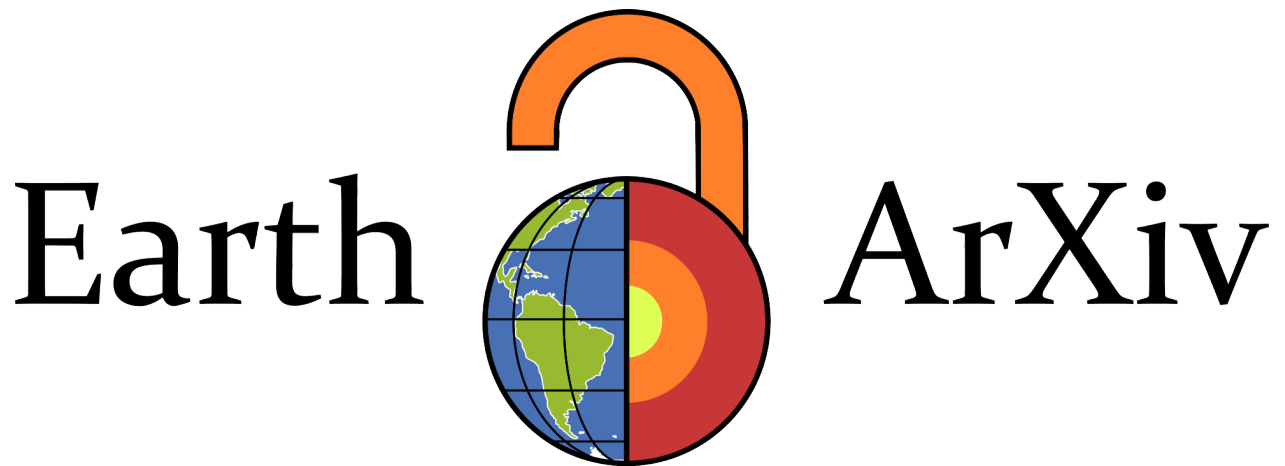




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Earth Embeddings as the Foundations of Geospatial Analysis

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ABSTRACT

Earth observation satellites generate petabytes of imagery each year, but extracting useful information remains constrained by limited labels, heterogeneous sensors, and the cost of processing large archives. Foundation models reduce part of this burden by learning transferable representations from multi-source observations. More recently, these representations have been precomputed over continental and global extents and released as embedding layers or datasets, with AlphaEarth and TESSERA as representative examples. This survey examines Earth embeddings as foundations for geospatial analysis through three interdependent questions: Represent, Relate, and Reason (3R). This perspective connects how embeddings represent the world, reveal relationships, and support scientific understanding. We compare pretrained models, reusable encoders, and released embedding products, examining how their learning principles and design choices influence these capabilities. We also review access infrastructure, evaluation benchmarks, and applications to assess current capabilities and limitations. Experimentally, we compare the structure and predictive utility of different embeddings across geospatial tasks. Finally, we summarize the technical and scientific challenges and outline future directions for developing, evaluating, and using Earth embeddings.

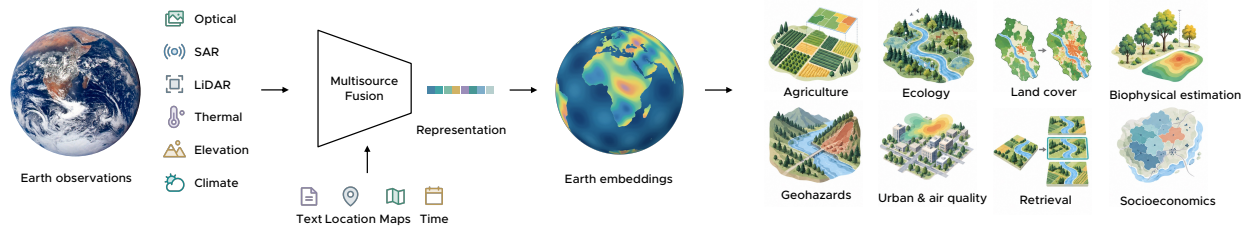


Figure 1: Learning Earth embeddings from multisource inputs and using them for geospatial applications.

1. Introduction

The volume of Earth observation (EO) data acquired each day has grown by orders of magnitude over the past decade. The Landsat archive provides a long-term observation record extending back to 1972 [1], complemented by Sentinel data distributed openly through the Copernicus programme [2]. To support joint use of these observations, NASA's Harmonized Landsat-Sentinel-2 (HLS) product harmonizes Landsat 8/9 observations from 2013 onward with Sentinel-2 observations from 2015 onward [3]. These archives record changes in land surfaces, oceans, and the atmosphere across space and time, yet extracting useful information from them remains difficult. Supervised learning, still the dominant approach for analyzing satellite images, depends on curated label sets that are expensive to collect, geographically biased toward well-studied regions, and quickly outdated in a changing world [4]. The gap between the volume of raw imagery and the limited availability of labels has become a central bottleneck in geospatial artificial intelligence.

Pretraining without manual labels offers a way around this bottleneck. By designing pretext tasks that extract supervisory signals from the data itself, methods such as con-

trastive learning [5, 6], masked image modeling [7], and self-distillation [8, 9] have produced geospatial foundation models (GFM), including image-based, location-based, and multimodal encoders pretrained on satellite and related Earth observation archives [10–13]. Most of these models, however, have been used primarily as backbones for downstream fine-tuning on tasks such as object detection, semantic segmentation, and land-cover classification, rather than released as directly reusable global representations. They have achieved state-of-the-art results on particular remote sensing tasks and benchmarks, but using them still requires downloading large model weights, preparing sensor-specific input pipelines, and running computationally intensive inference at every location of interest. Continental and global analysis therefore remains computationally expensive. During the past two years, products such as the Google Satellite Embedding dataset, generated with AlphaEarth Foundations, have begun to provide learned representations as precomputed, openly distributed geospatial data [14, 15]. Users can apply lightweight models, such as linear regressors or small classification heads, directly to these vectors without repeating large-scale inference.

An Earth embedding is a learned numerical vector that encodes properties of a geographic location or spatial unit for reuse across tasks [16]. Fig. 1 connects the learning of these vectors to their downstream use: multisource observations and

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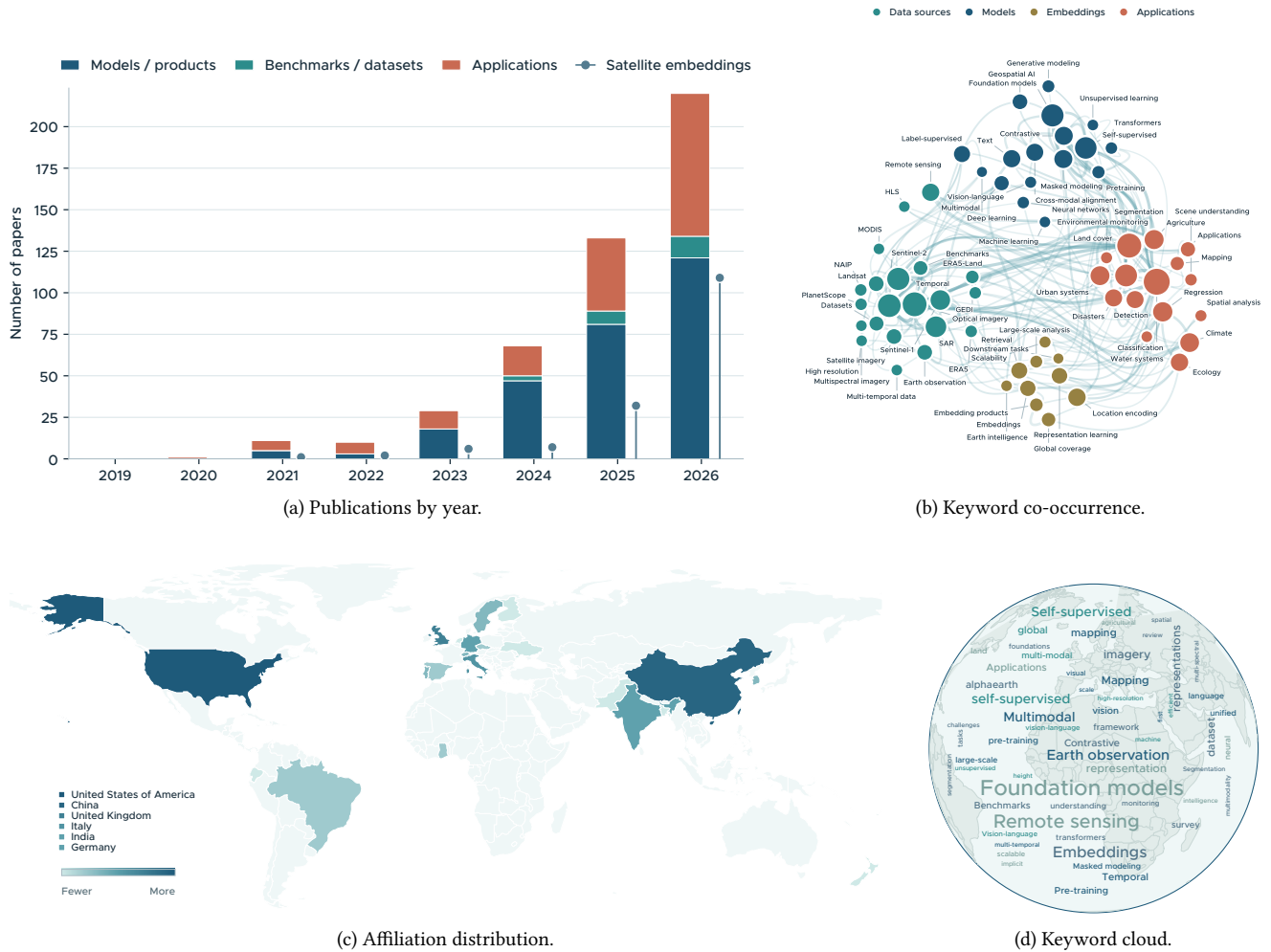


Figure 2: Bibliometric overview of the literature considered in this survey.

auxiliary information are encoded into representations that can support mapping, estimation, and retrieval. The right-hand examples illustrate applications ranging from agriculture and ecology to urban and socioeconomic analysis. The growth of this research direction is summarized in Fig. 2. Annual records retrieved through OpenAlex [17] and the satellite embedding literature both increase sharply after 2023. The keyword cloud emphasizes recurring terms such as *foundation models*, *Earth observation*, *embeddings*, *multimodal*, and *self-supervised*. The keyword co-occurrence network complements these frequencies by showing which topics are studied together. Its four groups distinguish data sources, models, embeddings, and applications, with links indicating terms that occur within the same surveyed study. The network links data sources such as *Sentinel-2*, *SAR*, and *Landsat* with learning methods, embedding concepts, and applications in land cover, agriculture, environmental monitoring, and ecology. Connections between these groups suggest that common representation-learning methods are being investigated across several application areas, while different observations contribute to related research questions. The affiliation map shows substantial contributions from North America, Europe, and Asia. Together, the four panels show that Earth embedding research is growing rapidly across methods, applications, and regions.

1.1. Related Surveys and Our Contributions

Existing surveys approach geospatial representation learning from several directions. Reviews of remote sensing foundation models organize architectures, pretraining objectives, transfer methods, and downstream tasks [18–20]. Multimodal surveys focus on sensor fusion and cross-modal learning [21–23], while broader analyses discuss the opportunities, development, and foundations of geospatial models [24–26]. The transition from unimodal to multimodal foundation models is examined separately by Hong et al. [27]. Within the more recent embedding literature, Rolf et al. [28] provide a concise perspective on reusable Earth representations, and Klemmer et al. [16] define their principal functions and propose a research agenda. Fang et al. [29] compare seven released products and implement common access through TorchGeo. Wang [30] develops an embedding-centered taxonomy and evaluates 19 models on a regional benchmark in Wuhan. Gomes et al. [31] examine neural compression, storage, and machine-to-machine transfer, whereas Stewart et al. [32] compare embedding types, coverage, resolution, storage, licensing, applications, and two practical workflows.

Limitations of existing reviews. These studies leave several parts of product-oriented evaluation disconnected. Foundation-model surveys do not systematically compare re-

leased global embedding layers and datasets. Conceptual papers define the functions of Earth embeddings and identify research priorities, but do not provide a product-level experimental comparison. The product taxonomy and common-access work addresses formats and software interfaces while leaving cross-product benchmarking for future work. The Wuhan benchmark provides a controlled regional comparison, but does not also examine global distribution infrastructure, long-term product maintenance, and the wider record of applications across scientific domains. The compression review addresses only one design dimension, and the recent practical chapter does not compare the same globally distributed samples across representation geometry, discrete and continuous prediction, and embedding dimension. None of these studies jointly connects data and pretraining, released products, access infrastructure, benchmarks, applications, and controlled cross-embedding experiments; the relevant information remains distributed across papers, product documentation, software repositories, and application studies.

Contributions of this survey. We propose Represent, Relate, and Reason (3R) as a conceptual basis for examining Earth embeddings: what geographic information they preserve, which relationships they support, and what conclusions can be drawn from them. Where existing reviews concentrate on model development, product access, or selected aspects of embedding use, we bring these topics into a comprehensive review spanning learning methods, models and products, distribution platforms, software libraries, evaluation benchmarks, and applications across scientific domains. This combined coverage allows us to examine connections between technical choices and practical use that are usually discussed separately. By comparing methodological choices with findings from benchmarks and applications, we identify conditions under which embeddings can be reused and where additional observations or adaptation remain necessary. Experiments on globally distributed samples complement this analysis by comparing embedding structure, predictive performance, and sensitivity to dimension. We hope that this review will inform future research and inspire new ways to develop and use Earth embeddings for geospatial analysis.

1.2. Organization of This Survey

Section 2 develops the Represent, Relate, and Reason perspective. Section 3 reviews the data, feature representations, and pretraining methods behind Earth embeddings, and Section 4 examines models, released products, design choices, distribution infrastructure, and evaluation benchmarks. Section 5 describes the evaluation data and analyzes representation geometry, downstream classification and regression, and sensitivity to embedding dimension. Section 6 reviews published applications, Section 7 discusses unresolved technical and scientific problems, and Section 8 concludes the survey.

2. Represent, Relate, and Reason

Geospatial analysis connects observations of the Earth with knowledge of its properties, organization, and change. Earth embeddings allow information learned from observations to be reused across research questions, including those not considered during representation learning. Earlier perspectives

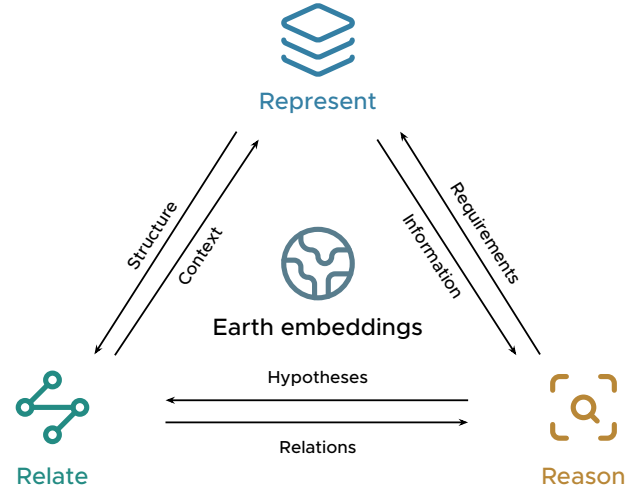


Figure 3: Represent, Relate, and Reason as interdependent questions for Earth embedding research.

have examined embeddings as reusable geographic descriptions and as geospatial datasets [16, 29]. We build on these perspectives through three interdependent questions: *Represent*, which properties remain available for analysis; *Relate*, how meaningful connections are established; and *Reason*, how those descriptions and connections support inference. We call this perspective 3R. Its central proposition is that the value of an Earth embedding depends on the connection between information preservation, geographic relationships, and the questions that researchers seek to answer. These are mutually informing aspects of analysis, rather than successive stages of model development.

