temporal coverage, data pre-processing, harmonisation, data validation, metadata documentation and integration of the collected data with derived forest-monitoring indicators. Landsat offers long-term consistency for monitoring forest-cover and tree-cover changes, whereas Sentinel supplies recent fine resolution observations for detecting fine resolution vegetation change, disturbance, canopy condition and fire. The review also leverages the Maharashtra case dataset, which includes tree-cover extent, annual tree-cover loss, primary forest loss, VIIRS fire alerts, biomass, carbon flux, plantations and dominant drivers of loss. These indicators help in the interpretation at the state and district level, but are subject to nuanced distinction between tree cover, natural forest and derived analytical products. The biggest challenges are the cloud cover in the monsoons, the deciduous nature of the phenology, the variation in the sensors, mixed pixels, the lack of ground validation, and the uncertainty in distinguishing between seasonal vegetation changes and degradation. The review underscores the need for harmonized, metadata-rich, machine learning enabled forest datasets at various regional scales in India to support monitoring; fire-risk assessment; biomass estimation; conservation planning and predictive vegetation-change modelling.

Keywords: Sentinel; Landsat; India forest datasets; time-series remote sensing; vegetation change monitoring; Global Forest Watch

1. Introduction

Satellite remote sensing has been used as a founding pillar for the development of forest and vegetation datasets that are reproducible, especially in areas where spatial variation and temporal change cannot be determined from field observations. Given the diversity of forest lands in India, from protected reserves to village-forest interfaces, plantations to shifting cultivation areas, dry deciduous to mangroves, wildlife corridors to fast-changing peri-urban areas, forest monitoring involves a wider range of land-cover mapping than in other countries. These conditions are making the collection of data a methodological problem, rather than just a data acquisition problem. Time-series data products based on Sentinel and Landsat observations can be used for analyzing vegetation condition, disturbance, recovery, fragmentation, fire response and biomass-based change, for repeated periods of time. The reliability of such analysis is however dependent on the selection, filtering, harmonization, validation and interpretation of the data sets within the Indian ecological and administrative contexts.

One of the key challenges in forest monitoring in India is the difference between forest cover, tree cover and forest change observed from satellites. The difference in estimates between national and global datasets could be caused by various definitions, spatial resolutions, classification rules, canopy thresholds and temporal update cycles. The distinction is directly relevant to India since forest indicators are employed in forest conservation planning, carbon accounting, forest governance, climate reporting and district environmental assessment. Pasha and Dadhwal (2024) demonstrated that there exist significant differences between the estimates of forest-cover dynamics computed using various techniques and data sources, highlighting the need for careful conceptual and methodological interpretation of time-series of forest data. Thus, in addition to the availability of images in the Sentinel and Landsat data sets, their consistency, comparability, and ecological significance of the data sets under construction needs to be reviewed.

Recent Indian studies also demonstrate that multi-sensor, multi-temporal and multi-scale approaches are the most suitable approaches to monitoring forest/vegetation degradation. Degradation is seldom a simple and uniform process, and can manifest itself as thinning in the forest canopy, seasonal stress, loss through fire, fragmentation, lower productivity, or change to non-forest land use. The need for structured data sets that incorporate both spectral, temporal, spatial and auxiliary information was highlighted by Sur et al. (2024) who showed that combination of remote sensing and machine learning is useful in monitoring the vegetation degradation cases in India. Landsat adds historical continuity from previous decades and Sentinel offers a recent, high-resolution image for finer landscape interpretation. Combination of these can help with long-term and near-current vegetation monitoring, if they are processed on consistent temporal windows, preprocessed on consistent standards and with consistent validation criteria.

Dry deciduous forests, seasonal leaf fall, fire events, human pressure, plantation mosaics and habitat fragmentation are a particular challenge for the Indian forests of Maharashtra and central India, in terms of the need to incorporate India-specific dataset design. Landscape-level indicators have been developed that are able to identify degradation patterns that are not apparent in coarser datasets, as demonstrated by very-high-resolution forest-health datasets prepared for central India. Khanwilkar et al. (2023) created land-cover and forest-health indicator datasets in central India, which showed the importance of region-specific data products for monitoring forest health. With this background, the present review focuses on the generation and processing of forest time-series data for India from Sentinel and Landsat as well as on the estimation of forest biomass, flux of carbon, fire alerts and loss of tree-cover using data from Global Forest Watch and analysis of forest disturbances drivers as a case dataset of the forest in Maharashtra. This helps in planning conservation at the regional level.

2. Need for India-Specific Forest Time-Series Datasets

2.1 Ecological and seasonal complexity of Indian forests

Forest time-series data specific to India is essential as forest landscapes in India are unique when compared with that of many forest-monitoring products developed and interpreted globally. Dry deciduous forests, moist deciduous forests, Himalayan forests, mangroves, plantation mosaics, shifting cultivation landscapes, peri-urban forests and protected areas under pressure are found in India. They have non uniform canopy behaviour throughout the year. Vegetation signals are related to monsoon rains, dry season stress, leaf drop, fire incidence, grazing, extraction, plantation cycles and land-use changes. If these circumstances are not taken into account, a dataset can give false estimates of vegetation change. One key driver of the design of the datasets is phenological complexity. There can be a canopy decline in deciduous forests that is only seasonal, depending on the dryness of the seasons, even if there had been no degradation. On the other hand, early degradation can be spectrally less noticeable if it involves changes such as canopy density, understory condition, or changes in forest structure but not conversion of land-cover. Sedha et al. (2024) pointed out that forest phenology research in India has the need to incorporate more satellite remote sensing and near ground based data to improve the understanding of seasonal vegetation dynamics, as it is still challenging to interpret the forest phenology. This is applicable to Sentinel and Landsat time series, as the different timings of the images affect NDVI, NBR, moisture indices and the classification results.

2.2 Disturbance drivers and landscape fragmentation

Regionalization of the design of the data sets needed for protected areas and surrounding landscape is necessary since forest disturbance is a function of particular ecological and social processes. Riverine dynamics, settlements, grazing, encroachment, invasive growth and agricultural pressure are the factors that impact forested landscapes in the northeast of India. Shah and Shah (2023) analyzed forest-cover change over time across the spatial extent of Dibru-Saikhowa National Park using remote sensing and GIS to emphasize the need for spatial monitoring at the level of the protected area and not relying solely on products at a broad scale. This helps to support datasets that capture the changes in the landscape at appropriate spatial and temporal scales.

