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REVIEW

Satellite-Based Change Detection Techniques for Land Use and Land Cover Dynamics

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ABSTRACT

The detection of change using satellites has become a fundamental feature to track the land use and land cover (LULC) dynamics at local to global levels. Through this review, the synthesis of progress in the Earth observation data sources, preprocessing, methodological frameworks, and validation practices has been taken into consideration, upon which credible mapping of LULC changes relies. We then give a brief overview of applications of optical, synthetic aperture radar (SAR), thermal, and emerging hyperspectral/structural products, with the outlook of how resolution-revisit trade-offs, co-registration, atmosphere/terrain normalization, vapor and speckle suppressing capabilities, and time-series separation of performance. We then classify change detection methodologies as formulations of the problem, including binary no change, multi-class transition mapping, and the estimation of change timing. Classical differencing and change vector analysis will be useful in interpretable settings with low data, whereas statistical breakpoint and trajectory models allow time and persistence reasoning that are sensitive to seasonality. Deep learning designs have been used to learn spatial-temporal representations using engineered multi-temporal features, and machine learning algorithms, such as Siamese and encoder-decoder networks and temporal convolutional and transformer models, can learn directly on imagery. New self-supervised and foundation model paradigms seek to enhance transferability in domain shift as well as label scarcity. We also check multi-sensor fusion and object-based approaches to the enhancement of semantic coherence at high resolution. Lastly, we speak about benchmark datasets, evaluation measures, and validation procedures, pointing

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out pitfalls due to spatial leakage and class imbalance, and emphasizing uncertainty-aware statistically defendable area estimation. We finish with operational monitoring that is driven by application and is open to challenges towards scalable, interpretable, and trustworthy operational monitoring.

Keywords: Land Use/Land Cover; Change Detection; Time-Series Remote Sensing; SAR-Optical Fusion; Uncertainty Quantification

1. Introduction

The satellite-based change detection has emerged as a pillar of modern studies and practice to understand dynamism in land use and land cover (LULC)[1]. With the increasing rate of human activities and the variability of climatic conditions, the landscape is rapidly being altered at unprecedented rates as a result of urban sprawl, agricultural intensification, deforestation and forest degradation, disappearing wetlands, shoreline alteration, and post-disaster reconstruction. The effects of these changes include changes in surface energy balance, carbon and water cycles, habitat connectivity, occurrence and intensity of hazards with direct consequences on biodiversity conservation, food and water security, mitigation, and adaptation to climate change. Due to the fact that most of these processes are spatially heterogeneous, episodic, and transpire across administrative borders, they are not easily identified by in-situ surveys. The Earth observation (EO) satellites offer an exceptionally consistent, scalable, and repeatable system of observing the surface of the Earth, making it possible to identify, map, and measure LULC change on local and global levels[2,3].

In a general sense, change detection is a process that determines the dissimilarity between the status of an object or phenomenon by observing this phenomenon at various moments of time. In the understanding of EO-based LULC analysis, it includes a collection of approaches that seek to identify and describe changes in land cover (e.g., forest to cropland), changes in the intensity of land use (e.g., increased frequency of cropping), and changes in surface properties (e.g., changes in vegetation structure following fire). It is noteworthy that change can either be sudden, as in the case of clear-cutting, flooding, or quick construction, or slow, as in the case of regrowth of forests, shrubs, or the process of urban densification. It can also be seasonal or cyclical, and it can get mixed up with phenological and seasonal management practices, thus the distinction between true land-cover conversion and normal temporal variation. The difference between land cover (physical state of the surface) and land use (the purpose, or function of human activity) further makes the task of interpretation difficult, as satellites detect physical characteristics, whereas land use may need contextual clues, additional information, or information-rich evidence to interpret management and intent. LULC change detection based on satellite is, therefore, at the convergence point of remote sensing physics, time-series analysis, pattern recognition, environmental, and socio-economic interpretation[4,5].

The present phase of EO presents opportunities and growing methodological complexity that have never been seen before. The deployment of a thickening network based on optical, thermal, and microwave sensors offers multiple, repeated coverage with varying spatial, spectral, and temporal attributes[6]. Multispectral results at medium resolution are useful in long-term, globally, consistent observance; high-resolution commercial and consumer missions exemplify the fine views of urban structure and also coarse disturbances, synthetic aperture radar (SAR) offers 24-hour-out, all-weather observance, which is invaluable in turbid tropics and at the moment of extreme occasions; and future generation products derived involving hyperspectral multispectral imaging or Light Detection and Ranging (LiDAR) can also provide more vectors of content and construction. In the meantime, cloud computing and open-data policies have increased access to petascale archives, which have made it possible to build dense time series, merge multi-sensor measurements, and run computationally costly models on a large scale. These developments have shifted change detection from a marginal methodological practice to an operationally useful field of use in the detection of deforestation and crop monitoring, as well as in disaster response and carbon accounting[7,8]. **Table 1** illustrates that various sources of satellite data (optical, SAR, thermal modes, etc.) have diverse capabilities and constraints towards identifying LULC change, depending on spatial resolution, ability to observe continuously, and content (among other factors).

Although this has been made, there is still a challenge of reliable and transferable change detection. At the data level, the apparent change that may occur due to differences in sensor calibration, viewing geometry, illumination, atmospheric conditions, and phenological stage may cause apparent changes not due to real LULC changes. Continuous obscuration, haze, snow, and shadowing produce missing data patterns with a bias to the naive comparisons, and mixed pixels and sub-pixel heterogeneity make mapping difficult in discontinuous landscapes. Speckle noise, terrain effects, and sensitivity to moisture can be confounding change signals in SAR unless addressed very carefully. Errors of co-registration between dates, which are typically small in absolute terms, can provide inappropriately large false alarms along edges and linear features, with high spatial resolution. Moreover, spectral similarity exists between a wide range of landscapes (e.g., bare soil and built-up surfaces, harvest and drought stress) and even within the biomes and seasons, a single process of change can appear differently. Consequently, the main scientific and operational question is not merely how change may be detected, but under what conditions it may be detected with considerable strength, correctly attributed, and with known error[9–12].

Table 1. Representative satellite data sources for land use and land cover (LULC) change detection.

Modality	Typical Information Content for LULC Change	Strengths	Common Limitations/Artifacts	Common Change-Detection Use Cases
Optical multispectral	Surface reflectance; vegetation vigor, moisture, bare soil and many urban materials	Intuitive interpretation; strong land-cover separability; long archives	Clouds/shadows/haze; BRDF/illumination effects; phenology confounding	Deforestation, crop expansion, urban growth, burn scars
SAR (C-/L-band; single/dual/full-pol)	Backscatter sensitive to structure, roughness, moisture; geometry-based urban response	All-weather, day/night; works in cloudy tropics; sensitive to inundation/structure	Speckle; terrain layover/shadow; moisture-driven variability	Flood/wetlands, forest disturbance under clouds, urban expansion
Thermal infrared	Land surface temperature; evapotranspiration proxies	Stress/heat-related signals; useful for urban climate dynamics	Often coarser resolution; atmospheric effects; emissivity issues	Drought impact, irrigation signals (with context), urban heat change
Hyperspectral	Material-specific spectral signatures; vegetation traits	Detect subtle biochemical changes; improved class discrimination	Limited global coverage; large data volumes; calibration complexity	Subtle vegetation stress, species/functional change (where available)
LiDAR/structural products (spaceborne/derived)	Canopy height/structure; vertical profile proxies	Direct structural sensitivity; complements optical/SAR	Sparse/mission-dependent; sampling gaps	Biomass change, degradation vs. regrowth separation

Note: The table summarizes important satellite modalities commonly used for change detection, their strengths, limitations, and typical use cases in LULC monitoring. BRDF, Bidirectional Reflectance Distribution Function; SAR, Synthetic Aperture Radar.

Methodologically, this field has developed out of the primitive pixel-based differencing and thresholding ways of space, time, and multi-sensor combinations, up to advanced statistical learning and deep neural networks. The classical methods, which are image differencing, ratioing, change vector analysis, and principal component methods, are appealing because of their interpretability and reasonable data demands, and are still employed in numerous working processes. Statistical time-series methods allow distinguishing breakpoints, trends, and anomalies, and give estimates of change timing and pathways as opposed to the before/after comparisons. Machine learning (ML) structures, such as random forests and support vector machines, have increased the ability to learn nonlinear terms and use a wide range of features, and recent deep learning (DL) structures, by themselves, Siames networks to bi-temporal mapping, U-Net variants to segmentation networks, and temporal convolutional and transformer structures to dense time series have performed well on benchmark data. Self-supervised pretraining and foundation-model paradigms are also being considered more and more frequently to ensure less reliance on labels, as well as to enhance cross-regional cross-sensor generalization[13,14].