2.1. Represent

Geographic abstraction. A representation makes selected properties of the world accessible while suppressing other variation. Its usefulness therefore depends on the distinctions it preserves, including those between persistent characteristics and meaningful change. Change-aware contrastive learning, for example, encourages invariance to seasonal variation while retaining sensitivity to longer-term changes [33]; temporal encoding in TESSERA instead uses within-year observations to retain information relevant to vegetation phenology [34]. These choices address different analytical needs. Seasonal variation can obscure a persistent land-cover category yet help distinguish vegetation types. We therefore view representation learning as the construction of geographic abstractions whose sensitivities should be assessed against the phenomena of interest, rather than judged by input volume or output dimension alone.

Complementary observations. Different measurements provide partial descriptions of the same phenomenon. Fusion allows a representation to combine information that is unavailable from any single observation, while preserving distinctions needed for later analysis. CROMA learns both separate radar and optical representations and a joint encoding, whereas AlphaEarth Foundations integrates spatial, temporal, and measurement contexts across multiple sources [14, 35]. These approaches illustrate different ways to organize complementary information. We argue that a reusable description

should preserve both shared properties and useful differences between observations. Whether this requires one vector, linked vectors, or a spatial feature field depends on what must remain distinguishable, such as a local feature and its surrounding context.

Representation Reuse. Reuse changes which parts of an analysis must be repeated. Observations retain the original measurements, while precomputed embeddings provide learned features for subsequent analyses. The shared features of MOSAICS and the released layers of AlphaEarth Foundations illustrate how encoding can be separated from subsequent prediction [14, 36]. This separation allows researchers to ask different questions of the same observations without independently reconstructing every feature. These data are complementary: embeddings support repeated analysis, while access to the measurements and encoding choices allows researchers to revisit information lost through aggregation or compression. Their scientific value consequently includes both immediate usability and the possibility of revising the description when a new question requires it.

2.2. Relate

Geographic similarity and dependence. Geospatial analysis draws on relationships as well as individual attributes. Nearby observations may share conditions, but comparable conditions can also occur far apart. Embeddings offer a way to investigate such similarities alongside geographic distance: Major TOM supports imagery search through feature similarity, while SatCLIP associates coordinates with satellite-derived visual characteristics [37, 38]. This broadens the basis for identifying comparable locations and recurring patterns. The intended relationship must nevertheless guide the comparison. Similar vegetation signatures can identify candidate environmental analogues; establishing shared ecological conditions requires corresponding measurements. A useful similarity measure is therefore one whose meaning can be checked against the geographic relationship being studied.

Correspondence across observations. Connecting different descriptions of a phenomenon is distinct from establishing interactions between phenomena. Spatial registration identifies co-located measurements; learned correspondence seeks the information that makes those measurements comparable. Radar-optical alignment in CROMA and image–location alignment in SatCLIP exemplify this distinction [35, 38]. They connect observations with different measurement properties or forms, allowing information learned from one description to inform another. From this perspective, alignment is valuable when it preserves the correspondence needed for an analysis while retaining complementary content. Paired retrieval and transfer tests can examine that correspondence; proximity between vectors alone does not establish a physical interaction between the places they describe.

Transfer and complementarity. Reusable analysis requires knowing which learned relationships remain informative under different conditions. Geographic adaptation experiments with SatCLIP investigate this question across regions [38]. Multiple encoder-derived collections in Major TOM and common-access work across products provide a basis for comparing alternative descriptions of the same locations [29, 37]. We propose that such comparisons should

assess both transferability and complementarity: whether a relationship learned in one setting remains useful elsewhere, and whether another representation contributes information that is missing. This allows diverse embeddings to support a common investigation without requiring a universal vector space. Common access makes the comparison possible; matched observations and downstream evaluation establish what can actually be transferred or combined.

2.3. Reason

Inference from shared descriptions. Geographic inference connects what has been observed with what remains unknown. Here, *Reason* denotes inference using embeddings, independent measurements, analytical methods, and domain knowledge, rather than reasoning performed by a vector itself. Shared representations already support this connection across multiple targets: MOSAICS uses common image features to estimate environmental and socioeconomic properties, while TESSERA evaluates temporal features across classification and continuous-variable estimation [34, 36]. The same embeddings can support several tasks without repeating feature extraction. Comparing the attributes recoverable from a fixed representation can then help establish its analytical scope and identify questions that require additional observations.

Scientific Hypotheses. A further research opportunity is to use representations to organize comparisons that inform geographic hypotheses. We propose examining agreement and discrepancy between encoded similarity and independently measured outcomes. For example, locations with similar vegetation embeddings but different biomass measurements could motivate tests of whether structural information is missing from the representation or whether observation dates are mismatched. The embedding helps identify a comparison; measurements and domain knowledge determine which account is plausible. This approach connects representation analysis with the design of further observations and tests. This use requires validation beyond prediction benchmarks, and causal conclusions require an appropriate causal research design.

Cumulative geographic knowledge. Using the same embeddings across studies allows their strengths and limitations to be compared. We propose that repeated use should build knowledge of which attributes are recoverable, which comparisons remain informative, and where the description needs revision. For example, an embedding that supports broad land-cover mapping but misses a disturbance observed in independent records would motivate closer examination of its temporal aggregation and sensitivity to change. Such findings can guide subsequent encoding and measurement choices. As summarized in Fig. 3, this feedback connects the three questions: *Represent* determines the information available, *Relate* establishes useful comparisons, and *Reason* draws conclusions that can revise both. Earth embeddings can thus provide shared, revisable foundations for analysis. Section 3 develops the technical background for examining these choices.

3. Preliminaries

Global embedding products encode heterogeneous Earth observation measurements as compact vectors. Interpreting

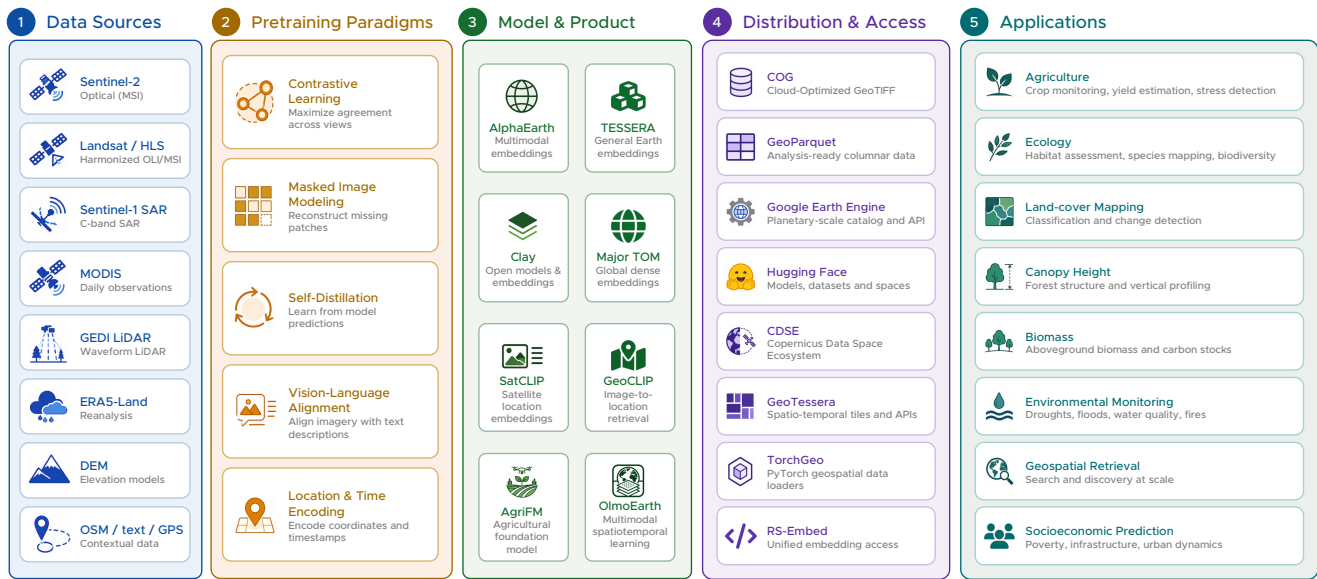


Figure 4: Data sources, pretraining methods, models, access infrastructure, and applications covered in this survey.

these vectors requires knowledge of their input data, feature representations, and pretraining objectives. Fig. 4 connects these components with models, access infrastructure, and applications; Section 4 examines the models, products, and evaluation protocols.

3.1. Earth Observation Data Sources

Earth observation sources enter representation learning in different roles: some are direct encoder inputs, some provide targets or auxiliary supervision during pretraining, and others are used only as downstream labels or covariates. Surface imagery from Sentinel-2, Landsat, HLS, and Sentinel-1 forms the main input to many of the models summarized here because these missions combine broad coverage with repeated observations [39–41]. ALOS-2 PALSAR-2 [42], GEDI [43], ERA5-Land [44], Copernicus GLO-30 DEM [45], VIIRS [46], Sentinel-3 [47], ICESat-2 ATL08 [48], Sentinel-5P [49], PlanetScope [50], and NAIP [51] contribute structural, environmental, atmospheric, or higher-resolution information in selected models and benchmarks. Embedded Seamless Data (ESD) [52] is generated from the Global 30 m Seamless Data Cube of Land Surface Reflectance (SDC30) [53], which harmonizes Landsat 5, 7, 8, and 9 with MODIS Terra into a gap-filled daily reflectance record.

Table 1 compares the listed sources and their use in geospatial representation learning. Sentinel-2 and Sentinel-1 appear most often in current GFM and embedding pipelines, while Landsat and HLS provide longer temporal coverage. GEDI and elevation products add information about vertical structure and terrain; ERA5-Land, ERA5, and Sentinel-5P supply environmental variables at coarser resolution. PlanetScope, NAIP, VIIRS, Sentinel-3, and ICESat-2 are used more selectively. Their use depends on geographic coverage, co-registration, temporal alignment, access conditions, cost, and licensing as well as information content.

Combining optical reflectance, SAR backscatter, terrain, and climate can preserve signals that are absent from any single source. AlphaEarth Foundations, for example, is trained with several observation and supervision sources, while inference

uses optical, thermal, and SAR observations from Sentinel-2, Landsat 8/9, and Sentinel-1 [14]. The combination also introduces source-specific errors and missing observations. Optical acquisitions are affected by clouds, which can obscure more than 50% of observations in tropical regions [73]; SAR data contain speckle and layover artifacts; and multi-temporal stacks are sampled irregularly because of orbit geometry and revisit gaps. Models that produce spatially consistent embeddings must account for these differences in availability, noise, and geometry [26, 74].

Models differ in how they combine these inputs. AlphaEarth Foundations [14] uses source-specific encoders whose outputs feed a common spatiotemporal representation; missing frames or input sources can be accommodated at inference. TESSERA [34] encodes optical and SAR time series separately, fuses their representations, and trains on independently sampled temporal views of each pixel. The Clay Foundation Model [75] uses wavelength-conditioned patch embeddings in a Vision Transformer, with spatial-resolution, location, and time information. TerraMind [76] and TerraFlow [77] quantize modalities into discrete tokens and predict target tokens from the available context. CROMA [35] uses cross-attention to reconstruct one modality from masked observations of another. The choice depends on source availability, temporal alignment, and missing-input handling.

3.2. Feature Representations

Feature representations convert Earth observation measurements into variables that downstream methods can use. Current remote sensing workflows use task-specific indices and texture descriptors, label-supervised feature maps, self-supervised encoders, and precomputed embedding layers. These representations differ in their supervisory signals, retained information, and downstream computation.

Hand-Crafted Descriptors. Hand-crafted indices and descriptors condense multi-band imagery into variables selected for a particular task. The normalized difference vegetation index (NDVI) [78], computed from red and near-infrared reflectance, remains a standard indicator of vegetation condition; related

Table 1

Representative Earth observation data sources used in geospatial representation learning.

Source / Product	Modality	Time span	Resolution	Cadence	Representative uses
Sentinel-2 MSI [39]	Optical multispectral (13 bands)	2015–	10–60 m	5 days	High (SatMAE [54]; Copernicus-FM [55]; AlphaEarth [14])
Landsat 8/9 [56]	Optical and thermal (11 bands)	2013/2021–	15/30/100 m	8 days	High (MOSAICS [36]; AlphaEarth [14])
HLS L30/S30 [3, 40]	Optical and thermal (10/13 bands)	2013/2015–	30 m	1.4 days avg.	Medium (Prithvi-EO [10]; GEO-Bench-2 [57])
MODIS [58]	Optical and thermal (36 bands)	2000–	250 m–1 km	1–2 days	Medium (ESD [52]; SEN12MS [59])
VIIRS [46]	Visible and infrared (22 bands)	2011–	375–750 m	daily	Low (few current foundation model examples)
Sentinel-3 (OLCI, SLSTR) [47]	Optical and thermal (21 + 9 channels)	2016–	300 m–1 km	1–2 days	Low (Copernicus-FM / Copernicus-Bench [55])
Sentinel-1 SAR [41]	C-band SAR	2014–	~20 × 22 m (IW GRD)	6–12 days	High (CROMA [35]; SoftCon [60]; AlphaEarth [14])
ALOS-2 PALSAR-2 [42]	L-band SAR	2014–	10–100 m	14 days	Low (AlphaEarth [14]; RingMoE [61])
GEDI [43]	Waveform LiDAR	2019–	25 m footprints	irregular	Medium (AlphaEarth [14]; MMEarth [62])
ICESat-2 ATL08 [48]	Photon LiDAR	2018–	100 m along-track	91 days	Low (few current foundation model examples)
Copernicus GLO-30 DEM [45]	Digital elevation model	static	30 m	static	Low (AlphaEarth [14]; Copernicus-FM [55])
SRTM [63]	Digital elevation model	static	30 m	static	Low (Presto [64])
ASTER GDEM [65]	Digital elevation model	static	30 m	static	Low (few current examples)
ERA5-Land [44]	Reanalysis	1950–	~9 km	hourly	Low (AlphaEarth [14])
ERA5 [66]	Reanalysis	1940–	~31 km	hourly	Medium (Presto [64]; ClimPitc [67]; MMEarth [62])
Sentinel-5P / TROPOMI [49]	Atmosphere	2017–	5.5–7 km	daily	Low (Copernicus-FM / Copernicus-Bench [55])
PlanetScope [50]	Commercial optical (4–8 bands)	2017–	3 m	near-daily	Medium (DynamicEarthNet [68]; SpaceNet7 [69]; GEO-Bench-2 [57])
NAIP [51]	Aerial optical (4 bands)	2003– (U.S.)	0.6–1 m	2–3 years	Medium (Tile2Vec [70]; SatlasPretrain [71]; USat [72])

formulations target water bodies (NDWI [79]), built-up areas (NDBI [80]), and snow cover (NDSI [81]). Grey-level co-occurrence matrices (GLCM) [82] and local binary patterns (LBP) [83] describe texture and are commonly paired with random forest (RF) or support vector machine (SVM) classifiers [84–86]. Such features are interpretable and inexpensive, but their task-specific definitions retain only selected spectral and spatial information.

