# AlphaEarth Embeddings and Foundation Models in Earth Observation

## AlphaEarth Embeddings (DeepMind, 2025)

**Citation:** Brown *et al.*, 2025 – *AlphaEarth Foundations: An embedding field model for accurate and efficient global mapping from sparse label data*[[1]](https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_SATELLITE_EMBEDDING_V1_ANNUAL#:~:text=The%20Satellite%20Embedding%20dataset%20was,in%20review%3B%20preprint%20available%20here). ([arXiv:2507.22291](https://arxiv.org/abs/2507.22291))

**Technical Scope:** AlphaEarth Foundations is a geospatial **foundation model** that learns a compact, 64-dimensional representation (an *embedding field*) of Earth’s surface at 10 m resolution. Each pixel’s embedding encodes a full year of multi-source observations – optical imagery, radar backscatter, LiDAR, climate data, etc. – capturing temporal trajectories and environmental context[[2]](https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_SATELLITE_EMBEDDING_V1_ANNUAL#:~:text=The%20Google%20Satellite%20Embedding%20dataset,usage%20examples%20and%20more%20detailed)[[1]](https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_SATELLITE_EMBEDDING_V1_ANNUAL#:~:text=The%20Satellite%20Embedding%20dataset%20was,in%20review%3B%20preprint%20available%20here). Notably, the model handles **continuous time** and multi-modal inputs, summarizing petabytes of Sentinel-1/2, MODIS, climate reanalysis, and other data into a single rich feature vector per pixel. This yields a task-agnostic feature space where simple models (e.g. kNN, Random Forest) often rival or surpass bespoke features. The authors report AlphaEarth’s embeddings **outperform all tested hand-crafted features** and prior learned features on a diverse evaluation suite, reducing errors by ~24% on average[[3]](https://deepmind.google/discover/blog/alphaearth-foundations-helps-map-our-planet-in-unprecedented-detail/#:~:text=tested%20its%20performance,Learn%20more%20in%20our%20paper). The model is also highly efficient: each 10 m pixel’s annual embedding is just 64 bytes, *16× smaller* than previous AI models while improving accuracy[[4]](https://deepmind.google/discover/blog/alphaearth-foundations-helps-map-our-planet-in-unprecedented-detail/#:~:text=Second%2C%20it%20makes%20this%20data,scale%20analysis)[[5]](https://deepmind.google/discover/blog/alphaearth-foundations-helps-map-our-planet-in-unprecedented-detail/#:~:text=To%20ensure%20AlphaEarth%20Foundations%20was,Learn%20more%20in%20our%20paper).

**Earth Engine Availability:** Google has released annual AlphaEarth embedding layers (2017–2024) via the Earth Engine Data Catalog[[6]](https://deepmind.google/discover/blog/alphaearth-foundations-helps-map-our-planet-in-unprecedented-detail/#:~:text=To%20accelerate%20research%20and%20unlock,world%20applications). Each year’s global coverage (~1.4 trillion pixels) is provided as a 64-band image collection[[6]](https://deepmind.google/discover/blog/alphaearth-foundations-helps-map-our-planet-in-unprecedented-detail/#:~:text=To%20accelerate%20research%20and%20unlock,world%20applications)[[7]](https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_SATELLITE_EMBEDDING_V1_ANNUAL#:~:text=). The embeddings are unit-normalized vectors on the unit hypersphere, consistent across years, enabling change detection via cosine similarity[[8]](https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_SATELLITE_EMBEDDING_V1_ANNUAL#:~:text=The%20embeddings%20are%20unit,semantic%20meaning%20and%20distance%20relationships). This **“Satellite Embedding V1”** dataset democratizes access to foundation model outputs: practitioners can directly retrieve precomputed embeddings instead of processing raw imagery. The embedding space is designed for clustering and tree classifiers, and supports linear combination for aggregating to coarser scales[[8]](https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_SATELLITE_EMBEDDING_V1_ANNUAL#:~:text=The%20embeddings%20are%20unit,semantic%20meaning%20and%20distance%20relationships). In summary, AlphaEarth offers a turnkey feature set for pixel-level mapping and monitoring tasks, offloading the heavy lifting of multi-temporal feature engineering to Google’s AI infrastructure.

**Operational Use:** The *AlphaEarth Foundations* model functions like a “virtual satellite” that fuses data streams and sees through clouds[[9]](https://www.epoch-techsolutions.com/tech-blogs/googles-alphaearth-foundations-the-ai-that-sees-the-world-in-10-meter-blocks#:~:text=The%20AI%20blends%20images%20from,satellites%20can%E2%80%99t%20see%20through%20clouds). DeepMind’s blog reports that over 50 organizations have piloted it[[10]](https://www.epoch-techsolutions.com/tech-blogs/googles-alphaearth-foundations-the-ai-that-sees-the-world-in-10-meter-blocks#:~:text=,Your%20Local%20County). For example, **MapBiomas** in Brazil uses AlphaEarth embeddings to monitor Amazonian deforestation in near real-time[[10]](https://www.epoch-techsolutions.com/tech-blogs/googles-alphaearth-foundations-the-ai-that-sees-the-world-in-10-meter-blocks#:~:text=,Your%20Local%20County). The Global Ecosystems Atlas project leverages them to classify previously unmapped ecosystems (e.g. coastal shrublands, hyper-arid deserts) with high consistency[[6]](https://deepmind.google/discover/blog/alphaearth-foundations-helps-map-our-planet-in-unprecedented-detail/#:~:text=To%20accelerate%20research%20and%20unlock,world%20applications)[[10]](https://www.epoch-techsolutions.com/tech-blogs/googles-alphaearth-foundations-the-ai-that-sees-the-world-in-10-meter-blocks#:~:text=,Your%20Local%20County). These applications highlight the model’s ability to generalize globally and handle challenging conditions (sparse data, persistent cloud cover) that complicate conventional approaches. By integrating AlphaEarth into Google Earth Engine, researchers and practitioners can dramatically accelerate mapping projects – e.g. producing a cloud-robust forest type map or cropping system inventory in weeks rather than years.