Nevertheless, the type of methodological improvements observed in controlled experiments is not always transferred to strong performance in other geographies, seasons, and sensing environments. The generalization and domain shift are still relentless: any model trained to perform excellently in one area can be rendered useless in a different one by the changes in phenology, land management approaches, materials used to construct the buildings, sensors, etc. Change-detecting labels are costly and also noisy, and usually, there is a time discrepancy between ground truth and satellite capture, vague class definitions, and class imbalance (since most landscapes have primarily no change). Such problems make it difficult to assess them and could cause inflated performance estimates when test samples are spatially autocorrelated with training data or when changes are not independently tested. In addition, numerous reports state pixel-level accuracy without providing area estimation bias, confidence intervals, or uncertainty propagation that are needed to have policy-relevant monitoring, including emissions accounting or compliance assessments. Since change detection has shifted its focus towards operational deployment, reproducibility, transparency, and uncertainty communication are starting to be equally significant as raw predictive accuracy [15].

The present review deals with satellite-based change detection methods to define the dynamics of LULC; it will pay attention to the principles of methodology, the workflow decisions, and the current trends. We combine the topography of EO data sources applied in change detection, optical and SAR modalities, and typical fusion approaches. We then structured and contrasted key families of change rate detectors, such as classical, statistical time-series, ML, and DL, and about what each one supposes, what their weaknesses are, and how and in which change regimes (abrupt vs. gradual), spatial scales, and data availability conditions they are suitable. We are aware that reliable inferences rely on a rational assessment and outline benchmark datasets, assessment approaches that suit the imbalance of change/no-change and transition mapping ideas, and also establish the utilization of a uniform assessment testing and reporting of these uncertainties. Lastly, we look at the important areas of application: forests, agriculture, urban systems, wetlands/coasts, and hazards that we will relate methodological considerations to real-world constraints like timeliness, interpretability, and computational scalability. In the process, we focus on the need to match the method choice with the nature of the change process, sensor, and time-series properties, and the desired decision context [16–18].

Many themes lead our minds. To begin with, preprocessing and harmonization are not fringe concepts but the main determinants of the quality of the change detection results since co-registration mistakes, atmospheric regulations, cloud masking, or radiometric normalization can control the downstream outputs. Second, the variability and change difference, particularly in the case of managed and seasonal systems, need time-series-conscious methods and experiment-wise designs. Third, generalization of models ought to be a primary goal, rather than an appendage, which drives geographic cross-validation, sensor-transfer tests, and strategies of adaptation. Fourth, quantifying uncertainty and reporting are critical steps toward making change maps actionable information, especially when they are used to make resource allocation, enforce regulations, or climate reports. Lastly, the recent development of self-supervised models and EO foundation models almost inevitably indicates a forthcoming change in the direction of more transferable representations in the field, though such advancements must be scrutinized critically through a variety of landscapes and with explicit focus on any biases, interpretability, or limiting operational characteristics [19–23]. **Figure 1** illustrates a conceptual framework of satellite-based LULC change detection, linking key components such as change drivers, sensor inputs, preprocessing steps, change detection methods, and outputs that inform decision-making.

The rest of the article is made in the following way. Section 2 will discuss satellite data modalities for LULC change detection, and decipher preprocessing and time-series construction practices, which they propose to make robust towards analysis. Section 3 conducts a survey of change detection approaches, starting with classical approaches to change detection and reaching advanced deep-learning-based approaches and multi-sensor fusion-based approaches, and addresses the issues of interpretability and uncertainty. Section 4 analyses datasets, evaluation metrics, and validation protocols with reproducibility and generalization being paramount to it. Section 5, it highlights major areas of application and new directions of research, such as foundation models, physics-guided learning, and operational near-real-time systems. Section 6 will contain the synthesis of major findings, open challenges, and future research and practice recommendations.

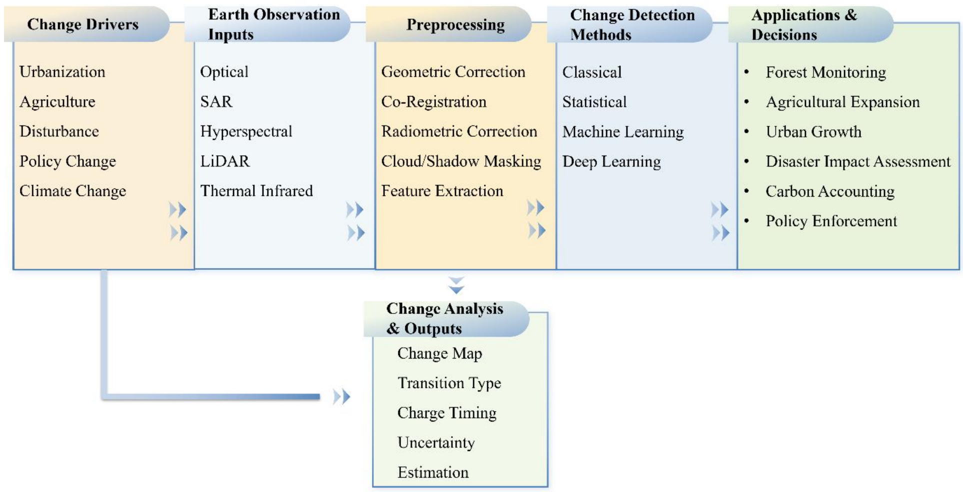

Figure 1. Conceptual framework of satellite-based LULC change detection.

2. Satellite Data Sources and Preprocessing for Change Detection

2.1. Earth Observation Data Modalities for LULC Change Detection

The sensing modality essentially influences the dynamics of satellite-based change detection of land use and land cover, since various sensors sense various physical characteristics of the surface of the earth. The optical multispectral systems record reflected solar radiation in the wavelengths of visible, near infrared, and short waves and therefore are very informative about vegetation vigor, canopy water content, bare soil exposure, and most built-up materials [24]. Their lengthy history of record and large-scale coverage area have caused them to be the standard set of backbone to multi-decadal LULC change studies, especially in matters of deforestation, agricultural development, and urbanization. The optical measurements are, however, limited by the atmospheric conditions and solar light. Signals may be obscured or distorted by cloud cover, haze, smoke and the geometry of sunsensors and this problem is particularly acute in all humid tropics, mountainous areas, as well as during extreme events where information is needed most urgently.

Synthetic aperture radar is an optical data complement that actively emits microwave energy and measures the backscattered response, allowing it to be used to make acquisitions regardless of sunlight availability and, to a large extent, cloudy and light precipitation [25]. SAR is also sensitive to roughness, geometry, and dielectric properties of the surface that are highly affected by the vegetation structure, soil moisture, inundation, as well as the existence of man-made objects. It is this sensitivity that is making SAR especially useful in mapping the dynamics of flooding and wetlands, forest disturbance in regions with constantly cloudy weather, and also changes in constructed environments where geometries generate different scattering behavior. Simultaneously, SAR imagery also presents some complexities, such as speckle, layover, and shadowing in rough terrain, seasonally varying moisture effects, which can simulate change unless they are adequately modeled. In addition to optical and SAR, thermal infrared measurements are used to provide information about surface temperature and proxies of evapotranspiration that can be used to analyse change related to droughts and urban heat dynamics, but are usually coarser in spatial resolution [26]. Hyperspectral imaging and LiDAR-based products provide more detailed spectral and structural description, which gives prospective advantages in distinguishing subtle variations and vegetation functional aspects, but are less readily available in any part of the world and may also need specific processing.

The growing availability of multi-sensor archives has promoted the combination of complementary measurements in order to decrease the ambiguity of the change interpretation [27]. Practically, the optical time series can capture the phenological and biochemical worlds effectively, whereas SAR can inform about structure and moisture-based information and enhance coverage during the clouds. The modalities can be utilized complementary to make the detection process more sensitive to actual changes, and also the portion of false alarms caused by unavailable data or seasonality should they reportedly differ across sensors, although this requires significant care in the preprocessing process.

2.2. Resolution, Revisit Frequency, and Cross-Sensor Harmonization

A trade-off between spatial resolution, temporal revisit, and spectral richness is determined that the detectability of LULC change is based on what trade-offs occur [28]. Small-scale spatial resolution enhances the potential to map narrow linear objects, small clearings, sporadic built-up areas, and heterogeneous land mosaics and, usually, is accompanied by smaller swaths or increased costs, thereby decreasing revisit frequency and making monitoring not as uniform. In contrast, moderate-resolution missions are generally high-frequency and systematic worldwide and contain long records, which are best in trend analysis and large-region change mapping, but small or fragmentary variations or a mixture of land-cover types within a pixel. Transient resolution is also implicationary. The thick revisit constructs the separation between short-term variability and long-term change better and constructs the timing of changes more accurately, whereas the sparsity of revisit formats analyses are more reliant on compositing tactics and are more prone to phenological incongruence between observational periods.

Cross-sensor research and operational systems are becoming more based on harmonization, since long-term analysis of change may require multiple missions and different instruments. Radiometric consistency, harmonizing the difference in spectral response functions, solving the problem of calibration and atmospheric correction, is a part of harmonization; geometric consistency, that the different images of multi-dates measure precisely at the sub-pixel level, is also part of harmonization; and temporal consistency, which observes the difference of overpass time and season sample-to-sample. With no harmonization, surface transitions may not be apparent, but may be due to sensor artifacts affecting imagery across platforms or when combining measurements taken using different modalities. In practice, harmonization is a collection of design decisions affecting both downstream modeling, such as the choice between using surface reflectance products or not, reducing the effects of big and direction on small sensors, and managing the varying information content of different sensors [29].