Label-Supervised Deep Representations. Label-supervised deep representations use scene labels, segmentation masks, or continuous target variables as the supervisory signal. Convolutional networks pretrained on ImageNet [87], including VGG [88] and ResNet [89], supplied hierarchical features for remote sensing scene classification and semantic segmentation [90, 91]. Recurrent networks, including long short-term memory networks [92], extended learned features to temporal sequences, and Vision Transformers introduced attention-based image representations [93]. These models capture spatial patterns that fixed descriptors do not encode, but their features depend on labeled training data. Transfer from natural imagery is also limited by differences in viewpoint, spectral channels, and spatial organization, especially for tasks that require spectral or temporal information [94, 95].

Self-Supervised EO Representations. Self-supervised EO methods derive supervision from the observations rather than task labels. Tile2Vec [70] uses spatial proximity, Seasonal Contrast (SeCo) [95] uses multi-date observations of the same location, and SSL4EO-S12 [96] supplies Sentinel-1/2 data for comparing contrastive, distillation, and reconstruction objectives. RingMo [97], SatMAE [54], Scale-MAE [12], SkySense [98], and DINOv3 [99] extend self-supervised learning to multispectral, multimodal, or multitemporal inputs. These methods reduce dependence on downstream labels, but users must still obtain the model weights, reproduce the required preprocessing, and run the encoder over their study regions.

Embedding Products. Embedding products release precomputed vectors rather than requiring every user to run the encoder. MOSAICS [36] provided a shared global feature set for environmental and socioeconomic prediction, while Major TOM [37, 100] released vectors from multiple frozen encoders over globally sampled satellite tiles. LGND distributes near-global chip embeddings generated with Clay [75, 101]; TESSERA v1 and the Google Satellite Embedding dataset

produced with AlphaEarth Foundations provide dense annual layers [14, 15, 34]; and ESD retains a temporally indexed record [52]. TESSERA v2 extends the product design with distilled temporal encoders and selectable output dimensions [102]. Downstream analysis can begin with released vectors and a task-specific prediction model, while storage, access, updating, version compatibility, and interpretation remain product concerns.

3.3. Pretraining Paradigms

Representation type determines both the available information and the computation required downstream, while the pretraining objective determines which differences between observations are suppressed and which information remains accessible. It therefore affects transfer performance, neighborhood structure, and compressibility. The discussion below relates each objective to these representation properties; storage and distribution are considered in Section 4.

Contrastive Objectives. Contrastive objectives learn representations by bringing matched views closer in embedding space and pushing mismatched views apart. Given a positive pair (z_i, z_j) and a set of $2N$ augmented views within a mini-batch, the InfoNCE loss [5, 103] is

$$\mathcal{L}_{\text{CL}} = -\log \frac{\exp(\text{sim}(z_i, z_j)/\tau)}{\sum_{k=1}^{2N} \mathbf{1}_{[k \neq i]} \exp(\text{sim}(z_i, z_k)/\tau)}, \quad (1)$$

where $\text{sim}(\cdot, \cdot)$ denotes cosine similarity and τ is a temperature parameter. In EO, the definition of positive and negative pairs is as important as the loss. SeCo [95] treats observations of the same location in different seasons as positives, encouraging invariance to seasonal and atmospheric variation. CACo [33] modifies temporal pairing to distinguish short-term variation from persistent change. Tile2Vec [70] instead defines pairs through geographic proximity and uses a triplet objective adapted from distributional semantics:

$$\mathcal{L}_{\text{triplet}} = \max(0, d(f(x_a), f(x_p)) - d(f(x_a), f(x_n)) + m), \quad (2)$$

where x_a , x_p , and x_n denote an anchor tile, a nearby tile, and a distant tile, respectively. SSL4EO-S12 [96] supplies Sentinel-1/2 data for comparing contrastive and alternative objectives at scale. Pairing policy determines the learned invariance:

Table 2

Feature-representation families in Earth observation.

Feature Representation	Supervision	Representative examples	Output form	Characteristics
Hand-crafted descriptors	Expert-designed formulas and statistics	Spectral indices (NDVI, NDWI, NDBI, NDSI) [78–81] Texture descriptors (GLCM, LBP) [82, 83] Classical ML (RF, SVM) [86]	Scalars or low-dimensional descriptors	Interpretable and inexpensive, but task-specific and context-limited
Label-supervised deep representations	Human annotations such as class labels, masks, or target variables	CNN-based features (VGG, ResNet) [88, 89] RNN-based temporal encoders (LSTM) [92] Transformer-based encoders (ViT) [93]	Feature maps or latent vectors	Hierarchical and task-effective, but label-dependent and domain-sensitive
Self-supervised EO representations	Pretext tasks derived from unlabeled EO archives	Contrastive models (Tile2Vec, SeCo) [70, 95] Masked autoencoders (SatMAE, Scale-MAE) [12, 54] Self-distillation (SSL4EO-S12 DINO, DINOv3) [96, 99]	Latent features extracted by inference	Scalable and domain-adapted, but still largely model-centric
Embedding products	Inherited from pretrained encoders and released in precomputed form	Global feature collections (MOSAICS, Major TOM) [36, 37, 100] Dense embedding products (LGND, TESSERA, Google Satellite Embedding, ESD) [14, 15, 34, 52, 75, 101]	Precomputed vector fields or embedding layers	Directly reusable, but constrained by storage, interoperability, and update cycles

seasonal pairs reduce sensitivity to seasonal variation, spatial pairs promote local similarity, and image–location pairs in SatCLIP and GeoCLIP [38, 104] introduce geographic information. These invariances are useful only when the downstream target does not require the suppressed variation.

Reconstruction Objectives. Reconstruction objectives mask part of the input and train the model to recover the missing content, encouraging the encoder to preserve local structure and context. For masked autoencoders [7], the loss is

$$\mathcal{L}_{\text{MAE}} = \frac{1}{|\mathcal{M}|} \sum_{p \in \mathcal{M}} \|\mathbf{x}_p - \hat{\mathbf{x}}_p\|^2, \quad (3)$$

where $\mathcal{M}$ is the set of masked patches, $\mathbf{x}_p$ is the original content, and $\hat{\mathbf{x}}_p$ is its reconstruction. RingMo [97], SatMAE [54], Scale-MAE [12], SpectralGPT [11], Clay [75], and Prithvi-EO-2.0 [10] apply this objective to multispectral, multiscale, or multitemporal inputs, while Presto [64] adapts reconstruction to multisensor pixel time series. Because the encoder must predict missing content, these objectives encourage retention of spatial, spectral, or temporal context. Benefits depend on the mask design, encoder output, and downstream adaptation.

Redundancy-Reduction Objectives. Some models aim not primarily to reconstruct the input, but to produce invariant embeddings with minimal redundancy across dimensions. The Barlow Twins criterion [105] operates on the cross-correlation matrix $\mathbf{C}$ between embeddings of two valid views:

$$\mathcal{L}_{\text{Barlow}} = \underbrace{\sum_i (1 - C_{ii})^2}_{\text{invariance}} + \lambda \underbrace{\sum_i \sum_{j \neq i} C_{ij}^2}_{\text{redundancy reduction}}, \quad (4)$$

where $C_{ij} = \sum_b z_{b,i}^A z_{b,j}^B / \sqrt{\sum_b (z_{b,i}^A)^2 \sum_b (z_{b,j}^B)^2}$ is the cross-correlation between dimensions i and j computed over a batch of augmented pairs (A, B) after centering each feature over the batch. TESSERA v1 [34] applies this criterion to annual Sentinel-1/2 time series, and TESSERA v2 [102] retains it while varying encoder capacity, training-data volume, and compute. DeCUR [106] uses a related objective to separate common and modality-specific information. Decorrelation reduces redundancy but does not measure retained task information.

Distillation Objectives. Distillation objectives replace explicit pixel reconstruction with consistency between a student and a teacher or target encoder. DINO [8], DINOv2 [9], and DINOv3 [99] provide frozen features learned through this

strategy. Panopticon [107] adapts DINOv2 to sensor-variable EO observations through channel attention and cross-sensor views of the same footprint. I-JEPA [108] and AnySat [109] instead predict targets in representation space. TESSERA v2 [102] distills a temporal teacher into compact student encoders whose 128-dimensional output can be shortened without retraining, while Major TOM [37, 100] distributes globally sampled vectors from frozen encoders in the DINOv2 family. Fair comparisons with reconstruction objectives require matched architectures, data, and evaluation protocols.

Alignment and Generative Objectives. Alignment objectives learn a shared space for paired modalities. CLIP [110] optimizes a symmetric image–text contrastive loss over a batch of N matched pairs:

$$\mathcal{L}_{\text{CLIP}} = -\frac{1}{2N} \sum_{i=1}^N \left[\log \frac{e^{\text{sim}(v_i, t_i)/\tau}}{\sum_j e^{\text{sim}(v_i, t_j)/\tau}} + \log \frac{e^{\text{sim}(t_i, v_i)/\tau}}{\sum_j e^{\text{sim}(t_i, v_j)/\tau}} \right] \quad (5)$$

where v_i and t_i are the image and text embeddings, respectively. In EO, the paired input may be text, coordinates, ground imagery, or another observation of the same place. RemoteCLIP [111], GRAFT [112], GeoCLIP [104], SatCLIP [38], SoundingEarth [113], and Sat2Cap [114] use different pairings to support retrieval, geolocalization, or cross-modal queries. The structure of the shared space consequently reflects both the data modality and the definition of matched locations.

Generative and predictive objectives infer a missing modality, timestamp, or token stream from the available context. TerraMind [76] tokenizes multiple geospatial modalities and predicts selected targets, and TerraFlow [77] applies this formulation to temporal inputs. Copernicus-FM [55] combines masked reconstruction with distillation from frozen teachers, whereas Galileo [115] uses global and local contrastive masked modeling. AlphaEarth Foundations [14] combines source-specific reconstruction, consistency constraints, and text alignment before releasing annual global embedding layers. Attributing a downstream property to one loss requires ablations that vary that loss while holding the other components fixed.

Each objective balances invariance against sufficiency by suppressing selected variation while retaining information needed for its training target. Contrastive and distillation methods tend to emphasize discrimination or agreement, reconstruction methods retain information needed to predict

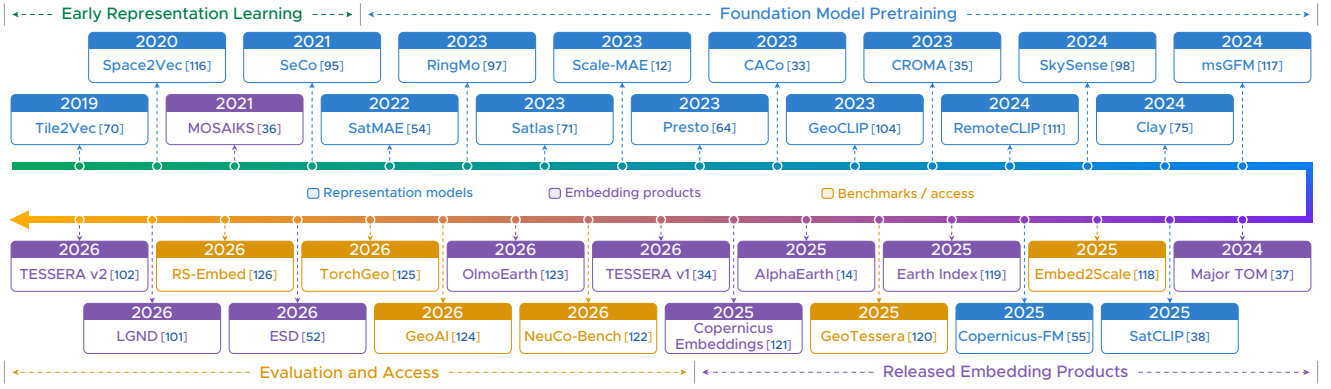


Figure 5: Evolution of Earth embedding research from representation learning to products, evaluation, and access.

missing inputs, and multimodal objectives preserve shared structure across sources. Objective names alone do not predict downstream suitability; performance depends on whether task-specific variation remains recoverable.

4. Models and Benchmarks

Earth observation representations are available as model weights, reusable encoders, and precomputed vectors. Spatially and temporally indexed vectors let users begin downstream analysis without first running the source model over the study area. Comparisons must therefore consider spatial support, temporal aggregation, compression, access, and fixed-feature evaluation in addition to architecture and pretraining.

4.1. Models and Products

Fig. 5 outlines four stages in the development of Earth embeddings. Early studies learned reusable features from satellite imagery; later work increased model scale and incorporated additional sensors and supervision. The most recent stage centers on large embedding collections, benchmark-based evaluation, common access tools, and data standards.

We distinguish releases by what users receive. Geospatial foundation models usually provide weights and code, reusable embedding encoders generate vectors for user-supplied inputs, and embedding products provide vectors computed over a spatial collection. Recent embedding-centered surveys similarly distinguish model access from direct access to embeddings [29, 30]. Table 3 compares representative models, embedding datasets, and released layers.

4.1.1. Geospatial Foundation Models

Geospatial foundation models learn transferable representations through pretraining on Earth observation data. Their training objectives and treatment of spatial, spectral, and temporal variation determine the information available for subsequent analysis. Masked reconstruction and scale-aware learning are explored by SatMAE [54], Scale-MAE [12], RingMo [97], Prithvi-EO [10], Presto [64], and USat [72]. Learning across sensors additionally requires models to accommodate differences in spectral bands, resolution, and observation frequency. CROMA [35], DOFA [13], Panopticon [107], OmniSat [127], AnySat [109], Galileo [115], and Copernicus-FM [55] address heterogeneous sensors or modalities, while SkySense [98],

TerraMind [76], and TerraFlow [77] incorporate temporal learning or generative objectives. Cross-sensor encoding and robustness to heterogeneous or incomplete inputs are further studied in msGFM, RobSense, and SkySense V2 [117, 128, 129]. Temporal coverage and supervision also shape the learned representations: SeaMo, TiMo, TerraFM, and GeoLink use seasonal sequences, satellite time series, globally sampled radar-optical imagery, and OpenStreetMap supervision, respectively [130–133]. These approaches offer different ways to learn from Earth observations; broader comparisons of architectures and pretraining methods are available in GFM surveys [19, 21–23, 25–27].

4.1.2. Released Embedding Products

Released embedding products provide precomputed vectors for a defined spatial and temporal collection. Users can download or query the vectors, join them with labels or covariates, and train downstream models without repeating the source encoder’s large-area inference. Tile2Vec [70], SeCo [95], GASSL [134], SSL4EO-S12 [96], SatMAE [54], Scale-MAE [12], SatCLIP [38], and GeoCLIP [104] established reusable image or location encoders but did not release complete global embedding layers. Precomputed collections differ in spatial support and completeness: MOSAICS provides global features [36], Major TOM Embeddings releases vectors from multiple encoders for globally sampled tiles [37, 100], and Earth Index encodes billions of overlapping patches [119]. Clay v1.5 is a model release [75], whereas LGND Clay Embeddings is a separate near-global dataset generated with that encoder [101].