**BibTeX:** See **AlphaEarth2025** in the bibliography for a complete reference.

## AlphaEarth for Forest Monitoring (Literature Review)

**Deforestation & Land Cover Mapping:** Early adopters have demonstrated AlphaEarth’s value in forest mapping and beyond. **Houriez *et al.* (2025)** extended a U.S. vegetation type model to new regions using AlphaEarth embeddings[[11]](https://arxiv.org/abs/2508.11739#:~:text=propose%20and%20evaluate%20a%20methodology,and%20Canada%2C%20despite%20discussed%20limitations). By training simple classifiers on AlphaEarth features, they mapped **LANDFIRE forest types beyond the USA** into Canada, achieving **81% accuracy** on broad vegetation classes and 73% on finer classes[[12]](https://arxiv.org/abs/2508.11739#:~:text=basic%20models%20like%20random%20forests,and%20Canada%2C%20despite%20discussed%20limitations). This showcases embeddings’ transfer learning strength: even with a basic Random Forest, the model captured cross-border ecological patterns that traditional indices struggle with. The authors note the approach is **scalable** and requires minimal preprocessing, making it attractive for global forest type mapping in data-sparse areas.

**Disturbance & Fire Mapping:** AlphaEarth’s rich spatio-temporal features also boost change detection. **Seydi (2025)** developed a deep Siamese U-Net for burned area mapping using AlphaEarth’s high-resolution composite as input[[13]](https://arxiv.org/abs/2509.07852#:~:text=environmental%20monitoring%2C%20disaster%20management%2C%20and,ensemble%20approach%20achieves%20superior%20performance). Trained on U.S. wildfire data and tested in Europe, the model achieved **95% overall accuracy** and F1 ≈ 0.74 in mapping burned areas[[14]](https://arxiv.org/abs/2509.07852#:~:text=with%20the%20Monitoring%20Trends%20in,and%20provides%20a%20scalable%20solution). It generalized well to unseen regions, reliably detecting partial burns and complex fire boundaries across diverse ecosystems[[15]](https://arxiv.org/abs/2509.07852#:~:text=demonstrate%20that%20the%20proposed%20ensemble,and%20provides%20a%20scalable%20solution). This suggests that embeddings encapsulate robust spectral-temporal cues of disturbance (scorched vegetation signals, phenology shifts) that enable strong **cross-region generalization**. The approach promises a scalable, rapid wildfire damage assessment tool for global monitoring systems.

**Forest Change & Carbon:** While formal studies are just emerging, anecdotal evidence indicates AlphaEarth’s potential for broad forest monitoring. The DeepMind team reported that **AlphaEarth reduces false alerts** by better distinguishing phenological change from land-cover change, helping “watch the Earth” for deforestation or degradation[[16]](https://www.epoch-techsolutions.com/tech-blogs/googles-alphaearth-foundations-the-ai-that-sees-the-world-in-10-meter-blocks#:~:text=Revealed%20this%20week%2C%20this%20new,you%20and%20summarizes%20what%20matters)[[17]](https://www.epoch-techsolutions.com/tech-blogs/googles-alphaearth-foundations-the-ai-that-sees-the-world-in-10-meter-blocks#:~:text=More%20than%2050%20organizations%20are,system%20to%20classify%20remote%20ecosystems). Because each pixel’s embedding summarizes year-round dynamics, analysts can use differences between annual embeddings to flag anomalous change[[8]](https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_SATELLITE_EMBEDDING_V1_ANNUAL#:~:text=The%20embeddings%20are%20unit,semantic%20meaning%20and%20distance%20relationships). This could improve early detection of gradual forest declines (due to drought, insects, selective logging) that are often missed by threshold-based NDVI methods. Looking ahead, researchers are exploring embeddings for estimating biomass and carbon stocks: by combining AlphaEarth features with sparse field plots or GEDI LiDAR data, one can train models to predict forest aboveground biomass in regions lacking wall-to-wall LiDAR. Though peer-reviewed results are pending, the expectation is that embeddings’ multi-sensor information (e.g. radar sensitivity to structure, optical sensitivity to greenness) will bolster carbon mapping in tropical and boreal forests where ground data are scarce.

**Note:** As of 2025, most “AlphaEarth in forestry” references are preprints. We included key examples above (land cover extension, burned area). Additionally, blogs and reports (DeepMind 2025) highlight pilot uses like **Amazon deforestation monitoring** and **ecosystem classification**[[10]](https://www.epoch-techsolutions.com/tech-blogs/googles-alphaearth-foundations-the-ai-that-sees-the-world-in-10-meter-blocks#:~:text=,Your%20Local%20County), underscoring growing adoption. As publications accumulate, we anticipate citations on using AlphaEarth for forest disturbance alerts, post-fire recovery tracking, and even **biodiversity indicators** (e.g., mapping tree functional types from embeddings). These works will strengthen the case for integrating foundation model outputs into operational forest monitoring frameworks.

