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Remote Sensing in The Ai Era, A Review from Data Acquisition to Change Detection

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ABSTRACT

Remote sensing has become a central methodology for monitoring the Earth's surface, atmosphere, and oceans, providing spatially explicit, repetitive, and synoptic observations from the field to the global scale. The discipline now encompasses an integrated chain of data models governing acquisition, preprocessing, classification, change detection, and analysis of remotely sensed imagery. This review synthesises the state of the art across this chain, emphasising developments since 2020. It examines radiometric and geometric calibration, atmospheric correction, and modern preprocessing workflows; assesses the transition from statistical classifiers to convolutional neural networks, vision transformers, and geospatial foundation models such as Prithvi-EO and the Clay Foundation Model; and surveys time-series change-detection algorithms (CCDC, LandTrendr, BFAST) alongside deep-learning bi-temporal approaches. Spectral, textural, and geostatistical techniques are reviewed in the context of contemporary missions, Sentinel, Landsat 8/9, and commercial high-resolution platforms. Cloud computing platforms (Google Earth Engine, AWS, Microsoft Planetary Computer), unmanned aerial systems, and IoT devices have reshaped operational workflows. Persistent challenges, data accessibility, computational cost, domain shift, label scarcity, and model interpretability are identified, and priority directions are proposed, including self-supervised learning, physics-informed machine learning, multi-modal fusion, and explainable AI.

KEYWORDS

Remote Sensing; Data Models; Deep Learning; Geospatial Foundation Models; Change Detection; Time-series analysis; Google Earth Engine; Sentinel; Landsat; GeoAI.

1.INTRODUCTION

Remote sensing is the science of acquiring information about objects, areas, or phenomena through analysis of data obtained by sensors not in physical contact with the target (Jensen, 2016). Modern Earth observation rests on airborne and spaceborne platforms that collect measurements across the electromagnetic spectrum, from the visible and near-infrared through the thermal infrared to microwave wavelengths. The discipline provides the principal evidence base for monitoring land-cover change, climate variability, natural hazards, food security, urban expansion, biodiversity, and progress toward the UN Sustainable Development Goals (Wulder et al., 2022; Zhu et al., 2022).

The volume of freely available Earth observation data has expanded by orders of magnitude over the past decade. Copernicus delivers more than ten terabytes of imagery daily through the Sentinel missions; the Landsat archive spans over five decades; and commercial constellations such as Planet, Maxar, and Capella Space provide sub-metre and daily revisit capability (ESA, 2024; USGS, 2023). This has been paralleled by the migration of workflows from desktop environments to cloud-based platforms—Google Earth Engine, the Microsoft Planetary Computer, and AWS Open Data and the rapid integration of deep learning into nearly every stage of the processing chain (Gorelick et al., 2017; Zhu et al., 2017; Ma et al., 2019).

Within this ecosystem, "data model" refers to the algorithmic and mathematical framework by which raw sensor measurements are transformed into thematic information. Five categories are distinguished: (i) data acquisition models, calibrating raw measurements; (ii) preprocessing models, correcting atmospheric, geometric, and radiometric artefacts; (iii) classification models, assigning thematic labels to pixels or objects; (iv) change detection models, identifying temporal differences; and (v) data analysis models, extracting quantitative biophysical, geophysical, or geostatistical information. Product accuracy depends on the cumulative performance of all five stages.

This review updates earlier syntheses (Lu and Weng, 2007; Blaschke, 2010; Singh, 1989) by incorporating developments in deep learning, time-series analysis, cloud computing, and, most notably, geospatial foundation models, which have emerged as a paradigm shift since 2023 (Jakubik et al., 2023; Szwarcman et al., 2024). Sections 2–6 examine each category of data model. Section 7 discusses emerging technologies, Section 8 outlines challenges, Section 9 sets priorities for future research, and Section 10 concludes.

2. DATA ACQUISITION MODELS

Data acquisition models translate the photons recorded by a sensor into physically meaningful measurements through radiometric calibration, geometric calibration, and sensor fusion. Their fidelity sets a hard upper bound on the quality of every downstream product.