Dense, temporally indexed releases include TESSERA v1 [34], the Google Satellite Embedding dataset produced with AlphaEarth Foundations [14, 15], and ESD, a record at 30 m resolution beginning in 2000 [52]. TESSERA v2 studies distilled temporal encoders and selectable dimensions within the same product family [102]. The Copernicus Data Space distributes more than 60 TB of embeddings generated by several frozen encoders [121], while Earth Embeddings as Products provides common loaders for accessing multiple releases [29].

Table 3 uses CL, MAE, SD, RCF, VLA, and FSQ for contrastive learning [5], masked autoencoding [7], self-distillation [8], random convolutional features [36], vision-language alignment [110], and finite scalar quantization [135], respectively. The year is the formal publication year of the cited paper or, for dataset records without a paper, the first

Table 3

Comparison of representative Earth embedding models and products.

Model / Product	Year	Architecture	Training objective	Dim.	Res.	Modalities	Time	Global	Format
Tile2Vec [70]	2019	ResNet-18	Triplet CL	512	1.5 km	Optical			Weights
MOSAICS [36]	2021	Random conv.	RCF	8192/4000	1.1 km	Optical		✓	CSV / NPY
SeCo [95]	2021	ResNet-50	MoCo-v2 CL	2048	2.65 km	Optical			Weights
CSP [136]	2023	MLP + ResNet-50	CL	256	Coordinate	Optical + coord.			PyTorch weights
GeoCLIP [104]	2023	Fourier features + MLP	Image-location CL	512	Coordinate	Image + coord.			PyTorch weights
Clay v1.5 [75]	2024	ViT	MAE + distillation	1024	–	MS + SAR			Weights
DINOV2 [9, 37, 137]	2024	ViT-L/14	SD	1024	2.24 km	Optical		✓	Parquet / HF
Major TOM Embeddings [37, 100]	2024	Multiple frozen encoders	Frozen inference	1024–2048	2.24–3.84 km	Optical + SAR		✓	Parquet / HF
SigLIP [37, 138, 139]	2024	ViT-SO400M/14	VLA	1152	3.84 km	Optical + text		✓	Parquet / HF
SSL4EO-DINO [37, 96]	2024	ResNet-50	DINO (SD)	2048	2.24 km	Multispectral		✓	Parquet / HF
SSL4EO-MoCo [37, 96]	2024	ResNet-50	MoCo-v2 CL	2048	2.24 km	SAR		✓	Parquet / HF
Alphaearth embedding [14, 15]	2025	STP encoder	Reconstruction + CL + vMF	64	10 m	Optical + thermal + SAR	✓	✓	Earth Engine / COG
Copernicus Embeddings [121]	2025	Multiple frozen encoders	Frozen inference	Varies	Varies	Optical + SAR		✓	GeoParquet / CDSE
Copernicus-Embed [55, 140]	2025	Copernicus-FM encoder	Frozen inference	768	0.25°	Multimodal EO + DEM	✓	✓	Parquet / NPZ / PT
Copernicus-FM [55]	2025	ViT	MAE + distillation	768	–	Multimodal EO + DEM	✓		PyTorch weights
DeCUR [106, 121]	2025	ResNet-50	Redundancy reduction	2048	2.24 km	Multispectral + SAR		✓	GeoParquet / CDSE
Earth Index [119]	2025	SoftCon ViT-S/14	Soft contrastive learning	384	320 m	Optical		✓	GeoParquet / Source Coop.
SatCLIP [38]	2025	Spherical-harmonic MLP	Image-location CL	256	Coordinate	Optical + coord.			PyTorch weights
ESD [52]	2026	Temporal CNN + FSQ	Reconstruction + supervised tasks	13	30 m	Optical + DEM	✓	✓	MGRS tiles
LGND Clay Embeddings [101]	2026	Clay v1.5 encoder	MAE + distillation	256/1024	1.28/2.56 km	Optical	✓	✓	GeoParquet / Source Coop.
OlmoEarth [123]	2026	ViT	Latent masked modeling + CL	128–1024	10–80 m	Optical + SAR + maps	✓		PyTorch weights
Prithvi-EO-2.0 [10]	2026	ViT-L / ViT-H	MAE	1024/1280	–	Multispectral	✓		HF / TerraTorch
TESSERA v1 [34]	2026	Transformer + GRU	Barlow Twins	128	10 m	Optical + SAR	✓	✓	NumPy / GeoTessera
TESSERA v2 [102]	2026	Dual-branch Transformer	Barlow Twins + distillation	16–128	10 m	Optical + SAR	✓		–

public-release year. *Res.* denotes the ground support of one vector; checkmarks under *Time* and *Global* indicate that one vector combines multiple dates and that a global or near-global collection is publicly available.

Spatial support ranges from coordinates and scenes to per-pixel grids, and training objectives distinguish models with otherwise similar architectures. Patch and tile collections include MOSAICS [36], Earth Index [119], Major TOM [37], the Copernicus Global Embedding Dataset [121], and LGND, which is generated with the separately released Clay v1.5 model [75, 101]. Annual pixel-level products include TESSERA v1 [34] and Google Satellite Embedding [14, 15], whereas ESD provides a compressed 30-meter record covering approximately a quarter century [52]. TESSERA v2 combines a temporal teacher with compact students and allows shorter vectors when storage is constrained [102].

4.1.3. Reusable Embedding Encoders

Publicly available pretrained weights allow users to generate embeddings for their own observations without repeating pretraining. The encoder can remain frozen while a downstream model is fitted to the extracted vectors. Image encoders such as Tile2Vec [70], SeCo [95], and those pretrained on SSL4EO-S12 [96] provide satellite features, while DINOV2 [9] and SigLIP [138] offer general-purpose visual features. Reuse requires matching observations to the encoder's expected bands, normalization, spatial resolution, and temporal input. Multimodal encoders such as DeCUR [106] and MMEarth [62] extend the available inputs; Panopticon uses channel-level conditioning to apply one frozen encoder to optical, hyperspectral, and radar observations [107]. The output also determines how the vectors can be used: spatial features can support local prediction, whereas pooled vectors summarize an image or region. Encoders trained to align imagery with text or co-located observations support comparisons across these inputs, as in RemoteCLIP [111], GeoRSClip [141], GRAFT [112], SkyScript [142], Sat2Cap [114], and SoundingEarth [113]. RS-Embed provides a common interface for extracting embeddings with selected pretrained encoders [126, 143].

4.1.4. Location Embeddings

Coordinate-based location encoders map geographic coordinates directly to vectors, without requiring imagery at query time. Table 4 compares their spatial representations and training information alongside related regional methods. Years refer to formal publication where available, otherwise to the preprint or model release. One group of methods determines how position is represented geometrically. Space2Vec uses multiscale periodic functions in planar coordinates [116], whereas Sphere2Vec and spherical-harmonic encoders operate on the Earth's surface to reduce projection distortion and represent several spatial scales [144, 145]. Localized Slepian encodings concentrate basis functions within a region of interest [146]. Continuous or adaptive representations instead learn spatial structure from observations: SINR learns a coordinate field for global species mapping [147], while Tessellating the Earth (TTE) replaces a fixed basis with learnable spherical Voronoi partitions and shared semantic tokens trained with satellite imagery [148].

The semantic content of a coordinate vector is determined by its supervision. CSP, SatCLIP, GeoCLIP, and SatCLE align coordinates with co-located imagery or image-derived semantics [38, 104, 136, 149]. Esri's Global Location Encoder (Sentinel-2) (GLE) applies the SatCLIP approach to globally sampled Sentinel-2 Level-2A imagery and is distributed as a pretrained model for generating location embeddings in ArcGIS [150]. OS-MGraphCLIP instead aligns coordinates with OpenStreetMap graph features [151]. Related regional representations retain information through different inputs: S2Vec encodes built-environment attributes rasterized within S2 cells, while MoRA learns from a mobility graph together with imagery, points of interest, and demographic information [152, 153]. UniGeoCLIP jointly aligns coordinates, aerial and street-level imagery, elevation, and text, while GAIR learns coordinate-level representations aligned with overhead and street-level imagery [154, 155]. The resulting proximity may therefore reflect physical distance, visual similarity, environmental conditions, or human activity.

Location encoders can also incorporate task-specific context rather than act as fixed geographic priors. RANGE augments coordinate embeddings with retrieved visual

Table 4

Location encoders and related regional representation methods.

Method	Year	Dim.	Training modalities	Spatial representation
Space2Vec [116]	2020	Variable	Coordinates, point-of-interest categories, geotagged images	Multiscale periodic coordinate encoding
Sphere2Vec [144]	2023	Variable	Coordinates and class labels; images for joint prediction	Multiscale spherical coordinate encoding
CSP [136]	2023	64–1,024	Coordinates, natural and satellite images	Location encoder aligned with image features
GeoCLIP [104]	2023	512	Coordinates and geotagged photographs	Multiscale coordinate encoder
SINR [147]	2023	256	Coordinates and species occurrence records	Continuous coordinate-to-feature mapping
SIRENNET(SH) [145]	2024	Variable	Coordinates, geographic labels, climate variables	Spherical harmonics with a sinusoidal network
SatCLIP [38]	2025	256	Coordinates and Sentinel-2 imagery	Spherical-harmonic location encoder
SatCLE [149]	2025	256	Coordinates and satellite imagery	Continuous location embedding
RANGE [156]	2025	1,280	Coordinates and satellite-image features from pretrained encoders	Location vector augmented by retrieved features; no additional encoder training
Hybrid Slepian [146]	2026	Variable	Coordinates and geographic measurements; image features in joint prediction	Localized Slepian basis combined with spherical harmonics
TTE [148]	2026	512	Coordinates and satellite imagery	Learned spherical partitions and semantic tokens
Esri GLE [150]	2026	256	Coordinates and Sentinel-2 Level-2A imagery	SatCLIP-based coordinate encoder
OSMGraphCLIP [151]	2026	256	Coordinates and OpenStreetMap graphs	Location encoder aligned with graph features
UniGeoCLIP [154]	2026	768	Coordinates, aerial and street-level images, elevation, text	Coordinate encoder in a multimodal embedding space
GAIR [155]	2026	768	Coordinates, overhead and street-level imagery	Location encoding and geo-aligned image features
S2Vec [152]	2026	256	Built-environment attributes: buildings, roads, points of interest	Rasterized attributes within S2 cells
MoRA [153]	2026	128	Mobility, points of interest, imagery, demographics	Spatial tokens and mobility-graph representations

features [156], whereas proxy consistency loss (PCL) incorporates widely available geospatial proxy variables into a trainable location encoder for sparsely labeled prediction tasks [157]. A task-adapted location representation is not interchangeable with a frozen general-purpose encoder. TorchSpatial and LocBench compare 15 location encoders across classification and regression tasks and examine geographic bias [158]. Unlike released raster layers, coordinate encoders can return a compact vector for an arbitrary coordinate, but its content depends on the training observations, spatial basis, and downstream adaptation protocol.

Reusable EO encoders have also been studied for multi-sensor transfer, sensor-variable imagery, cross-modal alignment, retrieval, and compression [34, 37, 38, 111, 112, 159–175]. Benchmarks, reviews, and software now compare fixed representations, compression, pooling, transfer, and access across products and encoders [16, 29, 30, 52, 122, 126, 176–180]. Further work evaluates released embeddings in land-cover mapping, geographic and temporal transfer, environmental and socioeconomic prediction, retrieval, uncertainty analysis, and combinations of multiple representations [181–209].

4.2. Product Design Trade-offs

A global per-pixel layer contains many more vectors than a scene-level collection, while temporal or multisensor inputs place more observations into each vector than a single-image encoder. Dimensionality, resolution, and temporal support must therefore be interpreted together.

4.2.1. Embedding Space Properties

Embedding geometry and dimensionality affect similarity calculations, storage, and interpretation [28]. For released embeddings, the main questions are whether vectors are constrained to a particular space, how training controls information retention, and how nominal dimension relates to the variation present in the vectors.

Many released encoders produce vectors in $\mathbb{R}^d$ without an explicit norm constraint. Examples include Clay [75], Prithvi-EO-2.0 [10], SatMAE [54], TESSERA [34], and the DINOv2-derived embeddings distributed by Major TOM [37]. Cosine

similarity is commonly used to compare such vectors $\mathbf{u}$ and $\mathbf{v}$:

$$\text{sim}(\mathbf{u}, \mathbf{v}) = \frac{\mathbf{u} \cdot \mathbf{v}}{\|\mathbf{u}\| \|\mathbf{v}\|}. \quad (6)$$

An unconstrained output can occupy a lower-dimensional subspace of the available coordinates, a behavior described as *dimensional collapse* [210]. Cosine similarity also removes vector norm at evaluation time even when norm was unconstrained during training. Uniformity on the hypersphere has been associated with downstream performance in general representation learning [211], although the relationship has not been established across Earth embedding products. AlphaEarth Foundations [14] explicitly places its output on the unit hypersphere $\mathbb{S}^{d-1}$ through a von Mises–Fisher (vMF) variational bottleneck. For $\mathbf{z} \in \mathbb{S}^{d-1}$, the distribution is parameterized by a mean direction $\boldsymbol{\mu} \in \mathbb{S}^{d-1}$ and concentration $\kappa \geq 0$:

$$p(\mathbf{z} \mid \boldsymbol{\mu}, \kappa) = C_d(\kappa) \exp(\kappa \boldsymbol{\mu}^\top \mathbf{z}), \quad (7)$$

where $C_d(\kappa)$ is a normalization constant. AlphaEarth combines this distribution with a batch-uniformity penalty that discourages concentration in a limited region of $\mathbb{S}^{63}$ [14]. Unlike the embeddings above, AlphaEarth uses spherical geometry; its effect requires evaluation with the same data and tasks.

Cross-modal encoders introduce a second geometric issue. Separate encoders can occupy different regions of a nominally shared space, a phenomenon termed the *modality gap* [212]. GeoCLIP [104] aligns images and coordinates, whereas RemoteCLIP [111] aligns remote sensing imagery and text. Work on natural images links the gap to zero-shot performance and fairness differences [212], but few geospatial studies have measured it. Recent analyses use sparse concept decompositions and neuroscience-inspired probes to examine the information carried by location and Earth observation embeddings [180, 213]. Within- and cross-modal neighborhood analyses can complement downstream accuracy when these spaces are evaluated.

The information bottleneck provides a conceptual description of how an encoder can discard input variation while retaining information about a target. Let X denote the input, Z the embedding, and Y a downstream target. For a stochastic encoder $p(\mathbf{z} \mid \mathbf{x})$, the objective is

$$\min_{p(\mathbf{z} \mid \mathbf{x})} I(Z; X) - \beta I(Z; Y), \quad (8)$$

where $\beta > 0$ controls the balance between compression and target relevance. In self-supervised pretraining, the set of future targets Y is unknown, so this equation offers an interpretation rather than a directly optimized objective for most Earth embedding models. AlphaEarth fixes the vMF concentration at $\kappa = 8 \times 10^3$ [14]; this controls distributional concentration but does not by itself provide a measured bound on $I(Z; X)$. TESSERA [34] reduces cross-dimensional correlation with Barlow Twins [105], whereas masked-autoencoder models such as Clay [75] rely primarily on architecture and output dimension to limit the code. Their relationship to mutual information has not been compared with matched EO data, architectures, and evaluation protocols [21, 26].