Forest change is not a single process, and is driven by the specificities of India, which requires India-specific datasets. Drivers are road expansion, shifting cultivation, settlement growth, fire, plantation development, extraction, mining, and natural disturbance. These drivers have different characteristics of their spectral or structural signatures. The study by Guria et al. (2024) on forest-cover change and deforestation susceptibility in Northeast India showed that a forest-cover change assessment could be enhanced by incorporating anthropogenic and environmental variables, in addition to the outputs of remote-sensing data. So, Sentinel and Landsat data should not only be stored as image collections but also as analytical data that are associated with the drivers of disturbance.

Another requirement is connectivity sensitive monitoring. Forest cover could still be present statistically yet be fragmented or become increasingly isolated by expanding edges and ecological continuity. Sathyakumar et al. (2025) examined the structural connectivity changes at the state level for India and stressed on the importance of geospatial aspects to grasp the forest cover of India. This is important for the region of Maharashtra and the intermediate parts of India where forest patches bridge the gap between forest patches, wildlife corridors, village boundaries and plantation areas. The datasets of the time series need to be capable of area based and structure based interpretation.

2.3 Requirement for regional dataset frameworks

For Maharashtra and central Indian landscapes, regional dataset frameworks must account for dry deciduous phenology, Western Ghats gradients, mangrove environments, fire-prone zones, village-forest interfaces, and district-level units. As illustrated in Figure 1, India-specific forest dataset construction should integrate Sentinel and Landsat imagery, derived indicators, validation sources, disturbance-driver layers, and ecological context before interpretation.

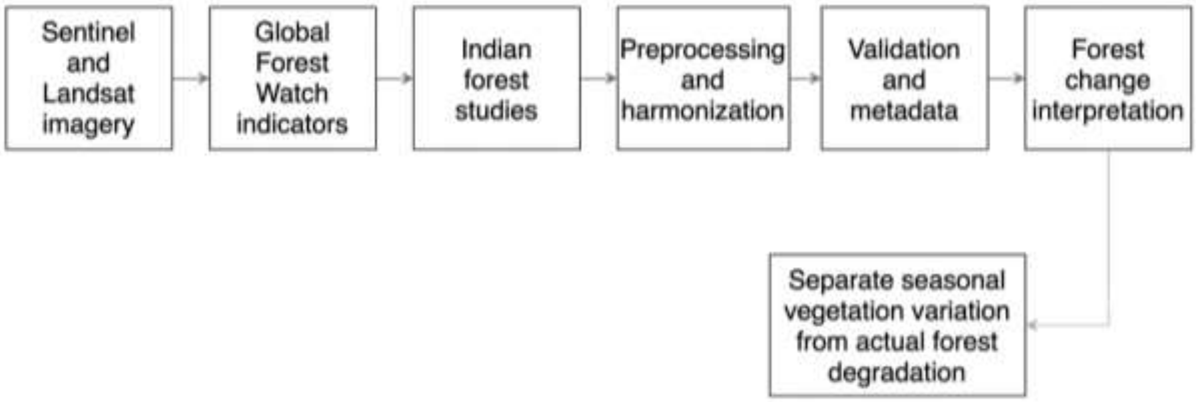

Figure 1. Conceptual framework for India-specific forest time-series dataset collection

Figure 1 shows that India-specific forest dataset construction requires integration of satellite imagery with derived indicators, validation data, and regional ecological knowledge. It also highlights the need to distinguish seasonal vegetation variation from actual forest degradation.

For these reasons, India-specific Sentinel and Landsat time-series datasets should be constructed with attention to seasonal windows, forest type, disturbance history, protected-area boundaries, administrative units, and regional ecological processes. Such datasets are essential for vegetation-cover monitoring, forest-health assessment, fire-risk interpretation, conservation planning, and predictive modelling.

3. Sentinel and Landsat as Core Satellite Sources

Sentinel and Landsat are basic sources of satellite data for India specific construction of time-series dataset for forest as they provide repeated, spatial observations across heterogeneous landscape. Landsat brings the historical continuity, and Sentinel with its high resolution observations, such as Sentinel-2. In India, these are not to be considered as mere archives of images for forest monitoring. They serve as observational foundation to derive vegetation indices, land-cover classes, fire-related signals, biomass proxies, disturbance layers and change trajectories. Use of both is significant when forest change is slow, seasonal, localised or caused by the interplay of several drivers.

The archive of Landsat is crucial to historical forest and land-cover analysis, continuing its role in this area for decades. This is useful in the context of India where forest conversion along with peri-urbanization, agriculture and infrastructure build-up have happened gradually over time rather than all at once. Landsat data proved relevant for monitoring land use and land cover changes in peri-urban Guwahati, Assam with multi-temporal satellite data as done by Bhattacharjee et al. (2022) on monitoring the spatial transformation in Indian landscapes. These applications demonstrate the ability of Landsat to reconstruct baseline conditions, determine long-term change periods, and determine if loss is ongoing or a seasonal change.

At larger scales, Landsat, in conjunction with machine-learning approaches, can be used for systematic classification. There are specific challenges with spectral variation in forests, croplands, settlements, barren surfaces, water bodies, plantations and mixed land use mosaics that need to be addressed by classification approaches for India's ecological diversity. Singh et al. (2021) demonstrated using machine learning on Landsat data to be mapped in India for land use and land cover, where they were able to transform a series of Landsat observations into thematic layers. It is important because the scientific value of the data from a time-series is realized only if the image observations are translated to similar outputs.

Sentinel's added value comes from its finer spatial resolution and from more recent observations that are more frequent. Sentinel-2 is particularly valuable for detecting the patch-level disturbance, forest edges, plantation blocks, agricultural encroachment, peri-urban expansion and narrow vegetation corridors which are difficult to detect in coarser datasets. Under fast-growing urbanization in India, Chatterjee et al. (2025) analysed forest-cover loss and its implications for ecosystem services using a 10 m ESA Sentinel-2 land-use and land-cover product. This helps to incorporate Sentinel datasets into forest monitoring, especially for fragmented landscapes.