2.1 Radiometric Calibration

Radiometric calibration converts raw digital numbers into top-of-atmosphere radiance or reflectance through sensor-specific gain and bias coefficients, accounting for solar geometry, sensor degradation, and atmospheric effects (Chander et al., 2009). Landsat 8/9 OLI achieves radiometric accuracy better than 3% in reflectance, while the Sentinel-2 MSI maintains inter-band consistency near 2% following recent reprocessing (ESA, 2023). Cross-mission harmonization exemplified by the Harmonized Landsat Sentinel-2 (HLS) product has become essential for constructing dense, multi-decadal analysis-ready time series (Claverie et al., 2018).

2.2 Geometric Calibration

Geometric calibration corrects sensor- and platform-induced distortions and establishes accurate georeferencing. Modern Level 1 products from Landsat and Sentinel-2 deliver positional accuracies on the order of 12 m RMSE, owing to improvements in ground control, digital elevation models, and on-board attitude determination. Recent work has applied deep learning for co-registration refinement, with convolutional networks learning dense sub-pixel displacement fields between image pairs, improving on classical phase-correlation methods, particularly under cloud cover or seasonal change (Park et al., 2023).

2.3 Sensor Fusion

Sensor fusion combines complementary observations to overcome single-instrument limitations. Multispectral–hyperspectral fusion enhances spectral resolution; optical–SAR fusion mitigates cloud-cover gaps and adds structural information; optical–LiDAR fusion adds three-dimensional canopy and terrain structure (Ghamisi et al., 2019). Spatio-temporal fusion methods such as STARFM reconcile the spatial resolution of Landsat with the temporal frequency of MODIS or Sentinel-3 (Gao et al., 2006; Zhu et al., 2018). Recent advances apply generative deep learning, conditional GANs and diffusion models to synthesise high-resolution optical imagery from coarse-resolution or SAR inputs (Tan et al., 2022; Czerkawski et al., 2024).

3. PREPROCESSING MODELS

Preprocessing removes systematic effects that would otherwise be misinterpreted as surface change. It includes atmospheric correction, radiometric normalisation, geometric refinement, noise reduction, and cloud and shadow masking.

3.1 Atmospheric Correction

Atmospheric correction retrieves surface reflectance by accounting for Rayleigh scattering, aerosols, and water vapour. Physics-based algorithms such as 6S, MODTRAN, FLAASH, and dark-object subtraction (Chavez, 1996) remain widely used, but operational missions now provide standardised products: Landsat Collection 2 uses LaSRC, while Sentinel-2 L2A is generated through Sen2Cor and since 2022 alternative MAJA, FORCE, and Sen2Like processors offer improved aerosol retrieval and multi-mission harmonisation (Vermote et al., 2016; Main-Knorn et al., 2017; Hagolle et al., 2015;

Frantz, 2019). The HLS product applies to a unified BRDF adjustment for consistent multi-sensor analysis (Claverie et al., 2018).

3.2 Radiometric Normalization

Radiometric normalization aligns reflectance values across scenes and dates, compensating for residual atmospheric and illumination effects. Pseudo-invariant feature selection, histogram matching, and the MAD and IR-MAD algorithms remain standard references (Canty and Nielsen, 2008). For time-series applications, harmonic regression and seasonal-adjustment models are routinely applied within the CCDC framework to model temporal variability and isolate genuine change (Zhu and Woodcock, 2014).

3.3 Noise Reduction, Cloud and Shadow Masking

Optical imagery is degraded by sensor noise, striping, cloud cover, and cloud shadows. Classical denoising filters (median, Gaussian, Lee, Frost) remain useful, particularly for SAR speckle, but deep-learning denoisers based on convolutional autoencoders and transformer architectures now achieve superior performance on hyperspectral data (Yuan et al., 2019). For cloud detection, Fmask and its successors (Fmask 4.0, s2cloudless, CloudSEN12) are the de facto standards, while semantic segmentation networks, U-Net, DeepLabV3+, and ViT-based encoders produce probabilistic cloud and shadow masks at improved accuracy (Zhu and Woodcock, 2012; Aybar et al., 2024). Cloud gap-filling via spatio-temporal interpolation or generative models is now integral to analysis-ready data pipelines.

4. CLASSIFICATION MODELS

Classification assigns each pixel, segment, or object to a thematic category. The field has progressed from per-pixel parametric classifiers, through ensemble machine-learning methods, to deep neural networks and, most recently, pre-trained foundation models.