Reported full output dimensions range from 64 for AlphaEarth [14] to 8,192 for MOSAICS [36], while TESSERA v2 [102] supports prefixes as short as 16 dimensions; Section 4 compares the associated storage costs. Nominal dimension does not reveal how many directions contain substantial variation. Participation ratio and effective rank summarize the spectrum of the embedding covariance matrix, whereas manifold estimators characterize nonlinear degrees of freedom. Rao et al. [214] estimate a manifold dimension of 2–10 for the geographic implicit neural representations studied in GeoINRID. That result applies to coordinate-based representations under the paper's data and estimator choices and should not be generalized to satellite embedding products. Effective dimension, compression loss, and downstream accuracy must be measured for each representation; principal component analysis (PCA) [215] and product quantization [216] provide possible reductions, but the attainable savings depend on the target and evaluation protocol. Product documentation should therefore report the nominal dimension, numeric precision, normalization, recommended distance measure, and any empirical estimate of effective dimension.

4.2.2. Dimensionality and Compression

Embedding dimensionality affects storage and the degrees of freedom available to encode variation. MOSAICS [36] uses 8,192 random convolutional features, and Clay [75] uses a 1,024-dimensional vector learned through masked autoencoding [7]. Smaller vectors impose different constraints. AlphaEarth Foundations [14] maps observations to a 64-dimensional unit hypersphere, and the released Google Satellite Embedding dataset stores the resulting 64-dimensional vectors [15]. TESSERA v1 [34] uses Barlow Twins [105] to limit cross-dimensional redundancy in a 128-dimensional vector. TESSERA v2 [102] orders a 128-dimensional student representation so that 64-, 32-, and 16-dimensional prefixes can be used directly; the 16-dimensional prefix retains approximately 92% of the reported full-vector aggregate performance with one eighth of the storage. The released ESD tiles provide 13 values per pixel-year [52]. These dimensions are therefore not interchangeable measures of information content, and each must be evaluated on the intended downstream tasks.

Numeric precision provides a separate compression mechanism. Google Satellite Embedding stores 64 signed 8-bit values, or 64 bytes per vector, in Cloud-Optimized GeoTIFFs [14, 217]. TESSERA v1 [34] stores 128 signed 8-bit values and provides access through GeoTessera [120]. For a fixed dimension, either representation occupies one quarter of the value storage

required by 32-bit floating point. Dimension and numeric precision should therefore be reported together.

Compression ratios depend on the reference data and the spatial and temporal support of one output. The 64-byte annual vectors in Google Satellite Embedding [14, 217] and the 128-byte annual vectors in TESSERA v1 [34] summarize different input archives, so neither implies a unique reduction relative to raw observations. TESSERA v2 changes vector storage through its 16–128-dimensional prefixes [102], whereas Clay's 1,024-dimensional 32-bit class token represents a 256×256 -pixel scene [75]. ESD reports approximately $340\times$ compression specifically against its global daily Landsat–MODIS archive; the released annual product provides 13 values per pixel and occupies about 2.4 TB per year [52]. NeuCo-Bench instead evaluates representation size jointly with downstream utility [122], while model slimmability studies reduce encoder computation rather than the storage of a released embedding [218]. Compression claims are comparable only when the input baseline, output support, precision, and task protocol are stated.

4.2.3. Temporal Representation

Temporal design determines whether a vector describes one acquisition, summarizes an interval, or preserves an ordered sequence. Tile2Vec [70], MOSAICS [36], and the DINOv2 [9] features distributed by Major TOM [37] encode individual images. SeCo uses observations from different seasons during pretraining, but its released image encoder still produces one vector from one image [95]; temporal supervision during training is therefore distinct from multi-date encoding at inference. Models that combine observations explicitly include AlphaEarth's time-conditioned annual summaries [14], SatMAE's temporal positional encoding [54], and Prithvi's three-dimensional patch embeddings [10]. TESSERA v1 samples annual optical and radar observations [34], while TESSERA v2 uses day-of-year encoding, attention pooling, and adaptive use of valid observations at inference [102]. ESD preserves within-year temporal information for every annual record from 2000 onward [52]. The appropriate design depends on whether the target follows phenology or rapid change [184, 219], or is sufficiently stable to be represented by a single-date or annual summary.

4.2.4. Multimodal Integration

Multimodal models differ in which sources they accept and where those sources interact. AlphaEarth is trained with optical, radar, LiDAR, environmental, topographic, and text observations; source-specific encoders feed a common spatiotemporal representation [14]. TESSERA v1 processes Sentinel-1 and Sentinel-2 time series in separate Transformer–GRU branches before concatenation and multilayer-perceptron fusion [34]. TESSERA v2 replaces this stage with modality-specific temporal Transformers followed by a fusion Transformer [102]. Clay supports several image modalities but processes an input according to its modality and conditions the encoder on location and time metadata [75]; support for several modalities does not necessarily mean that they are fused in one vector. Fusion can encode complementary measurements, but it also introduces requirements for co-registration, temporal alignment, and missing-source handling.

4.2.5. Spatial Support and Release Form

Spatial support determines both the smallest resolvable target and the number of vectors that must be distributed. SatCLIP [38] and GeoCLIP [104] return a vector for a coordinate without requiring a corresponding satellite image. MOSAICS [36], Clay [75], and Major TOM Embeddings [37] operate at scene or tile level. Google Satellite Embedding [14, 15] and TESSERA v1 [34] release pixel-wise embeddings at 10 m resolution; TESSERA v2 is evaluated at the same spatial support [102], and ESD [52] operates at 30 m. A simple land-area calculation gives approximately 1.5×10^{12} cells for a global land grid at 10 m resolution. At 64 bytes per cell, this is about 96 TB before masking, tiling, compression, metadata, and projection overhead. Scene-level products require fewer vectors but cannot resolve variation within an input footprint. Parcel, administrative, and plot targets require aggregation chosen for their within-unit variation [178].

The release format determines who performs the encoding. Precomputed layers from Google Satellite Embedding [14, 15], TESSERA v1 [34], and ESD [52] remove user-side global inference. Clay v1.5 releases weights for encoding new inputs when its preprocessing is reproduced [75], while LGND distributes a separate vector collection generated with that encoder [101]. Copernicus-FM similarly provides a model, whereas Copernicus-Embed-025deg provides 768-dimensional vectors on a global 0.25° grid [55, 140]. Model weights permit new inputs and preprocessing choices but retain inference costs; released vectors are immediately usable but inherit the producer's input archive, masking, compositing, temporal definition, and encoder version. Temporal and multimodal inputs increase the information represented by each vector, while fine spatial support increases the number of vectors stored and queried. Product choice should follow target scale, temporal sensitivity, source availability, and acceptable compression loss.

4.3. Distribution Infrastructure

Earth embeddings are distributed through cloud services, public data repositories, spatial indexes, product-specific software, and model libraries. Hosting services store collections; spatial indexes relate vectors to geographic footprints and source imagery; product-specific software implements queries and decoding; and model libraries provide interfaces to multiple datasets or encoders. Table 5 compares resources for publishing, accessing, and generating Earth embeddings.

Google Satellite Embedding can be analyzed server-side in Google Earth Engine or accessed as Cloud-Optimized GeoTIFF files in Google Cloud Storage [14, 15, 217]. The Copernicus Data Space Ecosystem publishes the Global Embeddings Dataset as GeoParquet files through EODATA S3 [220]. Hugging Face hosts Major TOM Core and embedding datasets [37, 221], while Source Cooperative provides catalog and object-storage access to LGND Clay Embeddings and Earth Index [101, 119, 222].

Data-organization tools, publication guidance, and product-specific clients do not host the same resources as cloud platforms. Major TOM defines a geographic grid and metadata conventions for organizing compatible EO datasets and their derived embeddings [100]. Geo-Embeddings provides recommendations for storing, documenting, and publishing gridded and irregular embedding collections, together with draft STAC and Zarr conventions that remain under development [225,

226]. GeoTessera is specific to TESSERA [34, 120, 227]: its versioned manifest indexes tiles, its client retrieves quantized NumPy arrays and scale factors from object storage, and its Zarr interface supports regional and point queries. It can also export georeferenced GeoTIFFs. Cloud-Optimized GeoTIFF, GeoParquet, NumPy, and Zarr provide different storage layouts, which affect how clients index, subset, and transfer embeddings.

Libraries for reusable encoders differ in breadth. TorchGeo [125, 228] provides geospatial dataset classes, spatial queries, and sampling for patch- and pixel-level embeddings, including Clay, Major TOM, Earth Index, Copernicus-Embed, TESSERA, Google Satellite Embedding, and ESD. TerraTorch is maintained within the TorchGeo organization and builds on TorchGeo and PyTorch Lightning to load, adapt, and extract embeddings from EO foundation models; it does not host precomputed global vectors [229]. RS-Embed [126, 143] uses one spatial and temporal query specification to retrieve selected precomputed products or run supported encoders on demand. GeoAI provides regional download, dequantization, comparison, and GeoTIFF export for Google Satellite Embedding; it also catalogs remote-sensing foundation models and loads supported backbones through TerraTorch [124, 230, 231]. AiTLAS [234, 235] provides model adapters, configuration, and task pipelines for EO models but does not itself publish a global precomputed embedding collection.

TorchSpatial implements 15 location encoders and LocBench in the same codebase [158]. SRAI combines vector-data acquisition, regionalization, and regional embedding methods for sources such as OpenStreetMap and Overture Maps [232, 233]. The LGND API exposes hosted Clay embedding collections, similarity search, and creation of new embedding collections from user-supplied imagery [75, 223, 224]. Catalog discovery, version tracking, spatial and temporal query, provenance, and cross-product composition remain divided among these interfaces.

4.4. Evaluation Benchmarks

Evaluation protocols determine which properties of an embedding are measured. Community benchmarks compare models using the same tasks, label budgets, and adaptation methods, but most were designed for foundation model adaptation rather than for precomputed vectors used as fixed geospatial data. Table 6 uses Cls, Seg, Reg, CD, OD, and IS for classification, semantic segmentation, regression, change detection, object detection, and instance segmentation, respectively; SDG denotes Sustainable Development Goal. The final "Sat. emb." column marks benchmarks designed specifically for fixed or precomputed satellite embeddings.

4.4.1. Task-Based Benchmarks

GEO-Bench [236] contains 6 classification and 6 semantic segmentation tasks and reports results for 20 baseline configurations. Prithvi-EO 2.0 reports an 8% improvement over its predecessor under this protocol [10]. GEO-Bench does not include regression or change detection, while FoMo-Bench [238] adds 15 multimodal forest monitoring datasets spanning classification, segmentation, and object detection.

PANGAEA [177] adds regression and temporal inputs and evaluates 9 selected model entries, with SSL4EO-S12

Table 5

Infrastructure for publishing, accessing, and generating Earth embeddings.

Infrastructure	Type	Primary function	Access / format	Representative resources	Link
Google Earth Engine and Cloud Storage [15, 217]	Cloud analysis and storage	Server-side analysis and direct access to annual embedding files	Earth Engine API; GCS / COG	Google Satellite Embedding [14]	☞
Copernicus Data Space Ecosystem [220]	Data hosting	Hosting and direct distribution of embedding collections	EODATA S3 / GeoParquet	Global Embeddings Dataset	☞
Hugging Face Hub [221]	Dataset repository	Versioned hosting and bulk distribution of EO datasets	Hub API / Parquet	Major TOM Core and embedding datasets [37]	☞
Source Cooperative [222]	Data publishing	Catalog and object access for public geospatial collections	HTTPS / S3; resource-specific formats	LGND Clay Embeddings [101]; Earth Index [119]	☞
LGND API [223, 224]	Hosted embedding service	Access, similarity search, and generation of embeddings from user imagery	REST API; bearer token; GeoParquet export	LGND Clay Embeddings and user-defined Clay collections [75, 101]	☞
Major TOM [100]	Data specification and tools	Shared geographic grid and metadata for compatible EO datasets	Python tools; grid and metadata schema	Major TOM Core and derived embedding collections [37]	☞
Geo-Embeddings [225, 226]	Conventions and registry	Guidance for storing, documenting, and publishing geospatial embeddings	Web documentation; draft STAC / Zarr conventions	Best practices, metadata templates, and implementation registry	☞
GeoTessera [120, 227]	Product client	Tile indexing, spatial query, dequantization, and export	Python / CLI; S3 / Zarr	TESSERA embeddings [34]	☞
TorchGeo [125, 228] TerraTorch [229]	Data and model toolkit	Geospatial data loading and sampling; foundation-model inference, embedding extraction, and adaptation	Python / PyPI; dataset API / CLI / YAML	Clay, Major TOM, Earth Index, TESSERA, Google Satellite Embedding, ESD, and EO foundation-model backbones [14, 34, 37, 52, 75, 119]	☞ ☞
RS-Embed [126, 143]	Embedding interface	Retrieval of precomputed vectors and on-demand encoder inference	Python / PyPI; Earth Engine / local inference	TESSERA, Google Satellite Embedding, Copernicus-Embed, and encoder adapters [14, 34, 55, 140]	☞
GeoAI [124, 230, 231]	Embedding and model toolkit	Download, analysis, and export of embeddings; discovery and loading of EO foundation models	Python / PyPI; COG / GeoTIFF; TerraTorch	Google Satellite Embedding and registered EO foundation models [14]	☞
TorchSpatial [158]	Location-embedding library	Implementation and evaluation of coordinate encoders	Python / source; PyTorch	Fifteen location encoders and LocBench	☞
SRAI [232, 233]	Regional-embedding framework	Data acquisition, regionalization, and embedding of vector geospatial data	Python / PyPI; OSM / Overture / H3	Count-based, contextual, and neural regional embeddings	☞
AiTLAS [234, 235]	Model integration toolkit	Model adapters, configuration, and task pipelines	Python / PyPI	AnySat, Copernicus-FM, CROMA, Galileo, Panopticon, Presto, and TerraMind [35, 55, 64, 76, 107, 109, 115]	☞

Table 6

Community benchmarks for geospatial foundation models and Earth observation embeddings.

Benchmark	Year	Venue	Scope	Sat. emb.
GEO-Bench [236]	2023	NeurIPS	12 tasks: 6 Cls, 6 Seg	
PhilEO Bench [237]	2024	IGARSS	Global Sentinel-2 data; Cls, Seg, Reg	
TorchSpatial / LocBench [158]	2024	NeurIPS	17 data sets: 7 Cls, 10 Reg	
FoMo-Bench [238]	2025	AAAI	15 data sets: Cls, Seg, OD	
PANGAEA [177]	2026	GRSM	11 data sets; Seg, CD, Reg	
Copernicus-Bench [55]	2025	ICCV	15 tasks using Sentinel-1, -2, -3, and -5P	
SustainFM [239]	2025	arXiv	16 tasks corresponding to SDGs 1–16	
GEO-Bench-2 [57]	2026	TMLR	19 data sets; Cls, Seg, Reg, OD, IS	
Landsat-Bench [240]	2025	ICMLW	3 Landsat benchmarks; Cls	
REOBench [241]	2025	NeurIPS	6 tasks; 12 corruption types	
NeuCo-Bench [122]	2026	CVPRW	5 data groups, 8 EO tasks; Cls, Reg	✓

represented by 4 variants, on 11 datasets for semantic segmentation, change detection, and regression. Its comparison with U-Net [242] and a standard Vision Transformer [93] shows that geospatial pretraining does not consistently outperform supervised models when labels are plentiful. GEO-Bench-2 [57] covers 19 datasets and 5 task types and reports normalized scores within capability groups. It uses TerraTorch [229] to apply a shared hyperparameter-search and repeated-seed protocol to 14 model configurations, including Clay [75], Prithvi [10], TerraMind [76], DOFA [13], DeCUR [106], SatlasPretrain [71], and DINOv3 [99]. The reported rankings vary by capability: natural-image ConvNeXt models [243] remain competitive for high-resolution RGB imagery and object detection, whereas EO pretraining is more useful for some multispectral and temporal

tasks. Landsat-Bench [240] narrows the comparison to 3 Landsat classification benchmarks evaluated with nearest-neighbor classification [244] and linear probing. Model rankings must therefore be read together with the task, sensor, adaptation method, and amount of labeled training data.