The complementary principle of use of two sensors is outlined in Table 1. Landsat has a better historical record and Sentinel has a better fine scale record. They complement each other in terms of enhancing temporal depth, spatial detail and interpretive reliability for Indian forest change assessment.

Table 1. Comparison of Sentinel and Landsat for Indian forest time-series dataset collection

Parameter	Landsat	Sentinel
Main satellite series	Landsat 5, 7, 8, 9	Sentinel-1 and Sentinel-2
Main sensor type	Optical multispectral	Sentinel-2: optical multispectral; Sentinel-1: SAR
Key strength	Long-term historical continuity	Recent high-resolution and frequent monitoring
Approximate spatial resolution	30 m for most multispectral bands	10 m and 20 m for Sentinel-2; radar observations from Sentinel-1

Temporal usefulness	Multi-decadal forest and land-cover change assessment	Recent vegetation condition, fragmentation, and disturbance monitoring
Suitable applications	Historical forest-cover change, baseline reconstruction, long-term vegetation trends	Fine-scale forest patches, plantation areas, village-forest interfaces, post-fire assessment
Indian forest relevance	Useful for reconstructing long-term change in central India, Western Ghats, peri-urban areas, and protected landscapes	Useful for detecting recent disturbance, canopy condition, fragmentation, and small-scale landscape change
Main limitations	Moderate spatial resolution; cloud contamination; sensor differences across missions	Shorter historical record; cloud contamination for Sentinel-2; processing complexity
Best use in this review	Historical time-series foundation	Recent high-resolution monitoring layer
Recommended use	Combine with Sentinel and GFW-derived products	Combine with Landsat and GFW-derived products

As seen in Table 1, Landsat offers historical continuity whereas, Sentinel offers higher resolution recent observations. They are used together to facilitate vegetation-index generation and land-cover classification, disturbance mapping and integration with derived forest-monitoring products.

Sentinel and Landsat have the potential to be even more useful for deforestation and disturbance monitoring when combined with computational approaches in a time series of images. With machine learning and deep learning, patterns can be learned from a large sequence of images, which makes the process less dependent on individual comparisons of images. Turning satellite archives into disturbance-monitoring datasets, Bhuyan et al. (2025) showed the use of time-series satellite data and deep learning techniques to monitor historical deforestation in the Eastern Himalayan foothills of India. This is important since forest cover loss in India can be localized, intermittent, georeferenced and/or linked to settlement or land-use change.

Thus, Sentinel and Landsat should be combined in a dataset workflow. Landsat provides historical perspectives, Sentinel provides recent spatial detail and both can be combined with derived products like Global Forest Watch. Derived layers should not be termed as raw Sentinel or Landsat images, however. Ensuring reliable construction of datasets relies on consistency of seasonal windows, surface-reflectance products, cloud masking, spatial alignment, and validation and documentation of metadata for forest landscapes.

4. India and Maharashtra Forest Dataset Sources

To develop forest datasets for India, a hierarchical approach that uses national, regional and landscape level data sources are required. In the context of a review based on Sentinel and Landsat time-series, there is no restriction on the source selection to only satellite scenes. Thematic layers, validation references, disturbance records, carbon indicators, administrative summaries and ecological context are also available, which enable the image observations to be translated into forest monitoring evidence. In India this selection should reflect the ecological diversity, uneven distribution of forest and the process of disturbance, and the difference between official forest statistics and products derived from satellites measuring tree-cover. Maharashtra is an appropriate State as it has Western Ghats forests, dry deciduous forests, forests in plantations, protected areas, village-forest interface, and districts with significant variations in forest loss, occurrence of fire and carbon dynamics.

One of the important aspect of the forest information pertaining Maharashtra is the representation of coastal and mangrove ecosystem. Mangroves differ from inland forests in the characteristics of the canopy, hydrological environment, tidal exposure, salinity influence, regeneration pattern, and behaviour of carbon storage. Thus, they cannot just be measured with generic forest-cover data sets. Pardeshi et al. (2024) studied mangrove carbon pool patterns in the state of Maharashtra and highlighted the need for region-specific data to gain insights into forest carbon in coastal habitats. This evidence relates to Sentinel and Landsat datasets collection as it is important that mangrove monitoring relies on spatially consistent imagery, interpretation of tidal and seasonal fluctuations and a connection between spectrum and the carbon related field or model attributes. Adding the datasets from Maharashtra mangroves extends the review into a much more diverse ecosystem than terrestrial dry forests, highlighting the ecological diversity in the state.

In addition, forest dataset sources for India should also enable the assessment of long-term changes in the areas with high biodiversity and disturbance. The studies from other landscapes in India have methodological parallels for time-series monitoring, although the major focus of the present dataset compilation is Maharashtra. Mahato et al. (2021) quantified the forest-cover change in northern parts of Sonitpur and Udalguri districts of Assam for the area, showing the usefulness of satellite based temporal analysis in detecting forest cover change in complex forest system. Evidence supported the use of Landsat derived historical monitoring and Sentinel derived recent mapping in landscapes where multiple drivers of change (deforestation, fragmentation, regeneration and seasonal vegetation change) are possible. These case studies from India minimize reliance on foreign studies to augment regional support for the design of datasets.

The present review uses the dataset source from Global Forest Watch which is used to offer practical subnational and national forest monitoring data for India and Maharashtra. It contains downloadable indicators like tree-cover extent, annual tree-cover loss, primary forest extent, primary forest loss, VIIRS fire alerts, aboveground biomass, forest-related greenhouse-gas emissions, net carbon flux, plantations and dominant drivers of tree-cover loss. Global Forest Watch (2025) provides India deforestation rates and statistics which can be used to generate a summary for the state/region and district. Global Forest Watch is used as a secondary forest monitoring data source, rather than Sentinel and Landsat data. This distinction is important since these products are analytical layers and not satellite scenes and many are based on satellite time-series processing.