2.3. Geometric Preparation: Co-Registration and Terrain Effects

Most change detection methods require accurate geometric alignment since misregistration over time may introduce edge artifacts, which can be interpreted as change, especially along boundaries separating land-cover classes and along edges with high contrast urban materials. Even minor sub-pixel misalignments can blow up false observations in bi-temporal differencing, supervised classification of change, and deep segmentation models that treat misaligned textures as transitions. Strong co-registration steps, such as the choice of suitable reference imagery, stable control features, and a warping model that is applicable to the sensor geometry and terrain, are implemented. Especially in mountainous areas, relief displacement may vary across acquisition geometries and cause systematic offset. Orthorectification is crucial in such areas. In the case of SAR, terrain correction is necessary to lessen the geometric distortions due to side-looking imaging, whereas topographic normalization can be used in optical sensors to reduce the illumination differences across slopes that would otherwise occur as spurious spectral change [30,31].

The geometry of terrain also has an effect on the physical signal, not just on its geometry. Slope and aspect alter the illumination conditions of optical images, and even without changing land cover, the reflectance is altered. In SAR, there is an effect of variation in incidence angle and local topography on scattering strength and shadowing that might produce strong spatial patterns not related to LULC dynamics. Correction of terrain effects may, therefore, need geometric correction and radiometric normalization, and the relative significance of each is determined by the complexity of the landforms, the sensor type, and the strength of the change signal of interest [32].

2.4. Radiometric and Atmospheric Processing for Optical Change Detection

Optical change detection is designed to measure the time-varying surface reflectance, which is, however, distorted by atmospheric scattering and absorption, sensor-specific calibration, and different illumination and viewing geometry [33,34]. Atmospheric correction deemphasizes the effects of aerosols, water vapor, and other atmospheric constituents so that changes that are observed are more indicative of what happens on the surface than changes in atmospheric conditions. This step is especially used when long time series are involved, and in the areas where aerosol loading is variable (e.g., dust, smoke, or industry). Temporal variability can also be caused by bidirectional reflectance effects, which are caused by surface anisotropy and sun-sensor geometry differences and appear as land-cover change, particularly on bright soils, sparse vegetation, and structured urban materials. The BRDF-induced variability techniques, along with the fact that the area is mountainous, can help increase temporal consistency and decrease erroneous detections.

The prevailing sources of optical time series missingness and error include cloud, cloud-shadow, haze, and snow contamination [35]. The masking techniques eliminate contaminated pixels but leave the process of irregular sampling, which may bias the measure of change unless it is mitigated. In order to create analysis-ready time series, composing strategies that combine observations by time period (such as monthly or seasonal windows) are adopted by a large proportion of such workflows to mitigate the effects of clouds and stabilize reflectance. The length of the compositing window determines implicitly the time resolution of change that can be detected: the shorter the compositing window, the better the timing resolution, but the longer the window, the less noisy and the less abrupt the change can be detected. The compositing strategy to be adopted should then be based on the desired change process and the acceptable detection latency under the desired application.

2.5. SAR-Specific Processing: Calibration, Speckle, and Temporal Consistency

The difference between SAR preprocessing and optical workflows lies in the fact that the physics of the measurement, as well as the nature of the noise, are different [36]. Radiometric calibration is used to transform the raw measurements into backscatter coefficients, which are physically meaningful and can be compared between scenes and times. Terrain correction is a method used to correct geometric distortions and to equalize the effect of incidence angle when further normalization may be necessary in cases where the acquisitions are very different in geometry or polarization arrangement. Speckle is a multiplicative noise of coherent imaging, which complicates the process of detecting change since it may inflate local variation and conceal small trends. Filtering and multi-looking can also help eliminate speckle, but also destroy spatial information, which presents an inverse relationship between noise reduction and the capability to detect small-scale change.

The moisture of the soil and vegetation, the occurrence of precipitation, and the freeze-thaw dynamics also determine the temporal consistency of the SAR time series [37]. Great changes to the backscatter intimate to not only LULC shifts can be generated by these factors, especially in agricultural systems and wetlands. Therefore, strong SAR change detection can be based on temporal aggregation, multi-polarization information, or modeling strategies that explicitly separate the structural change and the variability caused by the presence of moisture. Interferometric coherence will introduce a new dimension of change sensitivity where applicable, since coherence may plummet in response to perturbation, vegetation cover, or surface deformation. Nevertheless, temporal baselines, viewing geometry, and environmental conditions also influence the coherence, and therefore, when applying it to LULC applications, it should be interpreted carefully. **Table 2** summarizes the critical preprocessing and time-series construction choices and their impact on the quality of change detection, from co-registration to feature representation.

Table 2. Preprocessing and time-series construction choices and their impact.

Processing Stage	Objective	Typical Approaches	Failure Mode If Neglected	Practical Notes for Change Detection
Co-registration & orthorectification	Align pixels across time/sensors	Sub-pixel registration, stable tie points, DEM-based orthorectification	Edge "false change," noisy boundaries, inflated commission errors	Most critical for high-resolution and bi-temporal methods
Atmospheric/BRDF/topographic normalization (optical)	Improve radiometric comparability	Surface reflectance products; BRDF correction; terrain correction	Apparent change from aerosols/illumination rather than LULC	Essential for multi-year trends and mountainous regions
Cloud/shadow/snow masking (optical)	Remove contaminated observations	QA masks + refinements; temporal consistency checks	Missingness bias; spurious anomalies; class confusion	Masking quality often limits achievable accuracy

Table 2. *Cont.*

Processing Stage	Objective	Typical Approaches	Failure Mode If Neglected	Practical Notes for Change Detection
SAR calibration & terrain correction	Ensure physical comparability	Radiometric calibration; RTC/terrain flattening; incidence angle normalization	Geometry-driven "change," slope artifacts	Especially important in rugged terrain and mosaics
Speckle mitigation (SAR)	Reduce multiplicative noise	Filtering, multi-looking, temporal aggregation	High variance, salt-and-pepper change maps	Balance smoothing vs. small-change detectability
Compositing & gap filling	Build stable time series	Monthly/seasonal composites; medians; interpolation	Phenology mismatch; change timing blur	Window length controls detection latency vs. noise
Feature representation	Enhance separability	Indices, textures, temporal metrics; learned embeddings	Weak signal-to-noise; unstable thresholds	Choose features aligned with change process (abrupt vs. gradual)

Note: DEM, Digital Elevation Model; QA, Quality Assurance; RTC, Radiometric Terrain Correction.

2.6. Time-Series Construction and Feature Representation

How the multi-date observations are put together in the form of a time series directly affects the detectability of change[17]. Bi-temporal change, which is a form of change detection, compares two dates, e.g., before and after, and can be useful when quick events are needed, and appropriate cloud-free imagery is available. However, the LULC processes often occur within the framework of months and years, and even sudden situations can be hard to isolate when the before and after images cannot be compared in terms of phenological stage or acquisition conditions. Dense time series address such problems by having repeated observations, which can enable algorithms to learn the seasonal cycles, estimate baselines, and find deviations that cannot be attributed to normal variability[38,39].

The gap between raw measurements and change inference is represented by feature representation. Spectral indices and transformations can be used in optical analyses to increase sensitivity to vegetation condition and moisture content, burn severity, exposed bare soils, and built-up surfaces, and diminish dimensionality and sensitivity to certain illumination effects. As the spatial resolution gets higher, textural characteristics and the context of space gain more significance since change processes and LULC classes are frequently represented by patterns and not by single pixel values. Backscatter statistics, polarimetric ratios, and temporal measures can be used to describe the dynamics of both structure and moisture in SAR analyses, whereas coherence and multi-temporal descriptors give complementary information. More and more, deep learning models are being trained on raw or mildly processed inputs, and the performance of such models is still sensitive to the time series regularity, noise properties, and cross-scene stability of the time series that has been constructed during preprocessing[38].

2.7. Multi-Sensor Fusion and Data Integration

The need to eliminate ambiguity and expand temporal coverage is often the reason behind multi-sensor fusion[27,40]. The fusion of optical and SAR is especially popular since it can be combined with spectral sensitivity to vegetation and materials and structural and all-weather observation abilities. It is possible to perform fusion at the data level (joint feature stacks), the representation level (learned embeddings), or even at the decision level by summing change probabilities of a pair of independent models. Both strategies present their own set of normalization and alignment. Data-level fusion requires scrupulous scaling and handling of missing values, whereas the architecture-level fusion requires architectures that can balance between heterogeneous data noise and information content. Decision- level fusion can be more modular, but it might be missing synergistic cues that can only be visible when modalities are studied in combination.

Change interpretation can also be reinforced by integration with other ancillary geospatial data. Contextual data: Topography, climate normals, road networks, cadastral data, and socio-economic data can be used to disambiguate land use and land cover and aid in attributing change drivers[41]. However, ancillary data can be of lower spatial resolution, lower temporal currency, and less uncertainty compared to satellite imagery. In order to ensure successful integration, it is important to pay clear focus on temporal alignment and spreading uncertainty, particularly when change products are supposed to be used in policy or reporting applications.