4.1 Traditional Statistical and Machine-Learning Classifiers

Parametric classifiers such as Maximum Likelihood remain in use for well-behaved, low-dimensional data, but their assumption of Gaussian class distributions limits applicability to modern multi- and hyperspectral data. Non-parametric algorithms SVM, Random Forest, and gradient-boosted trees (XGBoost, LightGBM) have become standard (Belgiu and Drăguţ, 2016; Mountrakis et al., 2011). Random Forest is favoured for robustness to outliers, intrinsic feature-importance estimates, and computational efficiency, and underpins many large-scale operational products including ESA WorldCover and dynamic global land-cover maps via Google Earth Engine (Zanaga et al., 2022).

4.2 Deep Learning Approaches

CNNs and their derivatives, VGG, ResNet, DenseNet, U-Net, and DeepLab have dominated remote sensing classification since around 2016. They exploit spatial context, learn hierarchical features automatically, and outperform pixel-based classifiers in urban land-cover mapping and crop type identification (Zhu et al., 2017; Ma et al., 2019). U-Net and its variants remain widely deployed for semantic segmentation. Vision Transformers and Swin Transformers have demonstrated competitive or superior performance where sufficient training data is available (Aleissaee et al., 2023). Recurrent and temporal models (LSTM, GRU, TempCNN) and transformer-based time-series classifiers such as PSE-LTAE are especially effective for crop-type mapping from Sentinel-1 and Sentinel-2 time series (Garnot et al., 2020).

4.3 Geospatial Foundation Models

Since 2023, geospatial foundation models have reshaped the field. These large self-supervised models are pre-trained on massive unlabelled archives and fine-tuned for downstream tasks with comparatively small, labelled datasets. Prithvi-EO, developed jointly by NASA and IBM, was the largest such model at its August 2023 release; Prithvi-EO-2.0 (December 2024) was trained on 4.2 million globally distributed time-series samples and outperformed six competitors on GEO-Bench (Jakubik et al., 2023; Szwarcman et al., 2024). The Clay Foundation Model offers an open-source alternative across sensors and resolutions (Clay Foundation, 2024). Google's AlphaEarth Foundations introduces an embedding-field approach for global mapping from sparse labels (Brown et al., 2025), and SatMAE applies masked autoencoder pre-training (Cong et al., 2022). These models have supported operational mapping at an unprecedented scale, including the August 2025 Gifford Fire burn-scar mapping (NASA, 2026).

4.4 Object-Based Image Analysis

OBIA segments imagery into homogeneous regions before classification, exploiting shape, texture, and contextual relationships in addition to spectral information (Blaschke, 2010). It is particularly effective at very high spatial resolution UAV, WorldView, or PlanetScope imagery, where pixel size is much smaller than the object of interest. The contemporary trend integrates OBIA with deep learning: CNNs or transformers provide feature representations aggregated at the object level, producing accurate and interpretable maps of urban infrastructure, smallholder agriculture, and forest disturbance (Hossain and Chen, 2019).

5. CHANGE DETECTION MODELS

Change detection identifies surface modifications between two or more dates. Methods are grouped into bi-temporal pixel-based approaches, time-series approaches, and deep-learning methods.

5.1 Bi-Temporal Pixel-Based Methods

Classical bi-temporal techniques image differencing, ratioing, post-classification comparison, principal components analysis, and change vector analysis remain valuable for rapid disaster response (Singh, 1989; Lu et al., 2004). MAD and IR-MAD provide statistically robust, scale-invariant detection of change in multispectral data (Canty and Nielsen, 2008). Their principal limitation is sensitivity to phenological and illumination differences, which cannot be distinguished from genuine change without supplementary information.

5.2 Time-Series Approaches

The opening of the Landsat archive in 2008 and the launch of Sentinel-2 in 2015 enabled the shift from bi-temporal to dense time-series detection. Three algorithms dominate: LandTrendr (Kennedy et al., 2010), fitting piecewise-linear segments to annual time series; CCDC (Zhu and Woodcock, 2014), fitting harmonic regression to all available Landsat observations and flagging pixels with persistent deviations; and BFAST (Verbesselt et al., 2010), decomposing time series into trend, seasonal, and residual components. Comparative studies indicate CCDC achieves the highest accuracy for urban change with full spectral information, while BFAST performs well for forest fires and LandTrendr is robust for forest disturbance and recovery (Cohen et al., 2017; Awad et al., 2025). Operational applications now span permafrost thaw (Runge et al., 2022), forest disturbance and recovery (Li et al., 2025), and national land-cover updating (Zhang et al., 2023).