The Global Forest Watch dataset package enables interpretation of forest change at the subnational (state and district) level for the state of Maharashtra beginning in 2000. Loss of trees can be used to determine time and place for detailed Landsat historical analysis and recent fire alerts can be used to direct post-fire analysis using Sentinel. Biomass and carbon layers can be used for ecological interpretations where vegetation loss is correlated with degradation or carbon-stock loss or change in forest structure. The driver datasets are also useful to identify losses associated with permanent agriculture, logging, wildfire, shifting cultivation, settlement, infrastructure, and other drivers. These categories do, however, need to be interpreted with caution as tree cover is not necessarily interpreted as natural forest, and fire alerts are not always interpreted as a loss of forest.

In general, the data sources used for Forest in India and Maharashtra should be integrated into a complementary data system. Sentinel and Landsat supply a time series of images, Indian studies provide ecological and methodological context and Global Forest Watch provides derived indicators appropriate for state and district summaries. This will ensure that the review remains relevant to dataset collection for forest monitoring, the landscape of Maharashtra and practical vegetation change assessment. It also promotes the shift from foreign dependency towards forest time series datasets validated in each of the regions of India. In subsequent chapters these sources are grouped together into dataset profiles, selection criteria and pre-processing requirements, indicators and applications, enabling the implementation of Maharashtra as an empirical case for a forest-monitoring review for India, rather than as a theoretical discussion.

5. Maharashtra Forest Dataset Profile from Global Forest Watch

5.1 Dataset scope and source

The Maharashtra forest dataset used in this review is derived from Global Forest Watch and represents a secondary forest-monitoring source for interpreting Sentinel and Landsat time-series analysis. It covers Maharashtra, India, and provides state and district-level indicators from 2000 onward. The dataset includes tree-cover extent, annual tree-cover loss, primary forest extent, primary forest loss, VIIRS fire alerts, aboveground biomass, forest-related emissions, net carbon flux, plantations, and dominant drivers of loss. These products are not raw satellite scenes; they are derived analytical layers that support regional interpretation.

5.2 Baseline tree cover and primary forest indicators

The dataset records Maharashtra's total area as 30,733,894 ha and tree-cover extent in 2000 as 1,073,403 ha, representing about 3.49% of the state area. Primary forest extent in 2000 is recorded as 84,322 ha, with primary forest loss of 914 ha during 2001-2025. These values show the importance of distinguishing tree cover from natural forest, because tree-cover products may include plantations or other non-natural tree-covered areas.

5.3 Annual tree-cover loss pattern, 2001-2025

Annual tree-cover loss allows temporal interpretation of disturbance patterns across Maharashtra. The total tree-cover loss during 2001-2025 is 23,313 ha, with an average annual loss of approximately 933 ha. The highest recorded loss occurred in 2011, at about 2,022 ha, while the lowest occurred in 2015, at about 395 ha. As illustrated in Figure 2, the annual pattern indicates episodic disturbance years rather than a simple linear trend.

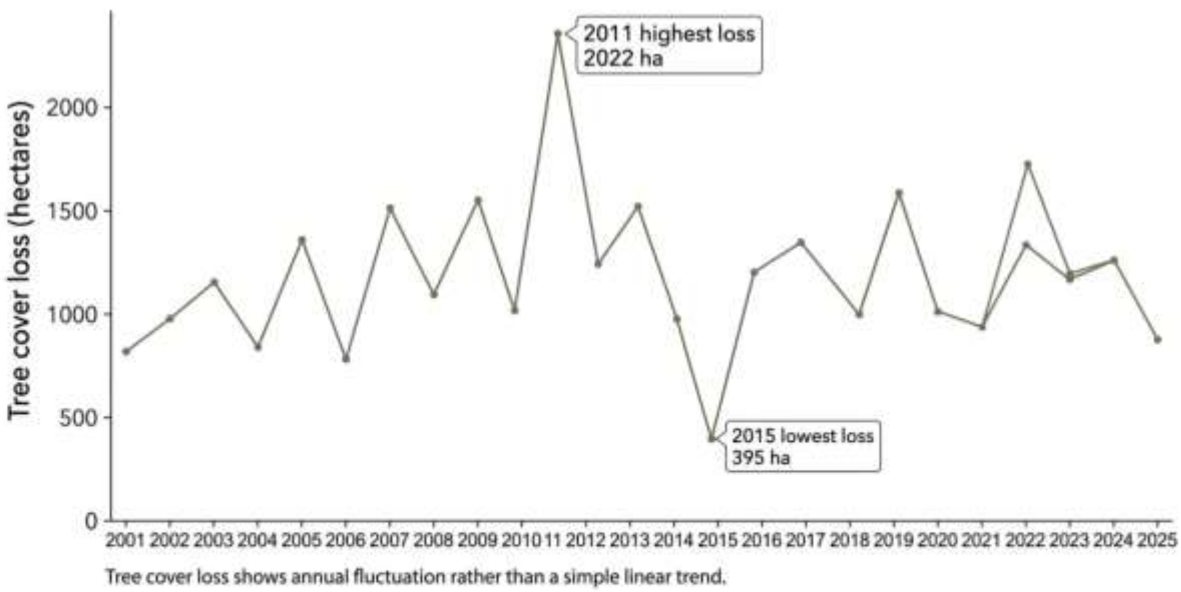

Figure 2. Annual tree-cover loss in Maharashtra, 2001-2025

Figure 2 shows that tree-cover loss fluctuates across years. Peak years should be examined using Landsat historical imagery, Sentinel recent imagery, fire alerts, and driver-based layers.

5.4 Summary of Maharashtra forest dataset indicators

The main forest-monitoring indicators from the Maharashtra dataset are summarized in Table 2. These indicators include baseline forest condition, annual loss, fire occurrence, biomass, emissions, removals, net carbon flux, and dominant drivers.