2.8. Computational Platforms and Reproducible Workflows

More and more change detection crimes require even more computational infrastructure capable of storing, accessing, and processing large EO archives. The analysis-ready data products and cloud-based platforms have reduced barriers to entry and also facilitated the study on a continental level, up to a global level, which was previously inconvenient. Scalability, however, comes with new issues of reproducibility and transparency of the methods. Minor discrepancies in the versions of products, the algorithms used in atmospheric correction, the masking operations, and the mosaicking policies can produce significantly different results in the change, despite the equality of downstream models. Reproducible workflows thus need well-documented information of data reference points, processing guidelines, time compositing principles, and spatial tiling approaches in addition to version control of code and input datasets [42].

Operational monitoring systems also restrict the preprocessing choices, in that they need a compromise between timeliness, cost of computation, and strength. Immediate availability is usually not a priority, and near-real-time applications can be provided with noisier inputs in order to lower latency, whilst long-term trend studies may prefer consistency and reduction of bias, rather than immediate availability. What needs to be done, in both instances, is a conscientious design of a pipeline - consisting of sensor choice, harmonization, masking, time-assembling features, and feature representations - and making sure that the resulting identified changes are the real dynamics of LULC, not artifacts of data processing [43].

3. Change Detection Methodologies

3.1. Problem Formulations and Conceptual Taxonomy

The change detection of land use and land cover dynamics via satellites can also be formulated in various closely related ways, and the formulation adopted largely determines the way the methodology is designed and evaluated. The most basic way to formulate it is binary change detection, whereby the objective is to find out whether a location has altered between two time points, irrespective of the nature of the change. This can usually suffice to do quick disturbance tracking, like when clearing the forest, where there is burning, or when the effects of a flood are being monitored, and the basic decision in these cases is whether or not to provide an alert. Multi-class change detection is a more sophisticated formulation, in which one specifies the various types of change events or different types of changed land-cover. An even more informative framing is that of transition mapping, which is occasionally known as from-to change, where the goal is to predict the land-cover class at time t1 and time t2, which clearly and explicitly names the transition, e.g., forest-to-cropland or cropland-to-urban. Since satellites cannot see land use directly, it is common to use a method that aims at land-use change to include longer-term context, the use of proxy variables, or additional data in order to detect changes in management or functioning and not simply biophysical cover [44,45].

On top of what changed, most applications need to know when the change occurred and how it changed [46]. The estimation of change timing aims at identifying the date of onset or breakpoint of a transition, which is key to the near real-time notification of deforestation, monitoring of crop calendars, and post-disaster evaluation. Trajectory analysis expands this by providing a model of the temporal pathway of change, the distinction between abrupt conversion and gradual degradation or recovery, and the division between structural change and cyclical variability. These formulations are not exclusive to each other, and indeed, they depict varying degrees of granularity and may be synthesized. As an illustration, a system can directly first identify the occurrence of change with the help of a time-series model, and subsequently the type of transition with a supervised classifier or deep network that takes into account both pre- and post-change signatures. **Figure 2** categorizes the major method families for satellite-based LULC change detection, from classical approaches to deep learning-based models, illustrating their respective inputs, strengths, and output types.

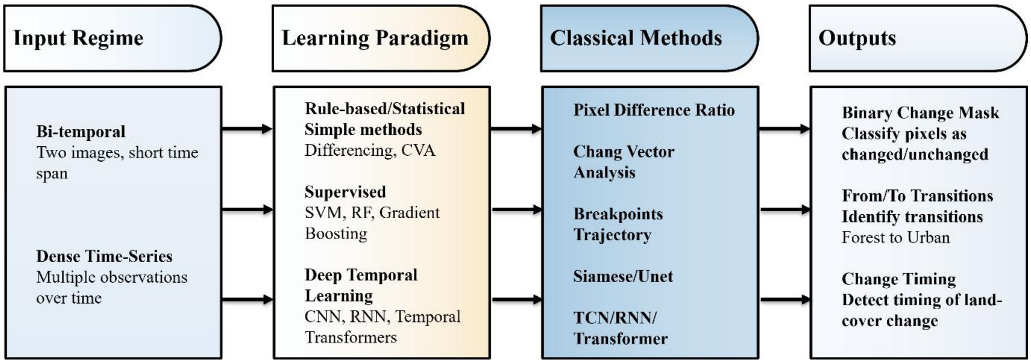

Figure 2. Method taxonomy map with representative architectures and outputs.

3.2. Classical Bi-Temporal and Multi-Temporal Approaches

The classical change detection algorithms were motivated by the requirement to obtain the change information on constrained temporal samples and relatively low-level computing capabilities. Image differencing and image rationing are used in bi-temporal applications of spectral bands or spectral indices between two dates; thresholds are applied to distinguish changed and unchanged pixels. These methodologies are conceptually simple and may work under conditions where atmospheric influences are managed and when variation is high as compared to natural fluctuations. Change vector analysis extends differencing to multi-band feature space, and represents change as a vector, the magnitude of which and its direction may be used to encode the strength and character of change. Principal component and transformation-based algorithms look to isolate change-related variance by projecting the multi-date data into a lower space where components that are constant across time are estimated to be separated from those that are constantly changing across time [47,48].

Multi-temporal contexts can traditionally use classical approaches based on the use of composing, temporal filtering, and rule-based reasoning to define change [49]. As an example, a constant decrease in vegetation indices in comparison with historical baselines can be a sign of deforestation or degradation, whereas a constant increase may be a sign of regrowth. Such operational methods are used in operational processes as they are clear and comparatively simple to execute within vast regions. Their performance is, however, highly dependent on the threshold selection, which may be sensitive to biome type, season, and sensor attributes. The main weakness of classical approaches is that they may find it difficult to deal with subtle variations, ambiguity of classes, and transfer to new domains, and may not explicitly provide a probabilistic system of uncertainty estimation, unless further modeling is added.

3.3. Statistical Time-Series Change Detection and Trajectory Modeling

Statistical time-series procedures assume that each pixel or spatial unit is a time process and attempt to separate normal variability and structural change [50]. One of them is the breakpoint, which is a time point when the statistical characteristics of the series change, including the level of the mean, trend, or seasonality. The breakpoint detection is of great importance in LULC monitoring since it gives a change decision and an approximation of the change time. These techniques are representable by piecewise regression, state-space models, or change-point models, which explicitly model regimes in pre-change and post-change. In the case of a seasonal cycle, which is common with vegetated landscapes, models that include seasonality may minimize false detections due to phenological variation and make change inference stronger.

Trajectory modeling is an extension of breakpoint detection that defines the form of change through time. Instead of viewing change as a single occurrence, one can model change as a gradual decline, a multi-phase conversion, or post-disturbance recovery. It is significant in systems where the mechanisms of land-cover change cannot be described by a single pre- and post- observation, e.g., forest thinning and clearing, agricultural development and shrub clearing, urbanization that occurs in stages of clearance, construction, and densification. There are also statistical methods that provide a way to quantify uncertainty, since residual variance, model diagnostic tools, and probability assumptions can be applied to indicate how confident one is about observed changes, as well as to estimate the delay before they can be detected. However, purely pixel-based time-series models can be under-exploiting spatial information, and can be susceptible to the data patterns and sensor variations unless preprocessing and composing are well thought out [51,52].

3.4. Supervised Machine Learning for Change Mapping

Supervised machine learning methods cannot be classified as change detectors; they consider change detection as a classification, with engineered features based on multi-date images, and are trained to learn decision boundaries between change classes [53,54]. Support vector machines and other traditional classifiers like random forests and gradient boosting have become very popular due to the fact that they can model non-linear relationships, mixed-type features, and moderate training data volumes. In reality, these methods tend to be stacked on spectral bands, spectral indices, spectral textural measures, and time-based summaries, e.g., pre-change medians and post-change differences. In the case of transition mapping, supervised ML can be used in two phases through the initial classification of land cover at each timescale and the subsequent derivation of transitions, or can be used directly to learn transition classes based on bi-temporal or even multi-temporal features.

One of the common pitfalls of supervised ML is label scarcity and label noise [55]. Labeling changes accurately in time, and interpretation is hard at scale, and no change often dominates the landscape, inducing serious class imbalance. Stratified sampling, cost-sensitive learning, and probability calibration are frequently helpful techniques necessary to prevent defaulting on predicting stability by a model. The other problem is domain shift: a model that has been trained in one area can learn proxies that are sensitive to local phenology or materials instead of actual semantic change, and this can decrease its performance in other areas. Methods that merge domain adaptation, transfer learning, or regionally stratified training are potentially more robust; such methods should be carefully validated to avoid optimistic estimates, which are caused by spatial autocorrelation between training samples and testing samples.

3.5. Deep Learning for Bi-Temporal and Time-Series Change Detection

Deep learning has transformed change detection in terms of learning hierarchical features directly by looking at images and incorporating the context of space in terms of convolutional designs [56,57]. Siamese networks and other dual-branch models are used in bi-temporal change detection, to process two images using a shared or partially shared set of weights, and learn change-related representations, the difference between which is the difference between two representations. The architectures based on encoders and decoders are common, including types of U-Net that obtain dense change masks at the pixel-level resolution with skip connections to preserve fine spatial resolution. Attention mechanisms are an additional improvement of such models as they enable the network to concentrate on salient parts and overpower irrelevant variability.