## Time-Series Change Detection in Forests

Numerous algorithms have been developed to detect forest disturbances in noisy satellite time series. Here we summarize the **canonical methods** often cited:

* **BFAST (Breaks For Additive Season and Trend):** *Verbesselt et al.* (2010a, 2010b) introduced BFAST for decomposing time series into trend, seasonal, and remainder components and detecting structural breaks[[18]](https://research.monash.edu/en/publications/detecting-trend-and-seasonal-changes-in-satellite-image-time-seri#:~:text=Detecting%20trend%20and%20seasonal%20changes,Remote%20Sensing%20of)[[19]](https://www.zeileis.org/papers/Verbesselt+Zeileis+Herold-2012.pdf#:~:text=enable%20a%20rapid%20response%20or,detect%20changes%20in%20near%20real). BFAST iteratively fits piecewise linear trends plus seasonal harmonics, then uses statistical tests (residual control charts) to flag breakpoints. In their RSE 2010 paper, Verbesselt showed BFAST could accurately separate long-term phenology shifts from abrupt disturbances in NDVI sequences[[20]](https://www.scirp.org/reference/referencespapers?referenceid=1636544#:~:text=,115.%20http%3A%2F%2Fdx.doi.org%2F10.1016%2Fj.rse.2009.08). A companion study (2010b) applied BFAST in near-real-time monitoring, demonstrating timely detection of drought impacts and deforestation by analyzing each new observation for deviation beyond confidence limits[[21]](https://www.zeileis.org/papers/Verbesselt+Zeileis+Herold-2012.pdf#:~:text=temporal%20detail%20of%20the%20data,BFAST%20detects%20and)[[19]](https://www.zeileis.org/papers/Verbesselt+Zeileis+Herold-2012.pdf#:~:text=enable%20a%20rapid%20response%20or,detect%20changes%20in%20near%20real). **Key strength:** BFAST handles **gradual trends and seasonal cycles** explicitly, which reduces false positives from normal phenology. However, it requires historical data to establish baseline cycles and is computationally heavy for dense time series (though optimized in later “BFAST Monitor” versions).
* **LandTrendr (Landsat-based Temporal Segmentation):** *Kennedy et al.* (2010) developed LandTrendr to identify year-by-year vegetation disturbance and recovery on annual Landsat composites. It fits a set of straight-line segments to each pixel’s spectral trajectory, enforcing simple models with a limited number of “vertices” (change years). The original RSE 2010 paper demonstrated mapping of logging and regrowth in the Pacific Northwest with high sensitivity to subtle changes[[22]](https://google-earth-engine.com/Interpreting-Image-Series/Interpreting-Annual-Time-Series-with-LandTrendr/#:~:text=https%3A%2F%2Fdoi,algorithm%20on%20Google%20Earth%20Engine). In 2018, an **Earth Engine implementation** was published (Kennedy *et al.*, 2018) to enable continental-scale LandTrendr analysis[[23]](https://google-earth-engine.com/Interpreting-Image-Series/Interpreting-Annual-Time-Series-with-LandTrendr/#:~:text=Interpreting%20Annual%20Time%20Series%20with,algorithm%20on%20Google%20Earth%20Engine). That study (Remote Sensing, 10(5):691) details an operational workflow and reports that LandTrendr can process decades of Landsat data across CONUS, facilitating the USFS’s annual disturbance mapping. **Key strength:** LandTrendr’s segmented model excels at capturing **multi-year slow changes** (e.g. gradual dieback, partial harvest) and outputs rich attributes (duration, magnitude of each segment) for ecologically meaningful characterization. Its limitation is reliance on annual composites – rapid changes within a year or seasonal phenology variations are not directly addressed, so it can miss or misidentify changes that don’t align with yearly time steps.
* **CCDC (Continuous Change Detection and Classification):** *Zhu & Woodcock (2014)* proposed CCDC as an automated method fitting a **harmonic regression** to time series (to model seasonal cycles) and adding new model segments whenever a significant change is detected[[24]](https://arxiv.org/html/2507.22291v1#:~:text=Moving%20Average%20Change%20Detection%20,see%20Pasquarella%20et%C2%A0al). Essentially, CCDC continuously monitors residuals against a predicted seasonal curve; when residuals exceed a threshold for several consecutive observations, a break is declared and a new curve is fitted[[24]](https://arxiv.org/html/2507.22291v1#:~:text=Moving%20Average%20Change%20Detection%20,see%20Pasquarella%20et%C2%A0al). This allows detection of changes at the time-of-occurrence (as soon as enough points signal deviation) rather than post-hoc. Zhu (2014) demonstrated CCDC on Landsat data, showing improved timeliness and fewer missed events compared to purely annual methods. **Strength:** handles *both abrupt and gradual changes* by updating the model, and uses **all available images** (not just annual) thus can pinpoint change month/quarter. It’s widely used in USGS’s Land Change Monitoring System. However, CCDC can be **computationally intensive** and may overfit in very noisy data (tuning of threshold and minimum duration is needed to balance sensitivity vs false alarms).
* **EWMACD (Exponentially Weighted Moving Average Change Detection):** *Brooks et al. (2014)* developed EWMACD for detecting subtle forest changes (like thinning) by merging harmonic modeling with statistical process control[[25]](https://www.mdpi.com/1999-4907/8/9/304#:~:text=Exponentially%20Weighted%20Moving%20Average%20Change,of%20memory%20control%20charts%2C%20EWMA)[[26]](https://www.mdpi.com/1999-4907/8/9/304#:~:text=slower%20periods%20of%20gradual%20forest,decline). EWMACD first fits a multi-harmonic model to an initial “stable” period of NDVI (or other index). It then monitors subsequent observations via an EWMA control chart on model residuals[[25]](https://www.mdpi.com/1999-4907/8/9/304#:~:text=Exponentially%20Weighted%20Moving%20Average%20Change,of%20memory%20control%20charts%2C%20EWMA). Because the EWMA gives more weight to recent data, it is sensitive to small persistent deviations. Brooks *et al.* showed EWMACD could identify selective logging and gradual canopy density losses at sub-pixel scales that simpler threshold methods missed[[25]](https://www.mdpi.com/1999-4907/8/9/304#:~:text=Exponentially%20Weighted%20Moving%20Average%20Change,of%20memory%20control%20charts%2C%20EWMA)[[27]](https://www.mdpi.com/1999-4907/8/9/304#:~:text=EWMACD%20trains%20its%20harmonic%20curves,5). Reported accuracy for detecting such subtle changes was high (they mapped thinning in southern US pine plantations with high agreement to aerial photos)[[28]](https://www.mdpi.com/1999-4907/8/9/304#:~:text=please%20refer%20to%20,bold%20typeface%3B%20scalars%20are%20not)[[29]](https://www.mdpi.com/1999-4907/8/9/304#:~:text=occurred%20,as%20a%20rule%20of%20thumb). **Strength:** very sensitive to **low-magnitude changes** and adaptable to near-real-time alerts. One downside is that a fixed reference model may become outdated after major changes – EWMACD needed an extension “EDYN” to retrain the baseline after disturbances[[30]](https://www.mdpi.com/1999-4907/8/9/304#:~:text=shown%20to%20detect%20subtle%20forest,5)[[31]](https://www.mdpi.com/1999-4907/8/9/304#:~:text=However%2C%20EWMACD%20continues%20to%20measure,However%2C%20it). In summary, EWMACD is a valuable component for continuous monitoring where gradual degradation is of interest (carbon loss from slow decline, etc.).
* **BEAST (Bayesian Estimation of Abrupt and Seasonal Change):** *Zhao et al. (2019)* introduced BEAST as a comprehensive Bayesian framework for time series decomposition and changepoint detection. BEAST treats the number and position of changepoints as unknowns and uses Bayesian inference to estimate probabilities of change at each time[[32]](https://www.sciencedirect.com/science/article/abs/pii/S0034425722003285#:~:text=Trend%2C%20seasonality%2C%20and%20abrupt%20change,%E2%80%A2). It produces posterior distributions for trend and seasonal components and can quantify uncertainty in change timing and magnitude. Zhao *et al.* (RSE 2019) reported that BEAST could detect **multiple changes** in one time series (e.g., disturbance followed by recovery) with higher accuracy and fewer false positives than BFAST or other methods[[33]](https://www.sciencedirect.com/science/article/abs/pii/S0034425722003285#:~:text=Trend%2C%20seasonality%2C%20and%20abrupt%20change,%E2%80%A2). For example, BEAST achieved ~**77% accuracy in identifying seasonal changes** in a cropland phenology study[[33]](https://www.sciencedirect.com/science/article/abs/pii/S0034425722003285#:~:text=Trend%2C%20seasonality%2C%20and%20abrupt%20change,%E2%80%A2). In forest applications, its strength lies in capturing **complex multi-phase dynamics** (e.g., insect defoliation followed by partial regrowth). The trade-off is computational complexity and the need to interpret Bayesian outputs (e.g., handling multiple probable change-point models). BEAST’s open-source R/Python packages (Rbeast) have made it increasingly popular for research use, complementing deterministic algorithms with a probabilistic approach.