Table 2. Summary of Maharashtra forest dataset indicators derived from Global Forest Watch

Indicator	Dataset value	Interpretation
Total area of Maharashtra in dataset	30,733,894 ha	Defines the state-level spatial reference area
Tree-cover extent in 2000	1,073,403 ha	Baseline tree-cover condition
Tree-cover share of state area	3.49%	Indicates proportion of mapped tree cover within Maharashtra
Total tree-cover loss, 2001–2025	23,313 ha	Cumulative annual tree-cover loss over the study period
Average annual tree-cover loss	933 ha/year	Mean yearly tree-cover loss
Highest tree-cover loss year	2011	Indicates an episodic disturbance peak
Highest annual tree-cover loss	2,022 ha	Maximum annual recorded loss
Lowest tree-cover loss year	2015	Indicates lowest annual disturbance in the period
Lowest annual tree-cover loss	395 ha	Minimum annual recorded loss
Primary forest extent in 2000	84,322 ha	Baseline primary forest indicator
Primary forest loss, 2001–2025	914 ha	Cumulative primary forest loss
Primary forest loss as % of 2000 primary forest	1.08%	Indicates relative primary forest reduction
Historical VIIRS fire alerts	693,515 alerts	Active fire occurrence indicator, not direct forest-loss measure
Highest fire-alert year	2018	Year with highest detected fire activity
Fire alerts in highest year	61,397 alerts	Peak annual fire-alert count
Recent fire-alert period	19 May 2026–18 June 2026	Recent fire-monitoring window in dataset
Recent fire alerts	3,673 alerts	Short-period active fire count
Tree-cover loss due to fires	679 ha	Fire-attributed tree-cover loss
Fire-related loss share	2.91%	Fire contributes a smaller direct share of total loss
Aboveground woody biomass stock, 2000	200.98 million Mg	Biomass stock baseline
Aboveground CO_2 stock, 2000	346.36 million Mg CO_2	Carbon-equivalent stock indicator
Gross forest-related GHG emissions, 2001–2025	11.36 Mt CO_2e	Emissions associated with forest/tree-cover change
Gross removals	113.41 Mt CO_2e	Carbon removals over the period
Net carbon flux	−102.05 Mt CO_2e	Indicates net sink condition in the dataset

Table 2 shows that GFW products provide a compact analytical base for Maharashtra forest monitoring. These values support state-level interpretation but require validation before local conservation decisions.

5.5 Dominant drivers and interpretation of loss

Driver data indicate that permanent agriculture, logging, and shifting cultivation account for most recorded tree-cover loss. Wildfire contributes a smaller direct share, although fire alerts remain useful for disturbance-risk interpretation in practice.

6. Dataset Collection and Selection Criteria

6.1 Spatial and temporal selection criteria

Collection of datasets on forest monitoring needs to be done in a standardised way to ensure consistency, repeatability and applicability of the product to Indian landscapes with Sentinel and Landsat. Selectability according to ecological relevance, temporal completeness, spatial resolution, level of preprocessing and compatibility with indicator. Protected forests, reserve forests, village adjacent forest, plantation, mangroves, corridors and fragmented patches should be included for Maharashtra and central India. The administrative boundaries should be in sync with the limits of the protected areas, forest divisions and district units in the satellite scenes and products. The need for forest-structure mapping (FSM) necessitates the need to combine satellite observations with the forest conditions in the region is established from forest height and biomass studies using GEDI and Sentinel (Bhandari et al., 2024). Thus, the selection of the datasets should be representative of canopy coverage and variability.

6.2 Sensor and product selection criteria

Second criterion is the suitability of the sensor. Optical data from Landsat and Sentinel-2 are crucial for vegetation indices, land-cover classification and change detection over long periods of time, while radar data can overcome cloud cover and provide information on the structure of the canopy. In areas susceptible to the seasonal shift from daytime to night time observations, SAR-based sources can be used to fill in the missing data. Singhal et al. (2024) demonstrated that C-band SAR data can be used effectively to characterize forests with EOS-04 satellite and integration of multi-sensor data can be beneficial for forest characterization in India. When helpful for interpretation, optical imagery, radar products, biomass layers, fire alerts and Global Forest Watch indicators should be included in datasets collection.

6.3 Dataset cleaning and quality control

The third is the validation and quality control. If possible, reference data, field observations, high-resolution imagery and/or benchmark products should be used to support time-series data sets. This is crucial for biomass and forest-condition data as estimates derived from the satellite could be different for different canopy density, forest types, terrain and sensor saturation. The methodological and data challenges to validate ESA-CCI forest biomass products over India were highlighted by Bhat et al. (2024), which further emphasizes the need to validate uncertainty prior to using any secondary datasets. The cleaning of the dataset should be able to identify duplicate Excel files, compare duplicate ZIP folders, remove invalid Excel files, add missing values to the data, and keep metadata describing source, date, scale, projection.

6.4 Dataset preparation workflow

The fourth is methodological compatibility. T
of indicators, indicator validation and standardized naming, as shown in Figure 3.

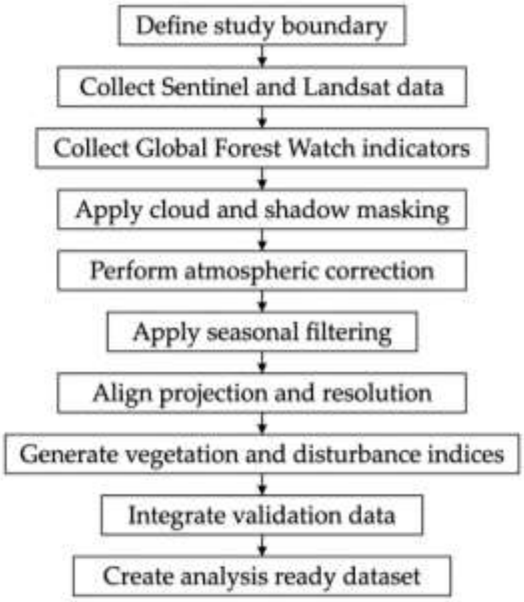

Figure 3. Workflow for Sentinel-Landsat-GFW dataset collection and preparation

Figure 3 shows that preparation begins with boundary definition and ends with an analysis-ready product. Each step reduces uncertainty and improves comparability across sensors, indicators, and Indian forest conditions.

7. Preprocessing and Harmonization Requirements

To produce Indian forest time-series datasets from Sentinel and Landsat observations, it is crucial to apply a rigorous pre-processing pipeline. The assessment of AVC (apparent vegetation change) depends on the pre-processing performed, which may result in false changes due to cloud, shadow, atmospheric difference, terrain difference, sensor difference and seasonal mismatch. This is essential for Indian landscapes due to frequent non-ideal image quality conditions such as monsoon cloud cover, dry season deciduous vegetation, smoke and haze, rugged landscapes and fragmented forest boundaries. Preprocessing should not be considered a "standard" technical step, but should be viewed as an integral component of the methodological approach.