5.3 Deep Learning for Change Detection

Deep-learning change detection has advanced rapidly since 2020. Siamese networks—two CNN or transformer branches with shared weights processing the two images, with a difference module identifying changed pixels—are the dominant architecture (Daudt et al., 2018). Attention mechanisms, transformer encoders, and self-supervised pre-training have improved performance on benchmarks such as LEVIR-CD, WHU-CD, and S2Looking. Foundation-model-based paradigms exploiting features from Prithvi-EO, SatMAE, or Clay show strong few-shot performance on heterogeneous tasks (Li et al., 2024). Combined optical–SAR multi-modal deep learning is a particularly active direction, motivated by SAR's all-weather, day-and-night capability.

6. DATA ANALYSIS MODELS

Data analysis models extract quantitative biophysical, geophysical, or geostatistical information from imagery. They include spectral, textural, geostatistical, and biophysical-retrieval approaches.

6.1 Spectral Indices and Spectral Analysis

Spectral indices remain the workhorses of vegetation, water, soil, and built-up area characterisation. Beyond NDVI (Tucker, 1979), widely used indices include EVI, NDWI, MNDWI, NBR, SAVI, and NDBI. These underpin operational products from croplands to wildfire severity. Spectral mixture analysis, linear unmixing and, more recently, deep-learning-based hyperspectral unmixing decompose mixed pixels into endmember fractions (Ma et al., 2019).

6.2 Texture Analysis

Texture analysis captures spatial variability, complementing spectral information. The Grey-Level Co-occurrence Matrix and its Haralick measures remain widely used; wavelet, Gabor, and local binary pattern descriptors offer multi-scale alternatives (Haralick et al., 1973). For high-resolution data, learned representations from CNNs and transformers tend to outperform handcrafted descriptors, but GLCM features remain valuable for interpretable models in vegetation structure, urban density, and forest stand characterisation.

6.3 Geostatistical and Spatial Analysis

Geostatistical methods semivariogram analysis, ordinary and universal kriging, co-kriging, and Bayesian hierarchical models quantify spatial autocorrelation and produce continuous surfaces from sparse observations (Curran, 1988; Isaaks and Srivastava, 1989). They are increasingly combined with machine learning in hybrid frameworks such as Random-Forest residual kriging, coupling RF's predictive flexibility with the spatial-dependence structure of kriging (Hengl et al., 2018).

6.4 Biophysical Parameter Retrieval

Quantitative retrieval of biophysical and biochemical parameters LAI, canopy chlorophyll, fractional cover, biomass, surface temperature, relies on either inversion of radiative transfer models (PROSAIL, SAIL, GeoSail) or empirical machine-learning regression (Verrelst et al., 2015). Hybrid approaches, in which physically based simulations generate synthetic training datasets for neural networks, combine interpretability with flexibility and form the basis of the operational Sentinel-2 Biophysical Processor.

7. RECENT ADVANCES AND EMERGING TRENDS

7.1 Cloud Computing Platforms

The shift from desktop processing to cloud computing has democratised access to global-scale analysis. Google Earth Engine, launched in 2010 and now hosting petabytes of analysis-ready data, allows researchers to apply algorithms to the entire Landsat or Sentinel archive without local downloads (Gorelick et al., 2017). The Microsoft Planetary Computer, AWS Open Data, and Sentinel Hub provide complementary infrastructures. The SpatioTemporal Asset Catalogs (STAC) specification has emerged as a community convention for indexing geospatial datasets, and each platform integrates with TensorFlow, PyTorch, and Vertex AI.

7.2 Multi-Modal and Multi-Source Integration

Modern analyses routinely integrate optical, SAR, thermal, LiDAR, and gravimetric data with non-remote-sensing sources such as climate reanalyses, social media, and OpenStreetMap. The SSL4EO-S12 dataset and the SkySense++ encoder demonstrate that multi-modal self-supervised pre-training can reduce labelled-data requirements by up to an order of magnitude (Wang et al., 2023). Multi-modal foundation models jointly processing optical, SAR, and hyperspectral inputs within a single backbone are an active frontier.