Deep models are able to learn temporal dependencies explicitly and are not limited to pairwise comparison, as is the case with dense time series [58,59]. Sequential patterns can be learned by using temporal convolutional networks and recurrent-based architectures and longer-range temporal relationships can be learned with transformer-based models as long as they are properly masked and positionally encoded. These methods are specifically useful in decomposing seasonal variations and structural change, and also in identifying the onset of change in continuous streams of monitors. Nonetheless, deep models tend to be data-hungry and potentially overfit to particular sensor seasons, or geographic conditions when training data are not indicative of the desired operational conditions. They are also susceptible to label noise, and their results can be ill-calibrated unless calibration-aware losses or post-hoc techniques are employed.

Interpretability is also one of the key questions of deep learning in LULC change detection [60]. Though deep models may perform better than classical methods on most benchmarks, the decision-maker may require knowing why a change was observed and the confidence that the system can have in a particular problem code, especially in policy contexts. Saliency map, attention visualisation, and feature attribution can offer partial information, but they are volatile, and they might not be connected to causal change agents. This is why more focus is now paid to uncertainty estimation in deep networks, such as probabilistic outputs, ensemble techniques, and the generation of confidence layers that can be utilized to either emphasize manual inspection or to estimate areas with uncertainty intervals.

3.6. Self-Supervised Learning, Foundation Models, and Transferability

The exploitation of the unlabeled abundance of satellite imagery is a significant methodological trend in using self-supervised learning [61]. A general-purpose-representation where self-supervised pretraining [27] refers to such tasks is to solve proxy tasks, including: reconstruction of masked samples, prediction of global order, and comparison of augmented samples of the same scene. Such representations can then be optimized to detect change using fewer labelled samples, which increases the efficiency of samples and can lead to better generalization between regions and sensors. The foundation-model methodology builds on this concept by providing large models that are trained on general and diverse EO corpora to acquire transferable embeddings, which can be reused across a variety of downstream tasks, such as change detection, classification, and segmentation.

In the case of LULC change detection, not only the aspect of enhancing accuracy but also the aspect of stability in the presence of domain shift is crucial [15]. Operationally deployed models need to be able to cope with atmospheric variability, phenology, land management, and sensor configuration, and sometimes, have minimal time to react through retraining on the ground. Representation learning provides an avenue to diminish the use of region-specific features; however, it also invites new issues concerning benchmarking, reproducibility, and the threat of implicit biases that are passed on to pretraining data distributions. The more such models are deployed, the more stringent assessment procedures that interrogate geographic, seasonal and sensor transfer are becoming imperative in order to validate arguments of generalization. **Table 3** provides an overview of the different method families for LULC change detection, detailing their inputs, strengths, and weaknesses based on the type of change and data available.

Table 3. Method families for satellite-based change detection: Strengths and limitations.

Method Family	Typical Inputs	Best Suited Change Regime	Strengths	Typical Weaknesses	Notes on Deployment/Generalization
Classical bi-temporal (diff/ratio/CVA)	Two dates; bands/indices	Strong, abrupt changes	Simple, interpretable, low training needs	Threshold sensitivity; phenology/atmosphere confounding	Works best with high-quality harmonized inputs
Statistical time-series (breakpoints/trajectory)	Dense or moderate time series	Abrupt + gradual; timing needed	Explicit timing; seasonality modeling; principled residual diagnostics	Pixel-wise methods may ignore spatial context; sensitive to missingness	Strong baseline for operational monitoring/alerts
Supervised ML (RF/SVM/GBM)	Engineered multi-temporal features	Diverse; when labels exist	Robust with modest data; handles heterogeneous features	Domain shift; label noise; imbalance	Needs spatial CV and transfer tests for credible claims
Deep bi-temporal (Siamese/U-Net)	Two images (often stacked)	Complex spatial patterns; high-res	Learns spatial context; strong segmentation	Data-hungry; calibration/interpretability issues	Performance can drop sharply out-of-region/sensor
Deep temporal (TCN/RNN/Transformer)	Dense time series (multi-modal)	Seasonality-heavy systems; timing/trajectories	Captures long temporal dependencies; reduces phenology confusion	Irregular sampling & missing data handling; compute cost	Benefits from self-supervised pretraining
Self-supervised/foundation models	Large unlabeled archives + few labels	Transferability-focused	Better sample efficiency; potential robustness	Benchmarking still evolving; bias risks	Must evaluate with geographic/sensor OOD splits
Object-based/graph methods	Segments/objects + time	High-res, management units	Semantic coherence; aligns with parcels/stands	Segmentation consistency across time; boundary evolution	Useful for policy/management reporting units

Note: CVA, Change Vector Analysis; RF, Random Forest; SVM, Support Vector Machine; GBM, Gradient Boosting Machine; CV, Cross-Validation; TCN, Temporal Convolutional Network; RNN, Recurrent Neural Network; OOD, Out-of-Distribution.

3.7. Multi-Source Fusion and Object-Based Change Detection

The methodological developments in the direction of fusion across sources and scales become progressively more common. Optical SAR fusion may be applied during classical pipeline on the feature concatenation level or during a mechanism deep network to modality and joint fusion modules. Successful fusion should consider the various noise structures and patterns of missingness; optical data can be unavailable because of clouds, whereas SAR can change depending on the presence of moisture. There are systems that use gating or uncertainty-weighted fusion to weight unreliable modalities down during particular times and places. Fusion can be further improved by using spatiotemporal super-resolution and data assimilation methods to further improve effective temporal density or bring observations to a common grid and time cadence [62].

Object-based change detection can also be used at high spatial resolution to complement pixel-based mapping by analyzing imagery into objects, which can be fields, buildings, or forest stands, and evaluating change at the object scale [63]. This will be able to reduce the salt-and-pepper noise, enhance the semantic coherence, and match the outputs with the management units concerning land use decisions. Objects Object-based approaches can employ morphological segmentation, graph-based representations, or deep instance segmentation, and can take into account shape, context and neighborhood relationships, which are hard to represent using per-pixel features. Nevertheless, even object delineation can be imagery sensitive and can be sensitive to any temporal variation, and it is not trivial to have consistent segmentation over time of objects that change.

3.8. Uncertainty Quantification, Calibration, and Interpretability in Change Products

Irrespective of the methodological family, there is an increasing requirement for change detection output to be supplemented by an expression of confidence and uncertainty. The uncertainties are due to sensor noise, preprocessing errors, omission of data, model errors, and vagueness in the inferred semantics of the land-cover. Change maps can be interpreted as an output to enable risk-based decision-making and more robust aggregation to estimate areas [64]. To monitor operations, confidence layers can be used to do triage, with higher-confidence changes being followed up with taking action, and lower-confidence discoveries leading to further evidence generation [65].

The meaning of interpretability is strongly intertwined with uncertainty since they both endorse trust and accountability. Practically, interpretability can imply that it cannot only give a change mask but also supports that include the prevailing feature changes, the signal of change time, or the aspect that has made the greatest contribution towards detection. It can specifically be helpful to use hybrid solutions that use statistical time-series models to infer timing and supervised models to infer attribution, which provide more formal explanations than pure end-to-end deep models. Along with the growing application of change detection systems in sensitive situations, e.g., compliance monitoring, land tenure disputes, and conservation enforcement, transparent reporting of uncertainty, constraints, and possible biases is necessary to prevent future abuse as well as to make sure that automated results are not misinterpreted within a proper evidentiary context [66].

4. Benchmark Datasets, Evaluation Protocols, and Validation

4.1. The Role of Reference Data in LULC Change Detection

The twin pillars of satellite-based change detection development are benchmarking and validation, since changes that seem to have been made to the apparent methodological aspects can be motivated by dataset peculiarities and evaluation design as much as any real improvements in modeling. The definition of truth is of special concern to change detection. A change map may be pixel correct in a narrow sense but misleading when applied to real-world decision-making in case change timing is inaccurate, a mislabeled transition, or the product is incorrectly over- or underestimating the change area. This difficulty is further increased by the fact that land use and land cover are not recorded similarly: satellites capture physical data, but land use can be a management intention and socioeconomic environment. Therefore, most of the ground truth labels are practically reference interpretations based on imagery and supplementary information, and not actual field measurements. Evaluation credibility thus lies in the open reports of how the reference data was generated, what the uncertainties are in the data, and how the uncertainties affect the performance reported [2,67].

The types of changes that may be assessed are also determined by reference data. Time-series labels constructed out of a few dates of acquisitions emphasize bi-temporal variations and commonly favor visually obvious ones, whereas detailed time-series labels permit change timing and trajectories benchmarks at a very low cost, but are much more costly to produce. Moreover, change is unique on its own compared to stability in most landscapes, so the sampling strategy is a determinant of the reported accuracy. Without stratifying the evaluation samples based on the prevalence of change, land-cover type, and spatial heterogeneity, land-cover measures are prone to being dominated by the majority class of no-change and to missing weaknesses of transition detection in the rare and high-impact transitions [68].