The first is that the data must be standardized. When possible, Landsat or Sentinel images should be retrieved as surface-reflectance images in order to minimize the effects of top-of-atmosphere reflectance on date-to-date spectral differences. Images should be checked for the presence of cloud cover, cloud shadows, cirrus contamination, haze, scan-line errors and edge artefacts. The consistency throughout the season is also crucial. The images from the various phenological phases of the deciduous and semi-deciduous forests should not be compared directly without normalization. Two images taken during the dry season from Landsat and post-monsoon from Sentinel could appear differently in terms of greenness of the canopy even if there is no degradation. The temporal windows should, therefore, be determined as per the use, e.g. post monsoon composites for canopy condition or the pre- and post-fire composites for the assessment of burn.

The second is the harmonization in space and geometry. The spatial resolution, spectral band design, revisit time and geometry of observation characteristics vary between Sentinel and Landsat datasets. All images should be shown on a common coordinate system, cropped to the study area, co-registered, and resampled, all of which, are documented procedure. This is necessary as demonstrated in structural forest studies. In the northwest foothills of the Himalayan region in India, Nandy et al. (2021) combined ICESat-2, Sentinel-1 and Sentinel-2 data to map forest height and aboveground biomass, and emphasized the need to integrate the data consistently across them prior to modelling. The same is true for layers organized for Sentinel, Landsat, and GFW monitoring for the state of Maharashtra or the central region of India.

The third is derived variables preparation. Standardized band combinations should be used for the calculation of vegetation indices (NDVI, EVI, SAVI, NDWI and NBR) and should be accompanied by well defined metadata. When forest-structure or biomass interpretation is needed, the following texture measures, canopy-density proxies, radar backscatter, elevation derivatives, and spectral composites can be added. Singh et al. (2023) estimated aboveground forest biomass by using TLS data combined with ALOS PALSAR and machine learning; they found that the forest biomass estimated by satellite variables are more useful when used coupled with structural reference measurements. This further highlights the importance of making pre-processing decisions and sticking to them prior to modelling.

The fourth is temporal compositing. Monthly, seasonal, annual and multi-year composites should be made when data are sufficient and for ecological reasons. Annual composites can be used to remove noise and enhance change detection for long-term analysis of Landsat data. Seasonal composites can provide good insight of vegetation dynamics when monitoring Sentinel-2. Processed spectral layers in forest assessment that were derived from Landsat 8 OLI data were used by Bhandari and Nandy (2024) for aboveground biomass prediction. For fire, logging, encroachment or post-disturbance recovery studies, however, the disturbance timing should be preserved during the compositing.

Quality control and organizing of datasets is the last requirement. Meta data of sensor, date, preprocessing level, cloud threshold, index formula, projection, spatial resolution, masking criteria and uncertainty should be provided for each data set. Jagadish et al. (2024) demonstrated that multi-sensor satellite data may reach their saturation point for biomass estimation of mangroves, thus stressing the importance of reporting limitations. A defensible workflow should provide datasets that are ready to be analyzed, not just downloaded imagery. For Indian Forest monitoring it means to bring in a consistent and repeatable preprocessing, harmonization and validation workflow in the case of Sentinel, Landsat and derived products including metadata. This helps to make data more comparable, minimise erroneous change detection, enable clear interpretation, and make a region's data usable for a range of applications (e.g. vegetation monitoring, fire assessment, biomass estimation and predictive modelling).

8. Vegetation and Forest-Change Indicators

8.1 Greenness and canopy-condition indicators

The indicators of vegetation and forest change derived from Sentinel and Landsat observations are converted to indicators that can be measured to describe the condition of the canopy, the moisture status, the intensity of a disturbance, the biomass-related change, and the transformation of the landscape. These indicators are crucial in the forest monitoring context of India since many changes in forests are not necessarily reflected as a complete change from forest to non-forest. Degradation can be through canopy thinning, loss of greenness, moisture stress, fire scars, fragmentation or structural decline. Thus, depending on forest type, season, disturbance process, and the resolution of the datasets, indicator selection must be tailored. NDVI is a commonly used index for greenness and canopy activity and in dense forests could become saturated and less sensitive to biomass. In a tropical forest in India, Singhal et al. (2021) found that the use of spectral indicators requires interpretation with structural information in cases of carbon or biomass inference for a tree level carbon-stock assessment.

8.2 Soil, moisture, and dry-forest indicators

In areas of dry deciduous forests, sparse canopies and seasonally exposed soil backgrounds, the Soil-Adjusted Vegetation Index can aid in interpretation by decreasing the soil-brightness component. This is applicable in the central Indian and Maharashtra terrain where the post-monsoon greeness and dry season shedding of leaves create more distinct seasons. Moisture sensitive indices like NDWI can aid in the understanding of drought stress, canopy water status and post-rain recovery. In the case of tropical dry deciduous forest, Verma et al. (2024) evaluated the aboveground biomass using the PRISMA data, which demonstrated the need for sensitivity to forest canopy composition, spectral response, and forest seasonality.

8.3 Fire and disturbance indicators

The same applies to disturbance indicators. Normalized Burn Ratio and other spectral indices aid in the detection of fire effects, mortality, and recovery after disturbances. Fire alerts can also be used to supplement information on occurrence of active fires, but should not be used as direct evidence of tree-cover loss. In shifting cultivation landscapes, vegetation disturbance and regrowth is not one-way forest loss but occurs in cycles. Bhat et al. (2024) explored vegetation disturbances and regrowth in shifting cultivation areas, highlighting the value of the use of time-series indicators that differentiate between temporary disturbance, recovery and ongoing degradation.

8.4 Integrated indicator framework

Forest-change indicators should not just be used for classification but also for interpretation of the ecosystem. Habitat quality, ecosystem services and the resilience of the landscape are affected by changes in greenness, biomass, continuity of the canopy, moisture condition and fragmentation. Ramachandra et al. (2025) discussed the links between forest structure change and ecosystem services, emphasizing the importance of linking satellite-based metrics to ecosystem services. As shown in Figure 4, a combination of indicators, instead of a single indicator, should be used for forest monitoring in India.