Copernicus-Bench [55] contains 15 tasks using Sentinel-1, Sentinel-2, Sentinel-3, and Sentinel-5P data, organized into preprocessing, base applications, and specialized applications. PhilEO Bench [237] provides a 400 GB Sentinel-2 data set for land-cover classification, road segmentation, and building-density regression, using fixed decoders and label budgets. SustainFM [239] defines 16 tasks corresponding to Sustainable Development Goals 1–16 and extends evaluation to transferability, operational impact, and energy efficiency. REOBench [241] measures robustness across 6 tasks and 12 appearance-based or geometric image corruptions. Their protocols assess sensor dependence, transfer, efficiency, and robustness in addition to aggregate scores.

4.4.2. Evaluation of Fixed Embeddings

A benchmark for fixed embeddings evaluates precomputed satellite vectors rather than adapting the complete encoder. Using frozen features alone does not meet this definition. Landsat-Bench compares encoder outputs, and TorchSpatial / LocBench [158] evaluates 15 coordinate encoders on seven geo-aware image classification and ten image regression datasets.

LocBench also introduces a Geo-Bias Score, but its inputs are locations rather than satellite embedding products.

Existing embedding benchmarks test compression, hidden tasks, and model selection. NeuCo-Bench [122] organizes five data groups spanning eight EO tasks and evaluates fixed-size representations with one evaluation pipeline, hidden test labels, and a score that combines predictive quality with stability. A subsequent study using NeuCo-Bench reports fixed representations more than $500\times$ smaller than raw images and examines how pooling, normalization, and compression affect downstream performance [245].

Embed2Scale and the TESSERA v2 scaling study examine representation size in different ways. The Embed2Scale Challenge [118] represents each image by a single 1,024-dimensional vector, reducing the number of scalar values by more than $7,000\times$ relative to the source imagery; winning solutions fused features from several pretrained models [176, 246]. The TESSERA v2 study reports 395 training runs across 15 downstream tasks and finds that converged pretraining loss has a correlation below 0.2 in magnitude with aggregate downstream performance, while encoder capacity changes with training-data scale and projection-network size remains approximately fixed [102]. Downstream scores were more informative than pretraining loss within this model family; whether the result extends to other architectures, sensors, and objectives remains unknown.

4.4.3. Benchmark Results and Remaining Gaps

Benchmark results depend on the target and evaluation protocol. Temporal and multisensor representations such as AlphaEarth [14] and the TESSERA series [34, 102] are designed for targets that depend on seasonal or complementary sensor information. Dimension counts are comparable only with matched spatial support, inputs, and adaptation protocols. PANGAEA [177] evaluates models with 10%, 50%, and 100% of the labeled training data and finds that supervised baselines remain competitive on several tasks, with the relative benefit of pretraining depending on the task and label budget. Benchmark reports should therefore state the adaptation method, amount of labeled training data, input data, and target.

Geographic and temporal transfer remain weakly measured. PANGAEA, SustainFM, and GEO-Bench-2 include more regions [57, 177, 239], but regional and environmental coverage remains uneven. A 2026 agricultural benchmark [247] evaluates Prithvi [10], SpectralGPT [11], and SatMAE [54] on multitemporal crop segmentation and change detection across four U.S. states; region-separated splits report lower performance under geographic transfer. The result supports region-separated evaluation. Annual products also require tests across years and in regions undergoing rapid land-cover change. Cross-model scores are further confounded by differences in source imagery and preprocessing. Major TOM [37, 100] applies several encoders to the same tiles, while Earth Embeddings as Products [29] provides standardized TorchGeo loaders [228]. Geographic and temporal transfer should also be tested with identical source inputs.

Aggregate benchmark scores often rely on thousands of labeled pixels or patches, whereas many field studies have far fewer observations [177]. Reporting performance across several labeled training-set sizes would characterize applications with

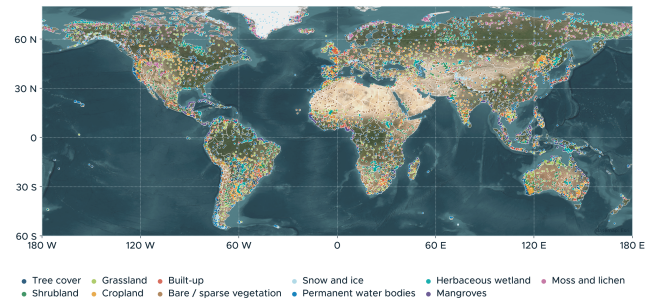


Figure 6: Global distribution and WorldCover classes of the evaluation samples.

limited labels more directly. Task composition introduces a second mismatch. Classification and segmentation dominate, while regression of biomass, canopy height, and yield, multi-year change detection, retrieval, and out-of-distribution generalization remain less common. Class separation does not guarantee that an embedding preserves the smooth variation required for continuous prediction. Current benchmarks also do not determine whether year-to-year distances distinguish gradual environmental change from sensor or preprocessing artifacts. GEO-Bench-2 [57] includes regression, and Embed2Scale [118] evaluates compression, but no benchmark combines continuous variables, temporal transfer, retrieval, and fixed label budgets in one protocol for fixed embeddings.

5. Experiments

The experiments examine how Earth embeddings organize the same geographically distributed samples and how well they support prediction of discrete and continuous land-surface properties. We first compare global and local structure using Uniform Manifold Approximation and Projection (UMAP) [248], linear centered kernel alignment (CKA) [249], and cosine-neighborhood overlap. We then evaluate land-cover classification, continuous-variable regression, and the sensitivity of predictive performance to PCA dimension after patch flattening.

5.1. Data

Fig. 6 shows the 9,132 candidate locations distributed across terrestrial land areas. Each location defines a $640\text{ m} \times 640\text{ m}$ patch and is associated with one of the 11 ESA WorldCover 2021 v200 reference classes [250]; these labels color the sample map and UMAP projections, while WorldCover also provides one of the downstream classification targets.

The inputs comprise reflectance from 3 observation sources and 7 learned embeddings. The observation sources are Sentinel-2 [39], Landsat [1], and MODIS [58]. The learned inputs are ESD [52], Google Satellite Embedding (GSE) [14, 15], AgriFM [251], Copernicus-FM [55], TESSERA [34], TerraMind [76], and WildSAT [252]. Representation-space and predictive comparisons use all 10 inputs, and the UMAP projection also includes their concatenation.

The classification targets are the Esri annual land-use and land-cover product at 10 m resolution [253], FROM-GLC10 2017 [254], and ESA WorldCover 2021 v200 [250]. The continuous targets are elevation from Copernicus GLO-30 [45], above-ground biomass from the ESA Climate Change Initiative [255],

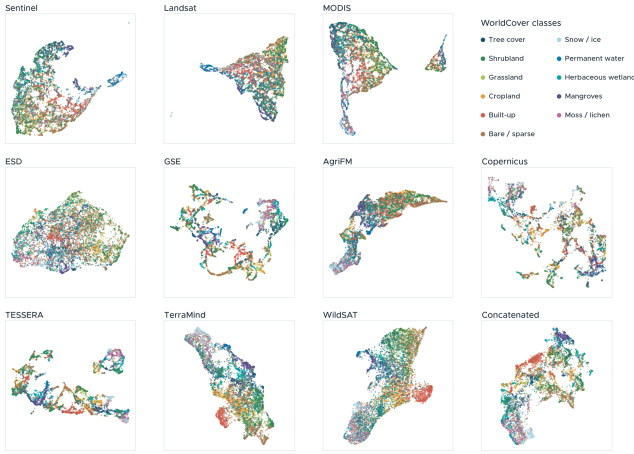


Figure 7: UMAP projections of the aligned feature sources, colored by WorldCover class.

and Meta global canopy height [256]. These datasets cover discrete surface types and continuous variables with different units, spatial patterns, and class or value distributions.

5.2. Internal Representation Analysis

The internal comparison does not use a downstream target. UMAP provides a qualitative view of local organization, while linear CKA and neighborhood overlap measure global geometric similarity and local retrieval consistency. All inputs undergo the same preprocessing before comparison.

5.2.1. Low-Dimensional Structure

Let $X^{(s)} \in \mathbb{R}^{n \times d_s}$ denote the processed matrix for input s , where rows correspond to the same locations and d_s may differ across inputs. Spatial features were mean pooled, ℓ_2 normalized, winsorized at the 1st and 99th percentiles, and scaled by the median and interquartile range. Land-cover labels color the projected points but do not enter the UMAP fit, CKA, or neighborhood-overlap calculations.

In Fig. 7, the aligned locations have different local arrangements across sources. The three reflectance inputs form broad, continuous manifolds, although their shapes are not identical, and ESD [52] has a similarly diffuse organization. GSE [14, 15], Copernicus-FM [55], and TESSERA [34] divide the samples into more fragmented local components, whereas AgriFM [251], TerraMind [76], and WildSAT [252] produce elongated structures with several class-dominated regions. The concatenated representation has a compact, multi-branch organization that does not reproduce any single input space, so concatenation changes the projected neighborhoods rather than merely enlarging one of the component manifolds.

No projection uniformly separates all land-cover classes. Some regions are dominated by a single class, but spectrally or structurally related surfaces still overlap. The UMAP panels are descriptive: coordinates, orientation, and distances are not comparable across independently fitted panels, and visual separation is not a quantitative clustering or prediction score. Linear CKA and neighborhood overlap provide pairwise comparisons of global geometry and local retrieval behavior.

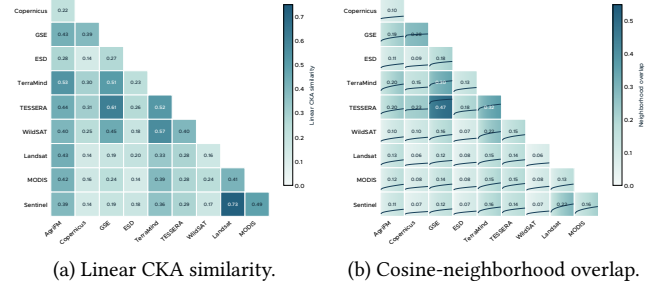


Figure 8: Pairwise similarity between feature spaces measured by linear CKA and cosine-neighborhood overlap.

5.2.2. Global Geometry and Local Neighborhoods

Linear CKA compares global representation geometry. For row-normalized and column-centered matrices X and Y , linear CKA is

$$\text{CKA}(X, Y) = \frac{\|X^T Y\|_F^2}{\|X^T X\|_F \|Y^T Y\|_F}. \quad (9)$$

CKA is invariant to orthogonal transformations and isotropic rescaling, allowing sources with different feature dimensions to be compared. A high value indicates similar centered linear geometry, not identical vectors or identical nearest-neighbor rankings.

Local agreement is measured directly from cosine neighborhoods. Let $\mathcal{N}_k^X(i)$ be the k nearest neighbors of location i in representation X under cosine distance. The overlap between two representations is

$$O_k(X, Y) = \frac{1}{n} \sum_{i=1}^n \frac{|\mathcal{N}_k^X(i) \cap \mathcal{N}_k^Y(i)|}{k}. \quad (10)$$

The score lies between zero and one and measures whether the same locations would be retrieved locally in both spaces. We evaluate k from 5 to 200; the value printed in each matrix cell is the mean across these neighborhood sizes. Both pairwise matrices are symmetric, so Fig. 8 shows only the lower triangle. Each neighborhood-overlap cell reports the change across the evaluated values of k on a common scale.

Fig. 8(a) shows two groups with relatively high global similarity. Among the reflectance inputs, Sentinel and Landsat are the closest pair (0.728), followed by Sentinel and MODIS (0.489), consistent with shared optical measurements but different spatial and temporal support. Among the learned representations, GSE [14, 15] and TESSERA [34] have the highest CKA (0.614). TerraMind [76] also has comparatively high CKA with WildSAT [252] (0.566), AgriFM [251] (0.534), TESSERA (0.519), and GSE (0.507). By contrast, CKA between Copernicus-FM [55] or ESD [52] and the reflectance inputs is only 0.135–0.203. These values describe linear geometry, not predictive quality or complementarity.

The local-overlap ranking in Fig. 8(b) is related but not identical. GSE and TESSERA again form the closest pair, with a mean overlap of 0.474 across the evaluated neighborhood sizes. TESSERA–TerraMind (0.318), GSE–TerraMind (0.303), and GSE–Copernicus-FM (0.281) form the next strongest learned-representation relations. For GSE and TESSERA, overlap rises

from 0.381 at $k = 5$ to 0.503 at $k = 200$, so the pair shares both small and broader neighborhoods. The increase with k is partly mechanical because larger neighborhoods offer more opportunities for intersection; comparisons among pairs at the same k are more informative than the increase alone.

Global and local agreement are nevertheless not interchangeable. Sentinel and Landsat have the highest CKA, yet their mean neighborhood overlap is only 0.222 and increases from 0.076 at $k = 5$ to 0.294 at $k = 200$. Their representations therefore share strong large-scale linear structure while differing more substantially in the identities of the nearest locations. CKA and neighborhood overlap identify related spaces but do not measure task utility. The following classification and regression experiments compare the target information available to the evaluated prediction models.

5.3. Downstream Predictive Performance

The downstream experiments use common data splits and prediction models to compare discrete land-cover classification and continuous-variable regression. Performance is reported by target and metric, followed by sensitivity to PCA dimension and variation across prediction models.

5.3.1. Experimental Design

Within each target, every input uses the same sampled locations and a fixed partition containing 70% training data and 30% held-out test data. Classification is stratified by class, whereas regression is split without target stratification. We evaluate 14 prediction models for each task. Linear and local methods comprise a learned linear head, k -nearest neighbors [244], a linear support vector classifier or regressor [85], logistic regression [257] for classification, and ridge regression [258] for regression. Tree ensembles comprise random forest [84], gradient boosting and histogram gradient boosting [259], XGBoost [260], LightGBM [261], and CatBoost [262]. The neural predictors are a multilayer perceptron (MLP) [263], a convolutional neural network (CNN) [264], a long short-term memory network (LSTM) [92], and a Vision Transformer (ViT) [93]. The MLP is the scikit-learn implementation [265]; the linear head, CNN, LSTM, and ViT are trained in PyTorch [266].

Hyperparameters are selected by fivefold cross-validation within the training partition. Where supported by the predictor, classification uses class-balanced sample or loss weights; regression targets are standardized using training-partition statistics and transformed back before evaluation. For scikit-learn predictors [265], each input is normalized per channel, flattened, and reduced by incremental principal component analysis (PCA) [267] fitted only on the corresponding training fold. The PyTorch predictors [266] instead use harmonized spatial tensors as input, preserving their channel and spatial organization. After hyperparameter selection, each predictor is refitted on the full training partition and evaluated on the held-out test partition.