4.2. Reference Data Generation and Its Sources of Uncertainty

It is hard to generate quality reference labels of change detection since it needs spatial precision as well as temporal accuracy [69]. Field surveys and inventory plots show good evidentiary value when available, are costly to obtain, distributed differently, and seldom synchronized to satellite acquisition timing at the temporal granularity of time needed for validation of change timing. Consequently, numerous datasets are dependent on manual analysis of high-resolution imagery, possibly aided by time-sensitive aerial photography, maps, or local information. Labeling based on interpretations might hold well to sharp transitions like urban growth or total destruction of a forest, and is less effective in detecting subtle changes like forest degradation, rotation intensity of crops, disturbance of the understory, and change in land-use that do not produce a great spectral change. Boundary delineation may be indistinct even in cases where interpreters concur on an event of change because of mixed pixels, transitional edges, and the graduality of certain conversions.

Crowdsourcing has come up as a means of scaling labeling; however, it creates inconsistency in the level of expertise and interpretation criteria [70]. The quality control is generally based on redundancy, consensus scoring, and expert adjudication, but conflicts tend to be an indication of actual ambiguity and not an error by the annotator. Another significant source of reference is national and regional land-cover products, which have standard taxonomies and are widely covered but often vary in the definition of classes, methods of mapping, or updating. The reference products can thus be used as reference labels to detect change, and thus introduce systematic biases to evaluation, especially where the reference product is based on similar sources of satellites and is likely to be correlated with the evaluated model. Another problem that is inherent to all sources is temporal mismatch: the labels can be based on a nominal year or season, but the change can occur at any time within that period. This mismatch may cause both false positives and false negatives with respect to the timeframe of the evaluation, and to how the model is identifying change sooner or later than the reference timestamp.

4.3. Dataset Design: Spatial, Temporal, and Semantic Coverage

Implicitly, a benchmark dataset describes what constitutes a good change detector by restricting the sensors, regions, time range, and name set. There is a wide range of datasets in terms of spatial resolution and geographic coverage. The high-resolution benchmarks are generally more urban change, building footprint, and fine land transformation, whereas moderate resolution is more prevalent in the areas of making the transition between regional to global LULC in forests and agriculture. Designing is also different in terms of time. Other benchmarks only give two dates, which suits methods that are optimized to compare bi-temporally and restricts the ability to evaluate seasonality processing. Multi-date sequences are offered by other people, allowing evaluation of time-series modeling and time-of-change. Such data sets are faced with missing data, uneven sampling, and differing acquisition conditions [71,72].

There is also semantic coverage [73]. Binary change/no-change data are simpler to label and assess, though not as informative when trying to implement transition-type attribution. Multi-class and from-to transition datasets can be more elaborate to evaluate, but they require the definition of taxonomies that can be used across landscapes. Taxonomy design is a trade-off: classes that are too broad obscure useful dynamics, whereas classes that are too narrow are too untrustworthy to be used to label and may not generalize to other parts of the world where land management is done differently. Another complication is that the type of change can be indicated by the transition of the physical cover or by the process that causes such change, e.g., logging, fire, flooding, or even urban constructions. Process-based labels are interesting to interpret and act upon; they need supplementary data and may be challenging to ascertain repeatedly and at scale.

Spatial autocorrelation and leakage are becoming an issue of concern in benchmark design. When training and test samples are drawn in the same contiguous areas, it is possible that models will seem to work, and this is due to the exploitation of local textures, phenology, or land management patterns that would never be replicated elsewhere. More robust benchmark designs, hence place more focus on the separation between training and testing regions geographically and split cross-region evaluation. Equally, in the case of the multi-sensor scenarios, benchmarks that incorporate sensor-transfer conditions give a more realistic understanding of the operational performance than when they are benchmarked in isolation (under a specific and set sensor configuration) [74].

4.4. Evaluation Metrics for Change Detection and Transition Mapping

LULC change detection metrics need to resolve the change-no change imbalance and should consider the target use of the product. Accuracy is not often informative, since high accuracy in no-change predictable landscapes can be obtained by predicting no-change everywhere. Under binary detection, one parameter of the choice that is used to describe the trade-off of false alarms versus missed changes is precision, and the harmonic mean of precision and recall is the overall detection capability when both types of errors are important. Dense change masks often use intersection-over-union and similar measures of overlap, which are sensitive to the quality of boundaries, which is of concern in detecting small clearings, roads, or building expansions. In the case of multi-class change detection, macro-averaged metrics can be used to avoid the prevalent classes dominating the evaluation, and the report of per-class results can be used to identify which transitions are systematically confused [75,76].

Transition mapping is a demanding process, as one may make an error when detecting change as well as when classifying the pre- or post-change class [77]. Transition label confusion matrices can be large and sparse with increasing classes, and they tend to obscure interesting patterns unless transitions are put in interpretable families, e.g., vegetation-to-built or wetland-to-open water. In most operational sense, the final objective is not a pixel-wise value, but some approximation of a change area by class or administrative unit. In this situation, bias and variance of area estimates should be considered, since a small systematic error in a change mask can result in large cumulative errors. This becomes especially crucial in carbon accounting as well as policy reporting, where the limits of uncertainty and the statistically justifiable estimators are needed to support their claims to emissions, deforestation rates, or even restoration consequences.

To evaluate time-series approaches, which approximate the timing of changes, a test should be taken beyond that of space to consider the accuracy of time [78]. The timing error measures the discrepancy between predicted and reference dates and may be specified in absolute terms, in distributional terms, or in terms of event-based delay. These measures are also sensitive to the definition of the reference timing, which is usually unclear or interval-based, and timing assessment; therefore, they might require treating reference change dates as ranges, instead of points. Also, certain applications will give more importance to early-detection than to ideal boundary-delimitation, whereas others will give more attention to low false-alarm rates in order to reduce expensive field verification. The choice of metrics must thus be clearly related to constraints within an application, and not chosen by default.

The metrics described above evaluate the quality of a change map at the pixel or object level. However, for policy and carbon accounting applications, the primary quantity of interest is often the total area of change (or area by transition type) with defensible uncertainty bounds. Map-level metrics alone do not guarantee unbiased area estimates, a map with high F1 can still produce biased area totals if errors are systematically distributed. Therefore, Section 4.6 extends the evaluation framework from map accuracy to statistically rigorous area estimation, showing how probability sampling and error-adjusted estimators work together with the metrics introduced here.

4.5. Experimental Protocols and Generalization Testing

Strong assessment relies just as much on the methodology of experiments as it relies on measurement. Random pixel-wise training-testing splits tend to be misleading since adjacent pixels have similar spectra and texture, and so models can learn to generalize locally without actually learning any transferable representations. A more realistic measure of performance under deployment conditions is spatial cross-validation, in which whole geographic blocks or regions are reserved to test them. In the same manner, temporal holdout tests (in which a certain time period is trained, and another time period is tested) may identify sensitivity to interannual variation, sensor drift, and varying land management behavior. Sensors-transfer tests are used in the context of multiple sensors to determine the ability of a model trained using a single sensor to work on a second sensor without significant degradation, which is a large need in long-term monitoring between missions [79].

The stratification of land-cover type, change prevalence, and ecological region should also be considered in the protocol design [80]. In the absence of stratification, test sets can either be too represented by easy cases, e.g., large, homogeneous clearings, or underrepresented by difficult cases, e.g., smallholder agriculture mosaics or semi-arid shrublands with a large spectral ambiguity. It is also necessary to address the uncertainty and ambiguity of the reference labels. Instead of imposing one and only correct labeling in borderline cases, evaluation procedures can use soft labels, blur lines at uncertain regions, or report performance statements in high-confidence and ambiguous fields of reference. Those strategies recognize that not all the errors are necessarily the failures of the models themselves, but the boundary of observability and labeling.

4.6. Validation Strategies: From Pixel Accuracy to Statistically Defensible Area Estimates

Building on the evaluation metrics introduced in Section 4.4, validation for operational and policy-relevant change detection must distinguish between map accuracy assessment (e.g., pixel-wise F1 Score (F1), Intersection over Union (IoU)) and statistically defensible area estimation. While metrics such as precision, recall, and F1 describe how well a map agrees with reference samples, they do not directly provide unbiased estimates of change extent or its uncertainty. This section therefore focuses on validation strategies that produce area estimates with confidence intervals, using probability sampling and error-adjusted estimators that complement the map-level metrics discussed above [81,82]. Pixel-based measures of accuracy provide a summary of the correspondence of a map to a reference sample, which necessarily does not provide unbiased measures of area of change or rate of transition. In most reporting applications, particularly those related to land management and climate mitigation, the area of change in a region and its uncertainty are the major quantities of interest. To obtain defensible estimated areas, probability sampling designs, including stratified random sampling whose strata are based on mapped change categories, ecological zones, or risk levels, are generally needed. The obtained reference sample can be used to estimate unbiased area totals and confidence intervals, and to estimate error-adjusted reporting, which takes account of misclassification.

This difference is essential in that change detector maps are often spatially structured, such as with boundary offsets, small change omission and commission errors concentrated in spectrally varying locations [83]. Even a map whose pixel-wise F1 is high may provide biased estimates of areas, assuming that the errors are systemically biased to some type of land-cover or that the sampling design does not match the structure of the errors. On the other hand, a map with intermediate pixel-wise statistics may be useful to provide good area estimates, provided errors are properly described and eliminated by statistically sound estimation. In the case of scientific reporting, this implies that they are not to be restricted to a single global score but should provide error matrices, strata-specific precision, and uncertainty bounds of area estimates, and effectively demonstrate the sampling scheme and the process of reference interpretation. **Table 4** summarizes the recommended evaluation protocols and metrics for various LULC change detection outputs, including binary masks, transition types, and change timing.