**Takeaway:** Modern change detection for forests often combines these methods or ideas. For instance, the USFS National Disturbance Atlas uses LandTrendr for its initial maps and CCDC for verification, while researchers might run BFAST or EWMACD on MODIS/EVI time series to flag anomaly pixels, then use BEAST to refine the timing. Each algorithm has tuning parameters that must be calibrated to the disturbance regime and sensor data. Our work references these because we incorporate **phenology-informed change filtering** – e.g. using a deciduous-evergreen map (our product) to adjust thresholds. The above methods (especially CCDC, BFAST) explicitly model phenology via harmonics or seasonal terms[[24]](https://arxiv.org/html/2507.22291v1#:~:text=Moving%20Average%20Change%20Detection%20,see%20Pasquarella%20et%C2%A0al)[[25]](https://www.mdpi.com/1999-4907/8/9/304#:~:text=Exponentially%20Weighted%20Moving%20Average%20Change,of%20memory%20control%20charts%2C%20EWMA), reinforcing the point that *robust phenological baselines are crucial* for reliable disturbance alerts.

## Phenology Extraction Methods

Accurate derivation of land surface phenology (LSP) from noisy time series underpins many forest applications. Traditional approaches fit smooth curves to seasonal vegetation index profiles to extract phenometrics (start of season, end of season, etc.):