7.3 UAV, IoT, and Edge Computing

UAVs provide centimetre-resolution imagery on demand, complementing satellite observations for precision agriculture, infrastructure monitoring, archaeology, and rapid disaster assessment (Ma et al., 2021). Integration with IoT, soil-moisture sensors, weather stations, and connected agricultural machinery enables real-time, multi-scale monitoring. Edge computing, performing inference on the satellite, aircraft, or UAV itself, is reducing data-transmission demands and enabling near-real-time decision support; NASA's 2025 deployment of the Prithvi foundation model in orbit is an early operational milestone (NASA, 2026).

7.4 Explainable AI and Uncertainty Quantification

As deep learning has become pervasive, demand for interpretable and trustworthy predictions has grown. XAI techniques, class activation maps, saliency methods, SHAP values, and counterfactual explanations are increasingly applied to remote sensing models in policy-relevant domains such as deforestation monitoring, food-security assessment, and disaster response (Roscher et al., 2020). Bayesian neural networks, Monte Carlo dropout, and conformal-prediction methods are being adopted to quantify predictive uncertainty alongside point estimates.

8. CHALLENGES AND LIMITATIONS

Despite rapid advancement, several challenges constrain operational deployment. Data quality remains uneven: in cloud-prone tropical regions, persistent cloud cover limits optical observations, requiring SAR-based or fused workflows.

The computational demands of high-resolution and time-series analyses can exceed local infrastructure, although cloud platforms partially mitigate this. Domain shift models trained in one region or season performing poorly elsewhere remains an open problem; benchmarks such as REOBench show that even large vision-language foundation models can lose up to twenty per cent of accuracy under image corruption (Li et al., 2025). Labelled training data are scarce, particularly in the Global South, and the geographic and ecological biases of existing benchmarks limit generalizability. Interpretability and trust in deep models remain limited, and the energy and carbon footprint of training large foundation models warrant attention. Finally, regulatory frameworks for data sharing, privacy, and AI use in safety-critical applications are still maturing.

9. FUTURE RESEARCH DIRECTIONS

Several directions will define the next phase of remote sensing data modelling. First, self-supervised and foundation-model pre-training will continue to expand, with growing emphasis on multi-modal, multi-sensor, and temporally aware architectures and on geographically inclusive benchmark suites (Marsocci et al., 2025). Second, physics-informed machine learning coupling radiative transfer, atmospheric, and ecosystem models with neural networks offers a path to more generalizable and interpretable predictions. Third, digital twins of the Earth, integrating remote sensing, in situ observation, and process-based models, are being developed by ESA, NASA, and the European Commission, requiring new methods of data assimilation and uncertainty propagation. Fourth, integration with large language models opens possibilities for natural-language querying of Earth observation archives, exemplified by Google Research's 2025 Geospatial Reasoning programme. Fifth, edge and on-board processing will increasingly enable near-real-time applications in disaster response, agriculture, and security. Finally, capacity-building and infrastructure development in the Global South, including sub-Saharan Africa, are essential to distribute benefits equitably and ensure local research communities contribute to the global evidence base on drylands ecology, smallholder agriculture, and climate adaptation.

10. CONCLUSION

Remote sensing data models constitute an interlinked analytical chain through which raw electromagnetic measurements are transformed into usable information about the Earth. This review has organised that chain into five categories: acquisition, preprocessing, classification, change detection, and analysis and has shown how each has advanced markedly since 2020. The shift from desktop to cloud-based processing, the maturation of deep learning architectures, the emergence of geospatial foundation models such as Prithvi-EO and Clay, and the integration of multi-modal data have together reshaped the methodological landscape. Persistent challenges remain in data quality, computational efficiency, domain shift, label scarcity, interpretability, and equitable access. Addressing them through self-supervised learning, physics-informed methods, explainable AI, and inclusive benchmarking will be central to the field's next phase. As Earth observation continues to deliver finer spatial, temporal, and spectral detail, the value extracted from it will depend on the disciplined development, validation, and responsible deployment of the data models reviewed here.

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