5.3.2. Evaluation Measures

Let n be the number of test samples, C the number of classes, and $\mathbf{s}_i$ the class-score vector for sample i . Classification

is summarized by accuracy, macro-F1, and top-3 accuracy:

$$\text{Accuracy} = \frac{1}{n} \sum_{i=1}^n \mathbb{I}(\hat{y}_i = y_i), \quad (11)$$

$$P_c = \frac{TP_c}{TP_c + FP_c}, \quad (12)$$

$$R_c = \frac{TP_c}{TP_c + FN_c}, \quad (13)$$

$$\text{MacroF1} = \frac{1}{C} \sum_{c=1}^C \frac{2P_c R_c}{P_c + R_c}, \quad (14)$$

$$\text{Top3} = \frac{1}{n} \sum_{i=1}^n \mathbb{I}(y_i \in \mathcal{T}_3(\mathbf{s}_i)). \quad (15)$$

where TP_c , FP_c , and FN_c are the true-positive, false-positive, and false-negative counts for class c , and $\mathcal{T}_3(\mathbf{s}_i)$ contains the three highest-scoring classes. Macro-F1 weights classes equally and is therefore the primary measure for imbalanced land-cover targets. Accuracy weights samples equally, while top-3 accuracy measures whether the reference class remains among the most plausible alternatives.

For continuous targets, we report the coefficient of determination (R^2) and root-mean-square error (RMSE) normalized by the test-target standard deviation. The latter is reported as normalized root-mean-square error (NRMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}, \quad (16)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}, \quad (17)$$

$$\text{NRMSE} = \frac{\text{RMSE}}{\sigma}. \quad (18)$$

Higher values are better for the three classification measures and R^2 ; lower values are better for NRMSE. Here, $\bar{y}$ and σ are the mean and standard deviation of the test targets, respectively. Normalization by σ permits comparison across elevation, biomass, and canopy height without conflating predictive error with their physical scales. In the heatmaps, model ranks order mean scores across embeddings and datasets; embedding ranks order mean scores across prediction models and datasets.

5.3.3. Land-Cover Classification

Fig. 9a compares macro-F1 across prediction models and embeddings on Esri LULC, FROM-GLC10, and WorldCover. Mean values are 0.718 for GSE [14, 15], 0.712 for TESSERA [34], and 0.666 for TerraMind [76] across the evaluated models and datasets. TESSERA is strongest on Esri LULC, whereas GSE leads on FROM-GLC10 and WorldCover; TerraMind ranks third on each dataset. AgriFM [251] follows at 0.596, while the remaining learned inputs, WildSAT [252], ESD [52], and Copernicus-FM [55], obtain lower means. The ordering is broadly stable across predictors, but the size of the difference depends on the prediction model. Nonlinear and boosting methods often narrow the differences among inputs, whereas linear predictors produce larger separations.

Accuracy gives nearly the same embedding ordering but places less weight on minority-class performance. GSE averages

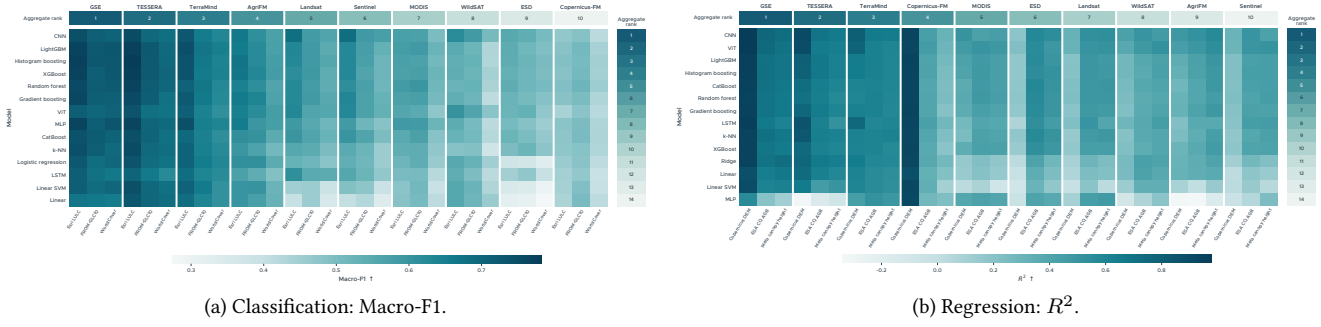


Figure 9: Classification and regression performance across prediction models, embeddings, and datasets.

0.711, TESSERA 0.705, and TerraMind 0.664, compared with 0.588 for AgriFM. At the predictor level, XGBoost, LightGBM, histogram gradient boosting, and random forest form a close group, while the CNN attains the highest average macro-F1. Macro-F1 highlights differences in minority-class performance that accuracy can mask.

Top-3 accuracy is more compressed across embeddings. GSE, TESSERA, and TerraMind reach mean values of 0.958, 0.951, and 0.940, respectively, and AgriFM reaches 0.907. The observation inputs also yield higher scores under this less restrictive criterion. The correct class often remains among the top three predictions, but macro-F1 remains the main measure for imbalanced classification.

Class-specific recall and error rates are averaged equally across the 14 predictors, each selected by macro-F1 within the training folds. These averages describe individual-model performance rather than an ensemble.

For Esri LULC, GSE and TESSERA have the most balanced class recalls, averaging 77.1% and 77.7%, respectively; TerraMind follows at 73.4%. Their main errors concern flooded vegetation and bare ground being assigned to rangeland. The lower-scoring inputs show more class-dependent behavior: WildSAT is strong for crops and built areas but reaches only 30.7% for flooded vegetation, while the mean class recalls of Copernicus-FM and ESD are close to 52%. The observation inputs preserve water, trees, and snow more reliably than flooded vegetation or crops.

For FROM-GLC10, GSE, TESSERA, and TerraMind achieve mean class recalls of 72.7%, 72.2%, and 67.8%, respectively. Cropland is most often confused with grassland, and grassland with shrubland; snow and ice are frequently assigned to bare land. These directions recur across learned embeddings and observation inputs. The embeddings differ mainly in error rates, not confusion types.

WorldCover is more difficult for the lower-scoring embeddings. GSE and TESSERA maintain mean class recalls above 71%, and TerraMind reaches 66.4%, but shrubland and grassland remain difficult to separate. Moss and lichen have lower recall than spectrally distinctive classes such as built-up land and snow or ice. Wetlands are often assigned to tree cover by the observation inputs, while WildSAT also confuses mangroves with tree cover. The class-level results explain why similar overall accuracy can conceal different class-specific errors.

5.3.4. Continuous-Variable Regression

Fig. 9b reports R^2 for Copernicus DEM elevation, ESA Climate Change Initiative above-ground biomass, and Meta canopy height. Regression performance is more task-dependent than classification performance. Across the three targets, GSE [14, 15] has the highest aggregate mean R^2 at 0.738, followed by TESSERA [34] at 0.612, TerraMind [76] at 0.609, and Copernicus-FM [55] at 0.519. The aggregate values conceal a marked target difference: Copernicus-FM records the highest mean for elevation (0.926), slightly above GSE (0.918), whereas GSE leads for biomass and canopy height. The high elevation score is expected because Copernicus-FM was pretrained on Copernicus GLO-30 DEM and the released Copernicus embedding therefore retains information derived from the same product used as the regression target [55]. TerraMind is second on both vegetation targets, while the other inputs have aggregate means between 0.30 and 0.36. CNN and ViT provide the strongest predictor-level averages, consistent with nonlinear interactions being useful for the continuous targets.

NRMSE gives the same aggregate ordering on a standardized error scale. GSE obtains the lowest mean NRMSE (0.476), followed by TESSERA (0.601), TerraMind (0.623), and Copernicus-FM (0.640); the remaining inputs range from 0.796 to 0.832. NRMSE permits comparison across elevation, biomass, and canopy height despite their different physical scales.

Prediction errors are also examined across target ranges using models selected within the training folds. The following mean R^2 values average the scores of the 14 predictors rather than the predictions themselves.

Elevation shows the strongest separation among embeddings. Copernicus-FM and GSE predict elevations close to the observed values over most of the range and have mean R^2 values of 0.925 and 0.919, respectively. TESSERA reaches 0.706 and TerraMind 0.643, with both increasingly underestimating the highest elevations. Predictions from the other inputs respond weakly to increases above approximately 1,000 m, with underestimation recurring across predictors.

Above-ground biomass is less accurately recovered than elevation. GSE has the highest mean R^2 (0.658), followed by TerraMind (0.596), TESSERA (0.572), and ESD [52] (0.494). Predictions from all embeddings are closer to observed values at low biomass and increasingly underestimate high-biomass locations. Greater variation across predictors at high biomass indicates stronger dependence on predictor choice where observations are sparse and the target range is large.

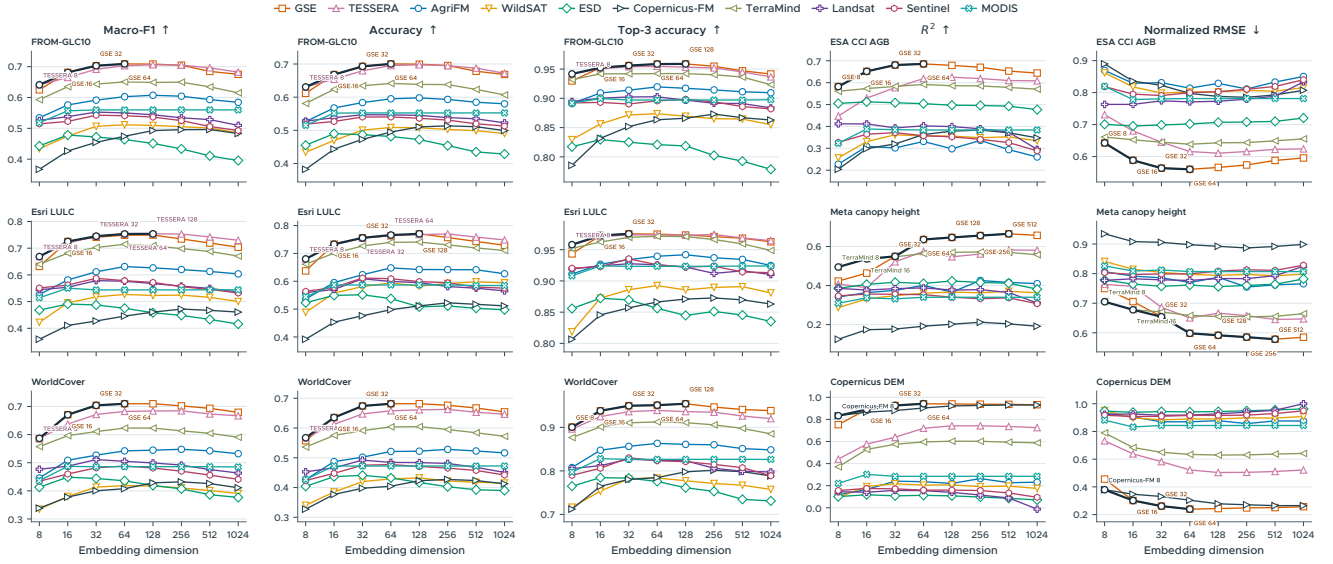


Figure 10: Predictive performance across embeddings, PCA dimensions, and downstream datasets.

The canopy-height results show a similar but weaker ordering. GSE, TerraMind, and TESSERA obtain mean R^2 values of 0.637, 0.578, and 0.547, respectively, while the other inputs range from 0.235 to 0.433. Model-averaged predictions are close to observed heights for low vegetation but increasingly underestimate taller canopies across all embeddings.

5.3.5. Dimensionality and Pareto Efficiency

Each input at a sampled location is represented as a tensor $\mathbf{X} \in \mathbb{R}^{H \times W \times C}$, where H and W are the spatial dimensions and C is the number of feature channels. For the dimensionality analysis, the normalized tensor is flattened and reduced by Incremental PCA to $d \in \{8, 16, 32, 64, 128, 256, 512, 1024\}$. Thus, d denotes the length of the reduced flattened vector, rather than the channel count of the original tensor. Figs. 10 and 11 compare predictive performance across all evaluated dimensions. For score $q_{r,p,d}$ obtained by representation r , predictor p , and dimension d , the mean scores across predictors and representations are

$$\bar{q}_{r,d} = \frac{1}{|\mathcal{P}_{r,d}|} \sum_{p \in \mathcal{P}_{r,d}} q_{r,p,d}, \quad (19)$$

$$\bar{q}_{p,d} = \frac{1}{|\mathcal{R}_{p,d}|} \sum_{r \in \mathcal{R}_{p,d}} q_{r,p,d}. \quad (20)$$

The first average compares representations over the evaluated predictors, and the second compares predictors over the evaluated representations. A point is Pareto efficient if no other point uses no more dimensions and performs no worse, with a strict improvement in at least one criterion; lower NRMSE indicates better performance.

The embedding profiles show that most gains occur at the lower end of the dimension sweep. Across the classification datasets, the best macro-F1, accuracy, and top-3 results occur between 32 and 128 dimensions. GSE [14, 15] achieves the best mean performance in all but one of the 15 dataset-metric comparisons: TESSERA [34] reaches the highest Esri-LULC macro-F1 (0.754) at 128 dimensions, while GSE leads the remaining classification metrics and all 6 regression comparisons.

Elevation and above-ground biomass peak at 64 dimensions for GSE, with R^2 values of 0.942 and 0.686. Canopy height is the main exception to early saturation and improves to $R^2 = 0.665$ at 512 dimensions. Higher dimensions improve some tasks but not others.

The predictor profiles reach a similar conclusion. Most predictor-level optima occur at 32–128 dimensions, with 256 dimensions preferred for Esri accuracy and canopy-height regression. Histogram gradient boosting, LightGBM, and XGBoost account for most of the best-performing combinations, while random forest is optimal for FROM-GLC10 top-3 accuracy at 32 dimensions. Embedding rankings change with the predictor and dimension.

Performance Across Models and Embeddings. Across the 5 metrics, GSE [14, 15], TESSERA [34], and TerraMind [76] perform consistently well on the discrete and continuous targets evaluated here, but their ordering and the differences among other inputs vary by target and predictor. Copernicus-FM [55] illustrates this task dependence by combining the strongest elevation result with substantially lower classification, biomass, and canopy-height scores. Learned embeddings do not uniformly outperform the observation inputs: Landsat [1], Sentinel-2 [39], and MODIS [58] remain competitive with several learned embeddings, particularly for classification. Downstream rankings also differ from the pairwise geometric relations because CKA and neighborhood overlap measure similarity between feature spaces, whereas the predictive experiments measure task performance.

6. Applications

Earth embeddings have been used for agriculture, ecological monitoring, biophysical estimation, environmental mapping, retrieval, and socioeconomic prediction, as illustrated on the right of Fig. 1. Fig. 12 links the evaluated embeddings to their reported downstream uses.

Agriculture and Ecology. Agricultural and ecological applications include crop and forest mapping, biomass estimation, vegetation monitoring, and biodiversity assessment [268–288].