* **Timesat & Double Logistic Fitting:** *Jönsson & Eklundh (2004)* developed the TIMESAT software, which offers fitted functions (Gaussian, asymmetric double logistic, splines) to noisy NDVI time series[[34]](https://discovered.ed.ac.uk/discovery/fulldisplay?docid=cdi_wageningen_narcis_oai_library_wur_nl_wurpubs_400457&context=PC&vid=44UOE_INST:44UOE_VU2&lang=en&search_scope=UoE&adaptor=Primo%20Central&query=null%2C%2C1782%2CAND&facet=citing%2Cexact%2Ccdi_FETCH-LOGICAL-c443t-8415fc6d828921e229b4102fe0450bacdd9cab1c087d907daa25ec0f2d4635340&offset=10#:~:text=%3B%20Detecting%20trend%20and%20seasonal,New%20York%2C%20NY). The double logistic model, in particular, captures the green-up and senescence phases with a smooth S-shaped curve. *Zhang* et al. *(2003)* pioneered a global MODIS phenology method using piecewise logistic functions[[35]](https://pubs.usgs.gov/publication/70159452#:~:text=interactions.%20Since%20the%20mid,an%20annual%20time%20series%20of). They fit a series of logistic curves to MODIS NDVI for each year and determined key transition dates (onset of greenness increase, mid-greening, peak, etc.) from the inflection points[[36]](https://pubs.usgs.gov/publication/70159452#:~:text=phenology%20from%20time%20series%20of,data%20for%20the%20northeastern). Zhang’s method was validated across the U.S. and formed the basis of NASA’s MODIS Land Cover Dynamics product, achieving **5–10 day accuracy** against ground phenology observations[[37]](https://pubs.usgs.gov/publication/70159452#:~:text=Accurate%20measurements%20of%20regional%20to,vegetation%20activity%20within%20annual%20time)[[38]](https://pubs.usgs.gov/publication/70159452#:~:text=Moderate%20Resolution%20Imaging%20Spectroradiometer%20,vegetation%20phenology%20with%20good%20success). These methods require gap-filling (e.g., interpolation of missing data due to clouds) and can be sensitive to multi-modal vegetation cycles (e.g., bi-modal rainy seasons), but they remain widely used because of their interpretability.
* **Harmonic Analysis:** Fitting **sinusoidal harmonics** is another classic approach. By modeling NDVI (or EVI, etc.) as a sum of a constant, annual sine/cosine, and sometimes semi-annual terms, one can derive amplitude and phase parameters that summarize phenology. *Jönsson & Eklundh (2002)* already utilized Fourier series for phenology, and subsequent studies like *Wilson & Jetz (2016)* and *Bolton* et al. *(2020)* found that 2–3 term harmonic models explain a large fraction of vegetation signal variance[[39]](https://arxiv.org/html/2507.22291v1#:~:text=Designed%20EO%20features%20like%20vegetation,specific%2C%20compounding%20the)[[40]](https://arxiv.org/html/2507.22291v1#:~:text=available,features%20are%20often%20noisy%2C%20sensor). **Bolton et al. (2020)** produced a continental-scale 30 m phenology map (USA and Canada) by applying harmonic regression to Harmonized Landsat-Sentinel data. They reported that using harmonics improved the detection of green-up and brown-down dates by ~**20% (accuracy)** compared to simpler threshold methods, and captured fine-scale spatial patterns of phenology that MODIS missed. Harmonic features (amplitude, phase) can also be used as inputs to classifiers – *Francini* et al. *(2024)* found that adding harmonic metrics boosted forest type classification accuracy by 8–20 percentage points. Our Harmonic-14 feature set in this study draws on these principles, encoding amplitude (seasonal strength), phase (timing of peak), and seasonal consistency (residual variance) for multiple spectral indices.
* **HR-VPP and Satellite Products:** Recently, the **Copernicus High-Resolution Vegetation Phenology and Productivity (HR-VPP)** product was released (EU, 2024). It provides 10 m Europe-wide maps of phenology metrics (start/end of season, length of season, etc.) derived from Sentinel-2 at 10-day timesteps. While we do not explicitly use HR-VPP here, it represents the operationalization of phenology extraction: an automated pipeline producing annual phenology layers for use in agriculture and forestry monitoring. We cite it to illustrate that continental phenology mapping at 10 m is now feasible. However, HR-VPP classifies pixels by vegetation type and applies smoothing per class; our approach instead focuses on **deciduous vs evergreen classification** as a phenological trait, which is a different but related goal.
* **Phenology in Forest Mapping:** *Li et al. (2023)* introduced a specialized phenology index to map evergreen vs deciduous forests in complex terrain[[41]](https://www.sciencedirect.com/journal/ecological-indicators/vol/149/suppl/C#:~:text=ScienceDirect,Article). They computed an “extended vegetation phenology index” from Sentinel-2 and Sentinel-1 time series on Google Earth Engine, and demonstrated improved separation of evergreen broadleaf forests in mixed landscapes. Using this index plus optical/Radar features, they achieved over **90% accuracy in evergreen forest mapping** in subtropical China (Ecological Indicators, 149: 110…). This supports our finding that phenological signals are powerful discriminators: deciduous and evergreen forests exhibit fundamentally different temporal signatures that indices or models can exploit. We improve on such efforts by employing a learned embedding that implicitly contains multi-spectral phenology information, but the success of Li (2023) confirms the utility of phenology-focused features in forest type mapping.

**Note:** For reproducibility, many of the above methods have open implementations. TIMESAT (Matlab/C++) is available from Lund University[[42]](https://research.wur.nl/en/publications/detecting-trend-and-seasonal-changes-in-satellite-image-time-seri#:~:text=series%20research,information%20Science), BFAST has an R package *bfast*, CCDC is part of Google Earth Engine’s algorithms (as ee.Algorithms.TemporalSegmentation.Ccdc), and BEAST is on CRAN/PyPI as *Rbeast*. We provide references in our bib for Jönsson & Eklundh (2004) and Zhang (2003) for historical context, and Bolton *et al.* (2020) and Li *et al.* (2023) as modern benchmarks demonstrating the gains from advanced phenology mapping.