Table 4. Evaluation and validation: Recommended protocols and metrics by task.

Task Output	Primary Metrics	Common Pitfalls	Recommended Protocol	Validation for Area Reporting
Binary change mask	Precision/Recall/F1; IoU	Accuracy dominated by "no-change"; boundary inflation	Spatially separated train/test; report PR trade-offs	Stratified probability sample; error-adjusted area with CIs
Multi-class change/change type	Macro-F1; per-class F1; confusion matrix	Rare transitions ignored; taxonomy mismatch	Geographic cross-validation; transition grouping for interpretability	Strata by transition family; report uncertainty per transition
From–to transition mapping	Transition matrix; per-transition F1	Error compounding from both dates	Hold out regions + time; avoid spatial leakage	Estimation by transition strata; bias-corrected totals
Change timing (breakpoint date)	Timing MAE; detection delay; event-based scoring	Reference timing uncertainty; interval mismatch	Evaluate with time windows; report early/late bias	Report timing uncertainty + fraction detected within window
Trajectory/gradual change	Trend error; trajectory similarity	Over-smoothing hides change; seasonal leakage	Multi-year holdout; sensitivity tests across seasons	Combine map accuracy + uncertainty-aware aggregation

Note: PR, Precision-Recall; CI, Confidence Interval; MAE, Mean Absolute Error.

4.7. Reproducibility, Reporting Standards, and Practical Pitfalls

Since change detection research begins to rely more on massive archives, sophisticated preprocessing, and deep learning, reproducibility turns out to be a determining factor in the scientific merit of reported outcomes [84]. Imposing relatively small differences on preprocessing, e.g., on cloud masking thresholds, composing rules, co-registration quality, or treatment of missing observations, can result in materially different change results. On the same note, training regimes, hyperparameter values, and augmentation policies can change the performance sufficiently to cause a false impression of methodological improvements rather than accidental ones. SCI-standard reporting thus has the advantage of clear descriptions of product and version of data, spatial and temporal coverage, provenance of reference labels, and train/test splits, and the complete metric set. As much as possible, publication of code and model weights, or at least an adequate methodological description, enhances comparability between studies.

There are a number of traps that are repeated in the literature. Training-testing assessments. When samples of training and testing are mixed within the same geographic region, overgeneralization is exaggerated. Inaccuracy may be inflated by datasets that contain label leakage by using temporally overlapping reference sources. The presence of benchmarks with a small number of visually evident transitions may tend to over-reward processes that are tuned to such transitions and under-reward more unobtrusive changes that have societal value. Lastly, it may be necessary to report only aggregate measures, which may conceal failure modes that are important to deployment, e.g., systematic false alarms in wetlands, confusion between harvest and clearing, or bad performance in cloudy areas. The evaluation of these problems demands designs that emphasize geographic transfer, realistic sampling, and uncertainty-conscious validation, and provide a clear coverage of the achievements and shortcomings [81].

5. Applications, Case Studies, and Emerging Trends

5.1. Application Contexts and the Translation from Methods to Decisions

Change detection of the dynamics of land use and land cover using satellites is ultimately useful since it is useful in decision-making and not so much because it generates maps [85,86]. The technical pipeline is fundamentally utilized differently across application areas to achieve radically different objectives, in either retrospective analysis, regulatory reporting, or near-real-time alerting. Retrospective studies usually value consistency with long time horizons, and can even tolerate a trade-off between time smoothing (to eliminate noise) and low latency, whereas operational monitoring systems value low latency and can even accept more uncertainty (when outputs can be triaged and confirmed). The balance between false alarms and missed detections, depending on the decision situation, is also acceptable. False positives can be expensive in terms of verification cost and can destroy trust in the enforcement-oriented system, whereas in the early-warning system, they can have more serious consequences than a false alarm of uncertain quality. These variations imply that there are seldom universal best methods; they depend on the geographical extent, time urgency, and availability of evidence that must support the use.

The third issue that is also emphasized by the case studies in the LULC change detection is the significance of linking change maps to explanatory variables as well as to institutional workflows. Even a technically correct change product cannot add value if it cannot be delivered at a pace that fits field operations, cannot be understood by non-experts, or uncertainty is not communicated in a manner that will facilitate prioritization. On the other hand, systems that combine both confidence layers, temporal signatures, and contextual information can still be of use in the presence of imperfect detectors, in that these systems allow human analysts to concentrate on the most probable or impactful changes [87].

5.2. Forest Disturbance, Deforestation, and Degradation Monitoring

Satellite change detection has been one of the main focuses on forested ecosystems due to the direct relationships between forest loss and degradation, carbon emission, decline of biodiversity, and alteration of hydrological patterns [88]. Large-scale deforestation in most areas creates high spectral and structural signals that can be measured using optical indices and SAR backscatter changes, resulting in good mapping of the forest-to-nanoforest transition. Thick time series provide estimation capability of when clearing would occur, as well as the differentiation between permanent conversion and short-lived canopy disturbance. Forest monitoring systems in operational settings tend to be based on repetitive anomaly detection relative to prior baselines and confidence levels in use are used to address false alarms, particularly those occurring in high cloud coverage areas or high seasonal variability zones.

In most cases, forest degradation can be more difficult than total removal since it can be a partial loss of the canopy, selective logging, disturbance of the understorey, or even progressive thinning and all of this can leave small signals and high confusion with the natural variability. Such environments in particular can be educative as scattering processes are sensitive to structural variations, but the variability of moisture can also cause spurious responses, as well as terrain effects. Several of the more successful methods thus are modal mixture, and making use of temporal persistence, where degradation is viewed not as a one-day departure but as a persistent deviation. The challenge of the reliable labeling of degradation has also contributed to the attraction of semi-supervised and self-supervised methods, where the models are trained on unlabeled data to learn general representations, and fewer high-quality examples of degradation are required to fine-tune the model. Besides this, area estimation of forests under uncertainty is becoming increasingly required in forest surveillance to serve greenhouse gas stocks and policy reporting, replacing the focus on the maps to numbers of change that are statistically plausible [89].

5.3. Agriculture: Cropping Dynamics, Expansion, and Land-Use Intensity

Farms are unique in terms of change detection challenges and opportunities [90]. In contrast to most natural systems, agricultural transformation can be characterized by both land-cover conversion and management choices, such as planting and harvesting cycles, crop rotation, irrigation, and fallowing. The processes have the capability to form powerful temporal signals that can be utilized by time-series models to identify changes in the intensity of cropping, the presence of transitions between crop types, and the mapping of expanding lands into grasslands, savannas, or forests. Nonetheless, phenology also confuses: a plowed field can be spectrally identical to bare ground or building projects, and seasonal change can be confused with conversion in case two dates that are dissimilar are compared.

Agricultural applications are of particular interest in dense time-series methods, where the models are capable of learning the expected seasonal trajectories and identifying the changes as deviations from those trajectories [91]. SAR is capable of enhancing monitoring beneath clouds that restrict the optical visibility and facilities sensitivity to crop structure and moisture, useful in differentiating between irrigated and rainfed systems, as well as sensing management shifts that do not appear as a big optical difference. Most case studies show that maximum useful value is not provided by an individual change map but through derived measures, including the frequency of crop, the date of planting, change in extent of irrigation, and between perennial and annual systems. These indicators may be used to aid in the process of food security evaluation, planning along with drought response strategies, and to assess the effects of land-use policies, although necessary validation must be undertaken due to infrequence of reference data on management policies, which are often regionally highly specific.

5.4. Urbanization and Built-Environment Dynamics

A common feature of urban land-cover change has been high-speed, spatially hectic changes, such as extension to peri-urban regions, intensification of existing urban centers, and infrastructural projects, such as roads, ports, and industrial estates [92]. The high-resolution optical imagery was conventionally at the heart of building footprint and fine-scale urban form mapping, and SAR provides the complementary sensitivity to the built environment and may otherwise be important where optical imaging is constrained by cloud cover or low lighting. Spatial-context modeling is frequently useful in urban change detection since the semantic meaning of urban features is highly related to the shape, texture, and neighborhood associations, and not the pixel spectra. Object-based methods and deep segmentation models are most commonly applied to this field because they can also outline coherent built-up regions and limit noise, which would otherwise predominate in pixel-wise differencing.

The difficulty in detecting urban change has consistently been to tell the difference between the actual construction and the temporary effects, like shadows, seasonal vegetation variation in the park, or change in the area's surface moisture, which influences reflectance and SAR backscatter. The other typical challenge is temporal staging, where land clearance, construction, and occupation are done in phases with unique signatures at a given period. Time-series approaches may be used to remedy this by identifying multi-stage paths, e.g., vegetation-bare-built-up surfaces and temporal persistence, to eliminate false alarms caused by temporary perturbations. The interpretability and responsible use are also more heightened with regard to urban applications, particularly change products that may be associated with sensitive issues, including informal settlements, displacement, or land tenure. In these contexts, the explicit expression of uncertainty and ethical management of monitoring outputs can be considered a part of the system design [93].