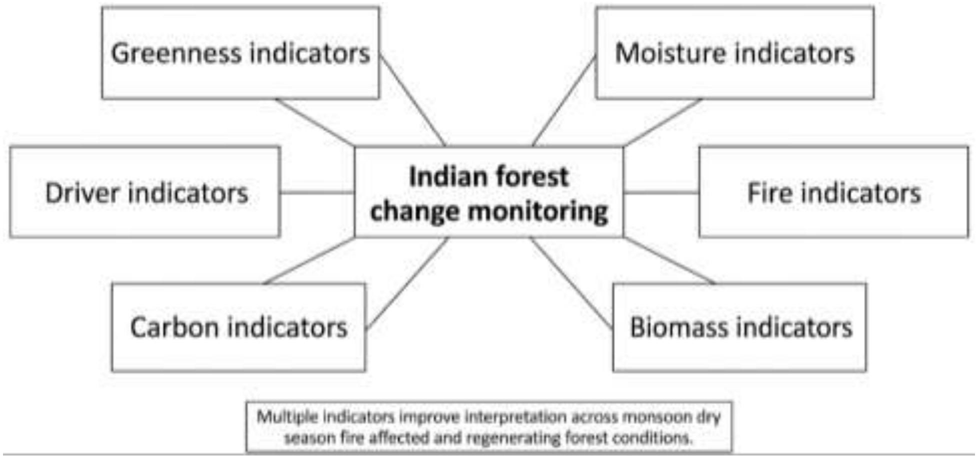

Figure 4. Indicator framework for Indian forest-change monitoring

Figure 4 shows that different indicators answer different forest-monitoring questions. Combining spectral, fire, biomass, carbon, and driver indicators strengthens interpretation across monsoon, dry-season, fire-affected, and regenerating forest conditions.

9. Application of Collected Datasets for Indian Forest Monitoring

9.1 Vegetation-cover and tree-cover change monitoring

Time-series of collected Sentinel and Landsat data can be useful for specific questions related to monitoring forests, such as: identifying vegetation-cover change, assessing degradation, analyzing fire burns, modeling biomass, and prioritizing actions by district. The applications are significant in India due to the following aspects of forest changes: canopy decline, patch clearance, fire disturbance, plantation growth, changing land use and fragmentation. Sentinel and Landsat indices provide information on greenness, moisture, burn effects and recovery, and Global Forest Watch tree-cover loss identifies districts and/or periods for detailed interpretation.

9.2 Fire-risk and disturbance interpretation

Canopy loss, vegetation stress, soil exposure, carbon emissions and regeneration are affected by forest fires, particularly in dry deciduous and Himalayan forest landscapes. Das et al. (2023) used statistical and weighted modelling to create forest fire susceptibility zonation over Eastern India, proving that remote-sensing data can be used to aid in spatial predictions of fire prone areas. This can be adapted to other regions like Maharashtra using Sentinel and Landsat indices, in addition to VIIRS fire alerts, slope, land use, land vegetation moisture, and distance to settlement and roads. Multiple spatial layers can identify vulnerable areas by applying remote sensing and GIS-based fuzzy AHP for forest-fire susceptibility analysis in the Indian Western Himalayas as demonstrated by Pragya et al. (2023).

9.3 Biomass, carbon, and ecosystem assessment

Another application is for biomass and carbon assessment. Satellite data allows for repeat observations of canopy conditions and machine-learning models can be developed to correlate canopy structural, terrain, and radar data with biomass estimates. Sainuddin et al. (2024) estimated aboveground biomass in the northern Western Ghats with machine-learning algorithms and data from multiple remote-sensing sensors, highlighting the importance of combining multiple variables derived from satellite observations for forest assessments on regional scales. This is pertinent for Maharashtra as the forests of the Western Ghats, dry deciduous forests, mangroves and plantations have different canopy density and biomass distribution.

9.4 Conservation planning and predictive modelling

Time-series datasets can also support long-term fire-dynamics assessment. Majumdar (2025) analysed satellite-detected biomass fires across India from 2012 to 2023, showing that repeated observations reveal spatio-temporal variability in fire activity. The main applications of collected datasets are summarized in Table 3.

Table 3. Applications of collected datasets for Indian forest monitoring

Application	Required dataset/layer	Main purpose
Vegetation-cover monitoring	Sentinel-2, Landsat, NDVI, EVI	Tracks canopy greenness, seasonal vegetation condition, and long-term vegetation change
Tree-cover loss analysis	GFW annual tree-cover loss, Landsat time series	Identifies cumulative and annual tree-cover loss patterns
Historical forest-change assessment	Landsat archive, land-cover maps	Reconstructs long-term forest and land-use change

Fine-scale disturbance detection	Sentinel-2, NBR, NDWI, high-resolution land-cover products	Detects patch-level disturbance, canopy stress, and fragmentation
Fire-risk interpretation	VIIRS fire alerts, NBR, NDWI, slope, land-use layers	Supports fire-prone area identification and post-fire assessment
Biomass assessment	GFW biomass, GEDI, Sentinel, Landsat, SAR data	Estimates forest structure, aboveground biomass, and biomass-related change
Carbon-dynamics assessment	GFW emissions, removals, net carbon flux	Interprets carbon impacts of tree-cover loss and forest recovery
Driver analysis	GFW dominant-driver dataset	Links tree-cover loss with agriculture, logging, shifting cultivation, wildfire, and infrastructure
Protected-area monitoring	Sentinel, Landsat, forest/protected-area boundaries	Supports conservation planning and protected landscape assessment
District-level prioritization	GFW district summaries, Sentinel/Landsat indicators	Identifies districts requiring detailed monitoring or field verification
Predictive vegetation-change modelling	Harmonized Sentinel-Landsat-GFW dataset, validation data	Supports machine-learning-based forecasting of vegetation change
Field and drone validation	Ground plots, drone imagery, high-resolution reference data	Reduces uncertainty and validates satellite-derived results

Table 3 shows that each monitoring objective requires a different combination of satellite images, derived indicators, and validation sources. This helps convert collected datasets into practical tools for conservation planning and predictive modelling. It also supports district prioritization for targeted field verification and management.