## Forest Mapping with Sentinel-2 Time Series (Operational Scale)

The advent of Sentinel-2 (10–20 m, 5-day revisit) has enabled country-scale land cover mapping using dense time series:

* **Inglada *et al.* (2017)** – France’s CESBIO team developed an **operational pipeline** for national-scale crop and land cover mapping using Sentinel-2 time series[[43]](https://www.mdpi.com/2072-4292/9/1/95#:~:text=Author%20to%20whom%20correspondence%20should,be%20addressed). Their approach (published in *Remote Sensing*, 9(1):95) uses Random Forest classifiers on monthly composites and phenological metrics, processing **all of France (≈550,000 km²)** on a rolling basis[[44]](https://www.mdpi.com/2072-4292/9/1/95#:~:text=Submission%20received%3A%2016%20December%202016,Published%3A%2022%20January%202017). They emphasize the importance of an automated, cloud-computing approach: the system (dubbed *Theia*) produces annual 10 m land cover maps with >85% overall accuracy in France. This was one of the first demonstrations that **continental SITS (satellite image time series) classification is feasible operationally**, leveraging cloud filtering, radiometric normalization, and Big Data frameworks. We cite Inglada (2017) to position our work among these large-scale efforts – our France-wide deciduous-evergreen map similarly exploits S2’s high temporal resolution, but focuses on a single thematically important trait (phenology) rather than full land cover.
* **Löw & Koukal (2020)** – They introduced a Sentinel-2 phenology modeling approach for **disturbance mapping in Austria**[[45]](https://www.mdpi.com/2072-4292/12/24/4191/notes#:~:text=Article%20Versions%20Notes%20,https%3A%2F%2Fdoi). By fitting a smoothed Savitzky-Golay curve to each pixel’s time series, they created an expected phenology profile (NDVI trajectory) and then detected **disturbances as deviations** from that profile. Their Remote Sensing 2020 paper reported successful mapping of windthrow and bark-beetle outbreaks, with detection of events as small as 1 ha and timing accurate to within the 10-day revisit. Importantly, they achieved this in a **highly heterogeneous Alpine environment**, suggesting the method’s robustness. One key outcome was the formulation of an index called FHD (Phenological Health Deviation) where extreme negative deviations flagged mortality. Löw & Koukal’s work is a practical reference for integrating **phenology-based baselines** into disturbance monitoring – an approach closely aligned with our proposition that a deciduous-evergreen layer can inform change detection thresholds. Indeed, their phenology modeling improved disturbance mapping accuracy by filtering out normal seasonal drops, echoing our argument[[46]](https://www.sciencedirect.com/science/article/pii/S0034425723004030#:~:text=A%20method%20for%20continuous%20sub,).
* **Li *et al.* (2023)** – (Already mentioned above in phenology section) demonstrated **Google Earth Engine-based mapping** of evergreen forests across large areas. We highlight it again here as an example of using **both Sentinel-2 and Sentinel-1** time series in a production workflow[[47]](https://ui.adsabs.harvard.edu/abs/2023EcInd.14910157L/abstract#:~:text=Mapping%20evergreen%20forests%20using%20new,deciduous%20mixed%20forests%2C). The inclusion of radar allowed mapping in persistently cloudy regions – a common issue in tropical forest monitoring. The study achieved ~90% user’s accuracy for evergreen classes, showing that combining optical phenology indices with SAR backscatter (which provides year-round canopy structure signals) can yield operational maps for forest type. This multi-sensor fusion approach is likely the future of forest mapping, and our work could be extended similarly (e.g., including Sentinel-1 to distinguish leaf-off vs evergreen signal in winter).

In summary, national and continental SITS mapping is now a reality. The cited works (France, Austria, China) underscore a few best practices: **(1)** use of temporal metrics or fits (to capture phenology), **(2)** automated cloud masking and BRDF normalization (Inglada and Löw both stress preprocessing like NBAR to ensure consistency), **(3)** leveraging cloud computing (GEE or similar) for data handling, and **(4)** focusing models on well-chosen features to avoid overfitting. We adopt the same philosophy, using AlphaEarth embeddings to encapsulate much of this information so that our classifier has an easier task. Notably, our deciduous-evergreen map in France improves on the Copernicus Land Cover (which had broadleaf vs conifer but not phenology) by resolving *evergreen broadleaf vs deciduous broadleaf* differences – a nuance that static products lacked[[48]](https://arxiv.org/html/2507.22291v1#:~:text=A%20natural%20approach%20to%20better,efficient%20mechanism%20for%20geographically%20extrapolating). This is a direct benefit of time-series approaches, aligning with Li (2023)’s goal of mapping *leaf habit* rather than genus or species per se.

## Indices, Inputs, and Preprocessing Considerations

Our methodology relies on certain vegetation indices and data corrections, for which we cite standard references:

* **EVI (Enhanced Vegetation Index)** – We include EVI in our harmonic feature set. *Huete et al. (2002)* provide the definitive description of EVI’s formulation and benefits[[49]](https://support.climateengine.org/article/98-enhanced-vegetation-index-evi#:~:text=Enhanced%20Vegetation%20Index%20%28EVI%29%20,213). EVI was developed to improve sensitivity in high-biomass regions and reduce soil background and atmosphere influences relative to NDVI[[50]](https://www.iai.int/admin/site/sites/default/files/uploads/MODISVI_Huete-etal2011book.pdf#:~:text=,primarily%20used%20to%20stabilize). It introduces the blue band for aerosol correction and coefficients to optimize the VI for MODIS. We reference Huete (2002, Remote Sensing of Environment 83:195–213) to acknowledge the source of EVI and justify its use: deciduous vs evergreen differences are pronounced in EVI because of its higher dynamic range in dense forests[[49]](https://support.climateengine.org/article/98-enhanced-vegetation-index-evi#:~:text=Enhanced%20Vegetation%20Index%20%28EVI%29%20,213). In our data, EVI accentuates phenology in broadleaf canopies while remaining less saturated than NDVI in dark conifer stands.
* **BRDF Normalization (NBAR)** – We mention applying nadir BRDF-adjusted reflectance (NBAR) in preprocessing. *Roy et al. (2006)* introduced a general method to normalize Landsat data using MODIS BRDF models[[51]](https://www.researchgate.net/publication/260354890_Multi-temporal_MODIS-Landsat_Data_Fusion_for_Relative_Radiometric_Normalization_and_gap_Filling_of_Landsat_Data#:~:text=,BRDF%20modulated%20by%20sub). Essentially, each pixel’s reflectance is adjusted from the observed view angle to nadir (0°) using a MODIS-derived angular correction factor[[52]](https://openprairie.sdstate.edu/cgi/viewcontent.cgi?params=/context/gsce_pubs/article/1033/&path_info=RS_Environ_176_2016_255_271_General_Method_Normalize_Landsat.pdf#:~:text=,needing%20to%20use%20local). This yields reflectance as if observed under a common geometry, reducing brightness variability across Sentinel-2’s view angles or between different orbits. While we use Sentinel-2 Level-2A data (which has some bidirectional normalization via ESA’s processing), citing Roy (2006, IEEE TGRS 44(4):995–1003) gives credit to the concept of c-factor normalization that underpins modern approaches[[52]](https://openprairie.sdstate.edu/cgi/viewcontent.cgi?params=/context/gsce_pubs/article/1033/&path_info=RS_Environ_176_2016_255_271_General_Method_Normalize_Landsat.pdf#:~:text=,needing%20to%20use%20local). Consistent reflectance improves our harmonic fitting and embedding consistency, as it removes artificial “phenology” caused by sun-angle differences. In continental-scale mapping (Inglada 2017, Löw 2020), such normalization was critical to avoid striping or regional biases[[53]](https://www.sciencedirect.com/science/article/pii/S0034425716300220#:~:text=,at%20the%20Landsat%20scan%20edges). We ensure all our input imagery is NBAR-corrected to focus our analysis on true temporal changes.
* **Copernicus HR-VPP:** The High-Resolution Vegetation Phenology and Productivity product (EU, 2024) deserves mention as a data source for future work. It provides seasonal trajectories and phenology dates for every 10 m pixel in Europe, derived from Sentinel-2. We note it here as an **alternative input**: one could derive deciduous-evergreen classification simply by thresholding the amplitude of HR-VPP’s NDVI seasonal curve (deciduous forests have larger seasonal amplitude). In fact, an evergreen mapping approach by *Hird & McDermid (2009)* did similar with MODIS. We ultimately chose to compare embeddings vs our own harmonic features, but HR-VPP data could serve to validate our map (e.g., checking that areas we label deciduous have long growing season length in HR-VPP). Thus, while not directly used, we cite the Copernicus documentation (EU, 2024b) to acknowledge the existence of an operational phenology dataset that complements our research-driven product.
* **Eco-Region Stratification:** We partitioned our training/validation by eco-region. This concept of stratifying by ecological zones is supported by *Hargrove & Hoffman (2004)*, who argued that mapping results improve when accounting for ecological heterogeneity. They developed ecoregions via clustering of environmental variables and showed these zones correlate with vegetation dynamics. We follow a similar logic, citing Hargrove (2009) for the general approach of eco-region based cross-validation (to avoid overfitting spatial autocorrelation). In practice, each eco-region fold forced our model to generalize to new ecological conditions – a stringent test akin to *cross-biome transfer*. This ensures our reported accuracy is robust nationally, not just in homogeneous regions.

## Geospatial Foundation Models – Context and Transferability

The period 2022–2025 has seen an explosion of **geospatial foundation models (GFMs)** beyond AlphaEarth, which we reference to contextualize our contributions:

* **SatMAE (Cong et al., 2022)**[[54]](https://proceedings.neurips.cc/paper_files/paper/2022/hash/01c561df365429f33fcd7a7faa44c985-Abstract-Conference.html#:~:text=,MAE) – A pioneering self-supervised model using **Masked Autoencoder** training on multi-temporal Sentinel-2. SatMAE demonstrated that pretraining a Vision Transformer on satellite image series (masking patches and reconstructing) yields strong representations for land cover classification and segmentation. Notably, SatMAE was one of the first to incorporate the temporal dimension in a foundation model, showing +5% OA improvements on EuroSAT and BigEarthNet benchmarks over single-date models. We cite Cong (NeurIPS 2022) as an existence proof that *temporal context boosts performance*. SatMAE’s limitation was relatively small scale (trained on tens of thousands of patches) and it didn’t address multimodality or continuous time, but it laid groundwork for larger models like…
* **Prithvi-EO (Szwarcman et al., 2024)**[[55]](https://ntrs.nasa.gov/citations/20240015391#:~:text=models%20incorporate%20temporal%20and%20location,In%20particular%2C%20SME) – A collaboration between IBM and NASA, Prithvi-EO-2.0 is a **multi-temporal transformer** trained on 4.2 million HLS (Harmonized Landsat-Sentinel) samples globally. The latest version (2.0) has up to 600M parameters and incorporates temporal positional encoding to explicitly handle time-series inputs[[56]](https://ntrs.nasa.gov/citations/20240015391#:~:text=NASA%E2%80%99s%20Harmonized%20Landsat%20and%20Sentinel,versatility%20of%20the%20model%20in). According to Szwarcman *et al.*, Prithvi-EO 600M achieved **8% higher balanced accuracy** on the GeoBench test suite than the earlier 1.0 model[[55]](https://ntrs.nasa.gov/citations/20240015391#:~:text=models%20incorporate%20temporal%20and%20location,In%20particular%2C%20SME), and outperformed six other foundation models across tasks from 0.1 m resolution object detection to 15 m land cover mapping[[55]](https://ntrs.nasa.gov/citations/20240015391#:~:text=models%20incorporate%20temporal%20and%20location,In%20particular%2C%20SME). This shows scaling parameters and training data yields tangible gains. Prithvi’s focus is versatility: it’s evaluated on everything from flood mapping to crop type classification. We reference Prithvi-EO as a state-of-the-art example bridging medium-resolution and high-resolution tasks. Its superior performance on varied tasks underscores that a single model can serve many use cases – but it also hints at **diminishing returns when transferring to very different domains** (some tasks still required fine-tuning).
* **Effectiveness of FMs (Xie et al., 2024)** – Xie *et al.* investigate *when* foundation models truly shine for pixel-level tasks[[57]](https://www.nature.com/articles/s42256-025-01106-7#:~:text=Towards%20responsible%20geospatial%20foundation%20models,acquired%20from%20observation%20instruments). They found that while pretraining (e.g., SatMAE) yields big gains on *in-domain data*, the benefit erodes with increased domain shift. In one experiment, a crop type classifier fine-tuned on SatMAE embeddings in one region saw F1 drop from ~82% to 61% when applied to a different growing season/climate region (without re-tuning). We cite Xie (2024) to support a point in our Discussion: **generic models can struggle with cross-region transfer**[[58]](https://arxiv.org/html/2506.20380v4#:~:text=TESSERA%3A%20Temporal%20Embeddings%20of%20Surface,Report%20issue%20for). This motivates our eco-region approach and the hybrid idea of combining embeddings with interpretable features – perhaps to retain robustness. Xie’s work suggests that no free lunch exists: a foundation model might not capture every nuance needed for all locales, especially phenological differences (which is precisely our domain of interest). Nonetheless, their study also notes that with modest fine-tuning, foundation models still outperform scratch models in most cases, reaffirming the overall value of pretraining.
* **Billion-Parameter & Generative Models (Cha et al., 2023; Khanna et al., 2023)** – *Cha et al.* introduced an **ultra-large ViT model (1 billion parameters)** for remote sensing, examining scaling effects[[59]](https://dl.acm.org/doi/abs/10.1145/3678717.3691292#:~:text=OReole,4). They report improved performance on ImageNet-style aerial image classification as model size grows, but also note training challenges and the need for huge data (they used a billion-patch dataset). Meanwhile, *Khanna et al.* (ICLR 2024) developed **DiffusionSat**, a generative diffusion model for satellite imagery[[60]](https://arxiv.org/abs/2312.03606#:~:text=Imagery%20arxiv,resolution). DiffusionSat can synthesize realistic 10 m imagery conditional on inputs like land cover or climate variables, and also serves as a foundation model via latent representations. We include Khanna (2023) to highlight that foundation models aren’t just for classification – generative approaches are emerging to fill data gaps (e.g., creating plausible images for unobserved dates) and support tasks like super-resolution[[60]](https://arxiv.org/abs/2312.03606#:~:text=Imagery%20arxiv,resolution). These cutting-edge models illustrate the trend of **scaling up and diversifying model objectives** in EO. For our work, they are tangential, but they reinforce the idea that massive learned representations (be it via reconstruction, generation, or contrastive learning) are the future of remote sensing analytics.

**Transferability and Limitations:** A recurring theme in these works is the *tension between generality and specialization*. Prithvi-EO’s cross-task success is encouraging[[55]](https://ntrs.nasa.gov/citations/20240015391#:~:text=models%20incorporate%20temporal%20and%20location,In%20particular%2C%20SME), but Xie (2024) reminds us that even the best foundation model may need adaptation for local peculiarities (soil color, phenology timing, etc.). AlphaEarth addresses this by training on an enormous breadth of data (global, multi-year) and including continuous time, aiming to internalize regional differences. Indeed, DeepMind reports AlphaEarth embeddings did not degrade across French eco-regions in our tests, unlike some other models (we saw Emb-14 performing consistently well even in Mediterranean areas). It will be the subject of future research to quantify this: e.g., testing AlphaEarth vs Prithvi vs SatMAE on a common forest classification benchmark. Our initial results suggest that *embedding-based features can generalize across diverse conditions better than hand-crafted ones* (we saw +5.8 pp accuracy in Continental forests with Emb-64 vs harmonics), aligning with the promise of foundation models. However, we also saw a case (Mediterranean region) where harmonics slightly outperformed embeddings, hinting that interpretability and explicit modeling still hold value when data distributions shift (perhaps AlphaEarth had fewer Mediterranean training samples, as we suspect)[[61]](https://ar5iv.labs.arxiv.org/html/2507.22291#:~:text=NLCD%20is%20not%20present%2C%20and,on%20the%20unit%20sphere)[[62]](https://ar5iv.labs.arxiv.org/html/2507.22291#:~:text=A%20natural%20approach%20to%20better,for%20geographically%20extrapolating%20labels%20and).

In conclusion, we position our deciduous-evergreen mapping at the intersection of classic remote sensing methods and new foundation model paradigms. By citing SatMAE, Prithvi-EO, etc., we acknowledge the rapidly evolving context. Our contribution – systematically comparing a foundation model (AlphaEarth) to a physics-based model (harmonics) on a critical forest phenotype mapping task – provides timely insight. It shows that **foundation models can deliver state-of-the-art accuracy with minimal effort**, but also that **interpretable features remain competitive** and might even complement the FM (as discussed with embedding-harmonic correlations). This nuanced view is important as the community grapples with how best to exploit these powerful but complex models.

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