5.5. Wetlands, Water Dynamics, and Coastal Change

These landscapes are the wetlands, floodplains, and coastal areas, which can be classified as the most dynamic as well as the most environmentally important areas, but at the same time, they are the hardest to map in a uniform manner in terms of change [94]. Water cover may fluctuate between days and seasons, precipitation, tides, river discharge, and human water management can cause such changes, and the changes cannot be confused with permanent land-cover change unless they are placed in the context of time. SAR is especially useful in inundation mapping due to its ability to penetrate clouds and, in most circumstances, has good contrast between open water and the adjacent land. Flooded vegetation, rough water bodies caused by wind, and shallow flooding can, however, make interpretation tricky, and artifacts caused by the terrain may give a false signal in coastal and riverine settings.

Detection of change along the coasts must also struggle with the movement of the shoreline, erosion, accretion, and human alteration in the form of reclamation and infrastructure [95]. The correct temporal scale varies with the intended purpose, which is to identify effects of extreme events like erosion caused by storms or to measure long-term trends. Time-series methods that take into account tidal stage variability, seasonal variability, and multi-year baselines are commonly required in order to decompose episodic variability and the morphological change that is persistent. Moreover, wetlands and coastal uses frequently need to be combined with hydrological or oceanographic information in order to interpret observed shifts in terms of drivers, or in order to prevent misattribution. Validation is especially challenging due to the hard-to-access nature of fields, the inherently fuzzy nature of boundaries, and the possibility of sparse reference data.

5.6. Disturbance and Disaster Monitoring: Fire, Floods, Landslides, and Storm Impacts

Change detection in disasters puts emphasis on timeliness and reliability in unfavorable conditions of observation. Wildfires are capable of creating sudden spectral transformations, such as decreased vegetation indices and augmented charcoal and bare soil indicators, that can be mapped in a rapid manner when clouds and smoke allow. SAR-based detection is commonly used to discover floods since cloud cover is common post-storms and after storms, and also due to the high sensitivity of SAR to open water. Damage due to landslides and storms may be less obvious and can be detected only with care, baselines of time-series and context of spatial features to distinguish the actual disturbance and the change in soil moisture or seasonal changes in vegetation cover. Long-term land-cover conversion is not the main goal of disaster response in most cases but simply a fast process of locating the affected region to aid emergency response and recovery planning [96].

Monitoring of disasters that occur during operations is often based on modular systems which involve the quick identification of anomalies and their further refinement and attribution. An example includes the production of an initial SAR based flood extent map, which can be done in real time, after which optical validation and classification of the impacted land-cover types can be done after clear imagery is obtained. Equally, the measurement of fire damage can initiate with instant detection of burn and subsequent adoption of vegetation recovery patterns. These workflows raise another theme that change detection algorithms are usually most useful when viewed as constituents of an adaptive pipeline that is updated along with the incoming data, instead of a fixed model being executed on a fixed pair of images [97].

5.7. Common Failure Modes and Mitigation Strategies in Practice

In the fields of application, there are a number of failure modes that are common. The seasonal phenology is one of the major sources of confusion, particularly in agriculture and temperate forests, where phenomena of greenness changes may be taken as clearings or regrowth based on the day of observation selected. Artifacts of the cloud and shadow may contribute to systematic errors of omissions and commissions in case masking is not perfect or compositing produces biased images of conditions on the surface. Moisture-driven variability can simulate disturbance in the Surface Reflectance (SR)-based monitoring, especially in wetlands and croplands, and also speckle and terrain distortions may cause local false alarms [98–100].

Mitigation strategies usually involve both preprocessing rigors and modeling options, which place more emphasis on temporal persistence and spatial coherence. Spatial time series make individual-day artifacts less sensitive and allow a model to learn desired seasonal learning. Multi-sensor fusion enhances temporal coverage and offers complementary information, which can be used to detect changes that can be similar in a single modality. Layers of uncertainty and confidence calibration are used to allow operational systems to trade off sensitivity and false alarms by allowing threshold tuning and prioritization. Workflows that involve human-in-the-loop work in which analysts examine high-impact detection and provide corrections to the model refinement are becoming more common in areas where the impact of errors is significant [101].

5.8. Emerging Trends: Foundation Models, Physics-Guided Learning, and Operationalization

Representation learning and scalability are becoming the future drivers of the methodological frontier of LULC change detection [102]. Self-supervised pretraining and foundation models are also suggested to minimize the use of large labeled datasets and enhance cross-regional and cross-sensing transfer, which could make it potentially possible to operate in data-limited regions. Simultaneously, to be successful, such models should be thoroughly analyzed in the domain shift and transparently report the biases that pretraining data distributions induce. Physics-guided learning is also another general direction in which physics-based model constraints are used to enhance model robustness and usability (e.g., radiative, sensor geometry, simulation). These hybrid strategies may assist in preventing the acquisition of spurious correlations between the conditions of acquisition and the model, but careful integration is necessary, and these systems may become more complex.

System architecture is also being innovated through operationalization [15]. The real-time monitoring requires pipelines to take in new images at a given time, refresh time-series baselines, and generate alerts with constant uncertainty values. This has stimulated the derivation of streaming change detection and incremental learning methods, and computationally efficient strategies to tile, process in parallel, and deploy edges within a bandwidth-limited environment. In the meantime, the expanding adoption of change detection outputs in policy and applications involving finance has raised interest in governance, transparency, and auditability. In this regard, the field is shifting towards products which are not just accurate but also reproducible, uncertainty-sensitive, and interpretable to make defensible decisions.

6. Conclusions

Satellite-based change detection has become a developed and more functional field to define land use and land cover dynamics at spatial scales, ecosystem, and decision-making settings. The high rate of open EO archive growth, increased revisit rate, and enhanced access to the additional sensing capabilities, especially optical and SAR, have allowed change to be monitored more continuously and more resiliently to data lapses. Meanwhile, the discipline has shifted to fields beyond the simplistic before-and-after comparisons to time-series argumentation capable of isolating seasonal changes, as well as continually constant shifts, labeling when change occurs, and tracing the pattern of perturbation and recovery. They find applications in modern applications of forest surveying, agricultural processes, urbanization, coastal and wetland habitat fluctuation, and calamity reaction, where the worth of a change item is sometimes decided by both the timeliness, comprehensibility, and imprecise communication, and the exact mapping quality of a raw mapping item.

One apparent commonality among the literature is that model choice is seldom a limiting factor in change detection performance. The choice of co-registration, atmospheric and terrain correction, cloud and shadow treatment, SAR calibration, speckle reduction, and consistent time-series construction can often be the primary results of downstream performance and the key source of spurious change when poorly done. The choice of the method must then be informed by the change regime and the constraints it operates. Rule-based approaches and classical differencing are still applicable in situations where change indicators are intense, interpretability plays a paramount role, and training labels are few. Time-series statistical techniques offer theoretical combinations of detecting breaks and timing changes, especially when both seasonal cycles and missing entries cannot be furnished explicitly. Supervised machine learning can provide strong performance with engineered properties in the presence of representative labels, whereas deep learning can utilize strong spatial-temporal feature learning and has been particularly successful with high-resolution and complicated spatial contexts. Within the growing quantity of time-like-discrimination information pipelines, combining time-series detection with supervised attribution to the type of change has the potential to present an expedient trade-off between the amplitude, explicability, and practical performance.

Assessment and authentication still represent full stops to believable development. Due to the expense, temporal uncertainty, and image interpretation, benchmarking may be highly biased towards dataset design, spatial leakage between train and test splits, and metric choice in situations with extreme class imbalance. SCI-standard research is gradually required to show generalization using geographically discontinuous testing, temporal holdouts, and sensor-transfer experiments, and to provide per-class and transition-specific behavior instead of aggregate scores. Statistically defensible area estimations with uncertainty bounds are at least equivalent to pixel accuracy in many policy/reporting application scenarios; validation designs using probability sampling and error-compensating estimates must be considered as core components of change detection applications counts instead of rudimentary appendices.

In the future, enhancing transferability and trustworthiness will be the most promising developments. Self-supervised and EO foundation models provide a channel towards less reliance on labels, a model more robust to geographic coverage and the sensor types, although these assertions need to be proven by stringent out-of-distribution assessment and disclosed by the authors on biases in pre-training data. Multi-sensor fusion will remain central to ambiguity reduction and coverage enhancement, particularly in cloudy and disaster-prone areas, whereas physics-guided and uncertainty-conscious modeling will be useful in averting spurious detections based on acquisition conditions and improving explainability. The end-to-end reproducible pipelines, calibrated confidence layers, and human-in-the-loop workflows will be required by operational systems to support the verification, refinements, and accountability.

Altogether, satellite-based LULC dynamics change detection is moving to more of a decision-grade monitoring than a research-based mapping-oriented strategy. To do this transition successfully, this is done by matching techniques with the character of change and the sensing context, investing in hard preprocessing and harmonization, embracing evaluation measures that truly challenge generalization, and putting uncertainty quantification and transparent reporting on a par with accuracy. This set of priorities will play a key role in constructing scalable, interpretable, and trustworthy monitoring systems that will be able to serve environmental management, reduce risks, and support climate-related decision-making in a fast-changing world.

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