10. Challenges in Creating India-Specific Forest Datasets

10.1 Phenology, monsoon cloud cover, and seasonal uncertainty

The process of developing Indian specific forest datasets from the time series approach of Sentinel and Landsat datasets has its methodological challenges that question reliability, transferability and interpretation. An ecological diversity is the first challenge. The forest types in India are dry deciduous, sal forests, mangroves, Himalayan forests, plantations, degraded forest and mixed agro-forest mosaic. These systems cannot be uniformly represented by a single spectral rule and/or a single classification threshold. Spectral change can result from seasonality, monsoon greening, drought, and recovery from fire, but does not necessarily lead to permanent forest loss. The construction of datasets must therefore avoid consideration of degradation caused by disturbances and only include ecological seasonality.

10.2 Sensor mismatch and mixed-pixel limitations

The second challenge is related to limits of the atmosphere and of the sensors. Temporal gaps or false change signals can be caused by contrasting nature of the sensors, smoke, aerosols, monsoon cloud cover and terrain shadows. The Landsat and Sentinel have different spatial, spectral, revisit, and band configurations. Mixed pixels are frequently found in areas of fragmented forest, plantations, village/forest boundaries and in narrow corridors. Khan et al. (2025) investigated the impact of assimilation of EOS-06 data on quantitative interpretation of the forest fires in the Uttarakhand region, highlighting the importance of using the atmospheric information in interpreting fire-related datasets.

10.3 Fire complexity and model uncertainty

Another big hurdle is complexity due to fire. The occurrence of fire is dependent on elevation, moisture of vegetation, fuel quantity, access to fuel, and human activity. Bar et al. (2023) modelled the distribution of fires across an elevational gradient in the Western Himalayas, revealing that fire behaviour was not just a function of burned area signals, and is in fact spatially structured. Additionally, the susceptibility models can yield a variety of outputs for risk. The research by Tiwari et al. (2021) compared the three approaches of frequency ratio, analytic hierarchy process and fuzzy modelling for forest-fire susceptibility in Pauri Garhwal, and found that the choice of model has an impact on the interpretation. It is the responsibility of the dataset preparer to document input layers, assumptions and validation procedures for the dataset.

10.4 Validation and missing-driver limitations

The last challenge is to assimilate satellite, field and administrative data. A single optical index is often inadequate to characterize the canopy complexity, species diversity and stand density often found in Indian forests. Anandita et al. (2025) utilized satellite and ground data to estimate biomass in sal forests of Jharkhand with particular attention to calibration based on field data. Also, derived products are not necessarily directly measuring invasive species, village resettlement, encroachment and local governance changes. In the absence of validation, the data from Sentinel and Landsat can overestimate degradation, underestimate recovery, or even misrepresent seasonal vegetation changes as degradation of forest landscapes in India.

11. Research Gaps and Future Requirements

11.1 Need for benchmark-ready India forest datasets

However, the lack of uniformity in the satellite time-series datasets for forest monitoring for India makes them not suitable for research and operation use. The first missing piece is a framework that is reproducible and includes benchmark-ready datasets that combine optical imagery, radar observations, biomass products, fire records, field measurements and administrative forest boundaries. While most studies produce project-specific products, little of these are available in a format that can be compared within states, forest type or disturbance gradients.

11.2 Need for integrated carbon, fire, and vegetation layers

A second gap is related to the lack of link between forest carbon, fire dynamics and vegetation-cover change. Forest monitoring in India is typically segmented in the sense of mapping the land cover, estimating biomass, forecasting the fire-risk or assessing the forest ecosystem-service. Degradation can take multiple forms, though, as canopy can persist whilst biomass, connectivity, moisture stability or carbon-storage potential diminishes. Gorain et al. (2025) evaluated forest cover, carbon stocks and fire dynamics in India and highlighted the need to create integrated frameworks that will link the ecological condition, disturbance and valuation in forest.

11.3 Need for regional calibration and validation

A third is a more robust regional calibration. The phenology, canopy architecture, disturbance history and spectral response of the landscapes differ between the Central India, the Western Ghats, the Himalayas, mangroves. The thresholds should not be uniform and ecological stratification should be included in national datasets. Protected-area datasets, district-level products, wildlife-corridor layers, open metadata, uncertainty reporting, and field validation and drone-assisted verification for machine-ready structures should be considered as priorities for future work. Predictive modelling using Harmonized data from Sentinel-Landsat-GFW is possible only if the preprocessing, compositing and classification rules, and protocol for validation are transparent.

12. Conclusion

Time-series datasets provided by Sentinel and Landsat are important for reliable forest and vegetation monitoring in India. The present review demonstrates that dataset preparation is not just a mechanical task of downloading satellite data, but a method which affects the correctness of the data interpretation. Forest landscapes in India need to be monitored as they can be influenced by monsoon seasonality, deciduous phenology, fire disturbance, canopy fragmentation, plantation and pressure from humans. Hence it is vital to design the datasets specifically for India to help distinguish between the real forest degradation and seasonal or atmospheric or sensor variation. This is where these complementary attributes of Sentinel and Landsat are useful. Landsat is used for a longer-term historical assessment and Sentinel provides analysis of finer landscape changes with recent observations at high resolution. These satellite data can be used in conjunction with other products like the Global Forest Watch indicators, biomass layers, fire alerts, carbon-flux products and District-level summaries to facilitate comprehensive monitoring of tree-cover loss, vegetation health, biomass, carbon fluxes, and disturbance drivers. Their value is contingent upon quality pre-processing and pre-alignment, temporal compositing, validation, uncertainty reporting and documentation of metadata. These can be used as supplements for forest assessment, management of protected areas, fire-risk interpretation and predictive modelling of vegetation change for the Maharashtra and central Indian landscape. Collaborative research should be done to create harmonised, open, machine-learning ready datasets, incorporating satellite observations with field, drone and official forest datasets. A scientific basis for the Sentinel-Landsat-GFW framework would enhance reproducibility and reduce uncertainty in analyses, and would be a valuable basis for conservation planning and forest governance, and for long-term monitoring of India's diverse forest landscapes.

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