Earth Embeddings as the Foundations of Geospatial Analysis

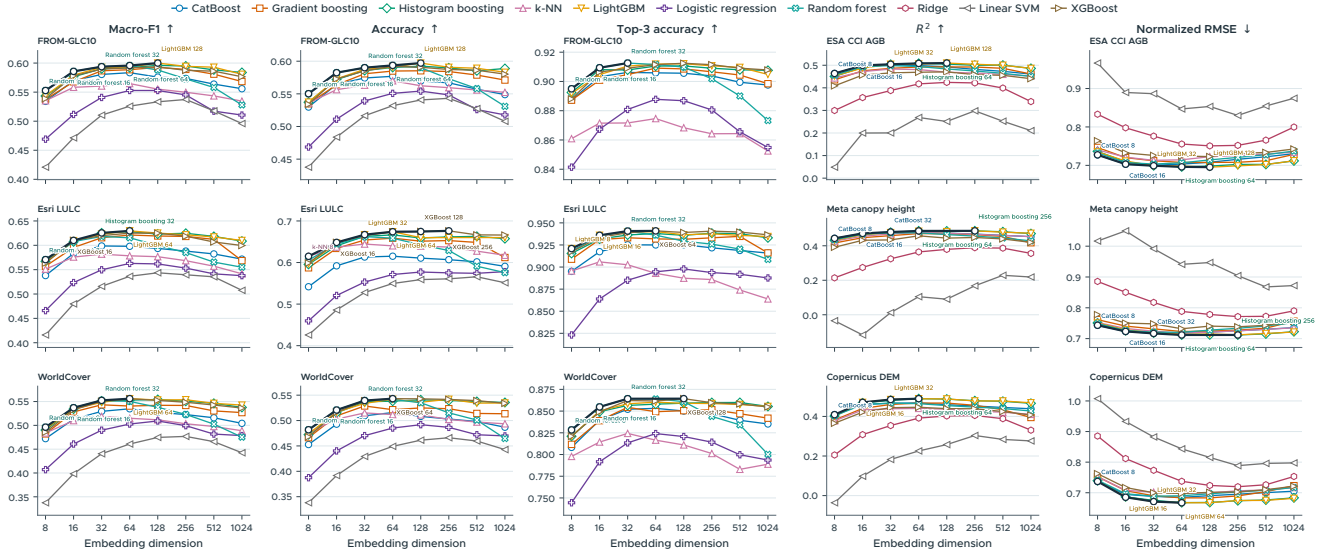


Figure 11: Predictive performance across prediction models, PCA dimensions, and downstream datasets.

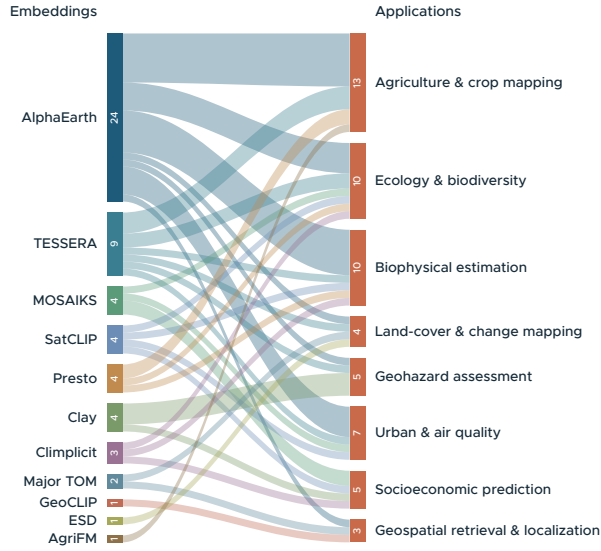


Figure 12: Links between Earth embeddings and downstream applications.

They use either released embedding layers or features extracted from reusable encoders, with representations frozen, pooled, or adapted before prediction. Recent ecological mapping experiments also apply Prithvi-EO 2.0 and TerraMind to land-cover generation, forest functional-trait mapping, and peatland detection [289].

Several studies report gains when few labeled samples are available, but the best representation varies by region and target. Wang et al. [290] combined 64-dimensional AlphaEarth embeddings [14] with Sentinel-2 spectral, textural, and topographic variables in a random-forest classifier [84]; the selected configuration reached 92.69% overall accuracy and a Kappa coefficient of 0.90 in Rizhao, China, and was applied without retraining in Qingdao. Because the model used a combined feature set, this result does not isolate the contribution of AlphaEarth. For 18 tree species and groups in Trentino, Ball et al. [278] found that AlphaEarth [14] and TESSERA [34]

increased weighted F1 from 0.80 to 0.83 and macro F1 from 0.50 to 0.55 relative to conventional Sentinel-1/2 composites; performance approached saturation with 5% of the training parcels. Across 5 crop datasets on 5 continents, SSL4EO-S12 initialization [96] outperformed ImageNet initialization [87], whereas SatlasPretrain [71] did not consistently improve performance. Training with data from other regions was most helpful when in-region labels were scarce [291].

Temporal alignment limits transfer even when local classification is accurate. In the Trentino experiment, cross-year weighted F1 decreased from 0.84 to 0.77 for TESSERA and from 0.85 to 0.73 for AlphaEarth [278]. In Senegal's groundnut basin, TESSERA [34] scored highest under the authors' performance, plausibility, transferability, and accessibility criteria; accuracy was 28% higher than the next-best method in one cross-year experiment [14, 219]. AlphaEarth was also competitive for locally trained crop-yield prediction and county-level tillage mapping in the United States, but it showed weaker spatial transfer, limited sensitivity to management timing, and lower interpretability [184]. Annual summaries are therefore less suited to agricultural targets determined by within-season events.

Large-area crop mapping also exposes the difference between reusable encoders and precomputed products. AgriFM uses multisource temporal representations for crop mapping, but users must run the released encoder [251]. Zvonkov et al. [270] generated 128-dimensional Presto embeddings [64] over all 56,785 km² of Togo in 16 hours at a reported cost of \$313.40, producing a 128.8 GB embedding dataset. On CropHarvest, the resulting map reached 0.897 overall accuracy and an F1 score of 0.808, compared with 0.859 and 0.745 for the corresponding AlphaEarth map. WorldCereal likewise uses Presto in its crop-mapping workflow and fine-tunes it on the WorldCereal reference database [292].

Biophysical Estimation and Environmental Monitoring. Biophysical estimation and environmental monitoring cover vegetation structure, hydrology, terrain, hazards, atmospheric variables, and ecosystem restoration [293–311]. The value of embeddings for continuous-variable prediction

depends on both the available environmental covariates and the downstream model. For Danish peatlands, AlphaEarth-only models had RMSE values 6% and 3% higher than expert-variable models for soil organic carbon and water-table depth; hybrid models combining the embeddings with topography, water proximity, and synthetic wet and drained conditions improved the spatial patterns [14, 312]. Over approximately 8,000 km² of Nouvelle-Aquitaine, ridge regression, U-Net, and U-Net++ all used the same AlphaEarth embeddings to estimate surface height. Test R^2 was 0.38 for ridge regression, 0.78 for U-Net [242] and 0.84 for U-Net++ [313]; U-Net++ had a test RMSE of 16.42 m [304]. These results show that both the choice of covariates and the downstream model's use of spatial information affect prediction.

Performance varies across target strata, regions, and forest types. Forest-biomass prediction from 89 plots at the Yunhe Forestry Station was weak when all plots were pooled ($R^2 = 0.06$), despite comparisons among random forest [84], support vector regression [85], a multilayer perceptron, and Gaussian-process regression. The best R^2 values differed by forest type: 0.33 for broad-leaved forest, 0.14 for mixed forest, and 0.48 for coniferous forest [277]. For landslide susceptibility in Nantou County, Hong Kong, and Emilia-Romagna, CNN1D [264], CNN2D, and Vision Transformer [93] classifiers using the full 64-dimensional AlphaEarth representation improved F1 by approximately 4–15% and AUC by 0.04–0.11 over conventional conditioning factors; PCA-reduced embeddings [215] were less accurate [302].

Temporal aggregation further constrains environmental monitoring. Annual AlphaEarth embeddings paired with records of 5 air pollutants in Quito produced $R^2 = 0.71$ for nitrogen dioxide and sulfur dioxide under fivefold cross-validation, compared with 0.55 for particulate matter, 0.61 for carbon monoxide, and a negative value for ozone [294]. Annual vectors can encode persistent land-use and urban-form correlates, but not all of the short-term chemistry and meteorology needed for atmospheric prediction.

Geospatial Retrieval and Socioeconomic Applications. Retrieval uses distances between embeddings directly, whereas socioeconomic prediction adds labels, aggregation choices, and a downstream model. GeoCLIP [104] evaluates worldwide image-to-coordinate retrieval, and Major TOM Embeddings [37] supports similarity search over its released vectors. RANGE [156] augments coordinate embeddings with visual features retrieved from an auxiliary database and reports gains of up to 13.1% on classification and 0.145 in R^2 on regression relative to the evaluated location-embedding baselines. EarthEmbeddingExplorer provides an interactive interface for similarity retrieval over Sentinel-2 imagery [314]. Dimension-level associations have also been used for retrieval with AlphaEarth [315], while FUSAR-GPT injects AlphaEarth spatiotemporal features into a SAR vision-language model for grounded interpretation [316].

Socioeconomic applications remain sensitive to the labels and spatial units used for prediction [317–322]. MOSAICS [36] used one precomputed feature set for forest cover, population density, road length, and housing value, and SatCLIP [38] evaluates coordinate embeddings on ecological and socioeconomic tasks. Sherman et al. [323] combined MOSAICS daytime features with nighttime imagery to estimate the

Human Development Index for 61,530 municipalities and 819,309 grid cells. Pettersson and Daoud [317] used AlphaEarth embeddings in a graph neural network across 37 Demographic and Health Survey datasets, where graph structure produced a small improvement over image-only baselines.

Aggregation changes the information presented to the downstream model. Corley et al. [178] compared 11 training-free and 2 parametric methods on 81,000 embedding GeoTIFFs from AlphaEarth, OlmoEarth [123], and TESSERA. With mean pooling, accuracy fell by over 10 points for some embeddings when evaluation changed from random to geographic splits. Concatenated minimum, maximum, mean, and standard-deviation statistics improved average accuracy on geographic splits at four times the embedding size; covariance pooling achieved higher accuracy in some settings, whereas generalized mean pooling did not consistently outperform mean pooling. An evaluation using NeuCo-Bench also found mean pooling competitive, although the best layer and objective varied by task [245].

Success Conditions, Limitations, and Practical Costs. Embeddings do not consistently outperform task-specific remote sensing features. Gains are reported when labeled training data are limited, including tea mapping, tree-species classification, and crop transfer with limited in-region training data [278, 290, 291]. Other studies find that embeddings match rather than exceed expert features, or that performance varies sharply across target strata [184, 277, 312]. Comparisons should therefore report the amount of labeled training data, spatial split, target resolution, and baseline feature set.

Temporal information helps when the target follows seasonal trajectories, but the available products do not resolve every temporal process. TESSERA performs well in the Senegal crop-transfer experiment [219], whereas annual AlphaEarth embeddings show limited sensitivity to tillage and cover-crop timing [184]. The same temporal limitation appears in the Quito study, where annual embeddings predict persistent pollution patterns more accurately than ozone dynamics [294]. Flood progression, active fires, and within-season crop management require observations or embeddings updated more frequently than once per year.

Spatial resolution constrains downstream use. A 10 m embedding can provide contextual information for objects smaller than one pixel, but it cannot directly resolve the geometry of individual tree crowns, narrow roads, or small buildings. Pixel-, patch-, scene-, and coordinate-level embeddings should therefore be compared only after matching their support to the label geometry. Pooling experiments further show that converting pixel embeddings to parcel or patch features can alter geographic transfer performance [178].

Geographic transfer remains dependent on the target region and the available labels. Chang et al. [291] found that training with data from other regions helped when in-region labels were scarce, but local data remained important as their availability increased. Ma et al. [184] similarly reported weaker spatial transfer for agricultural practices than for locally trained models. Frozen embeddings reduce feature-computation costs, but they do not correct a mismatch between the downstream labels and the geographic or temporal distribution represented during pretraining.

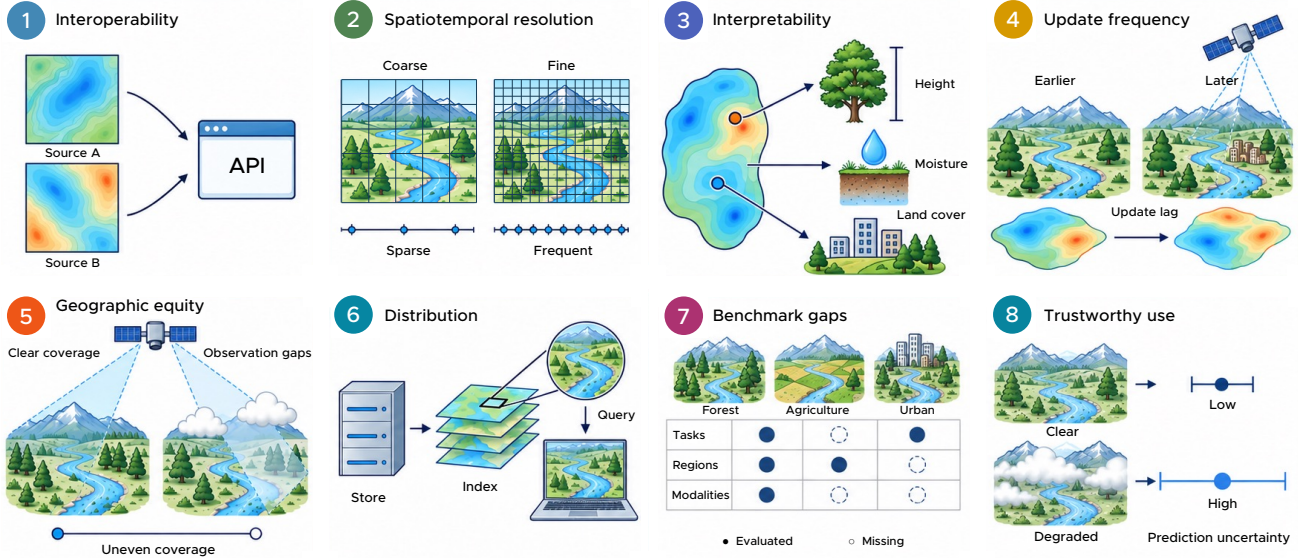


Figure 13: Challenges and potential research directions for global Earth embedding products.

Computational cost depends on whether vectors are pre-computed or generated for the study area. The Togo workflow generated Presto embeddings for 56,785 km² at a reported cost of \$313.40, or approximately \$5.52 per 1,000 km² for that cloud computation [270]. This estimate applies only to the reported computation. Precomputed products such as AlphaEarth avoid user-side encoding, but access, storage, label collection, and downstream validation still contribute to total cost.

7. Challenges and Future Perspectives

Reliable use of global embedding products requires consistent data specifications, stable representations, uncertainty assessment, and evaluation across regions and time.

7.1. Open Challenges

The main challenges concern whether embeddings remain comparable, informative, and accessible across locations, time periods, and products. Fig. 13 summarizes these challenges and potential research directions. Addressing them requires improvements in representation quality as well as data access and evaluation.

7.1.1. Standardization and Computational Sustainability

Current products differ in spatial support, file format, temporal definition, and access method. Google Satellite Embedding is distributed as annual, pixel-wise Cloud-Optimized GeoTIFFs [14, 217]; TESSERA uses quantized tiled arrays accessed through GeoTessera [34, 227]; and Major TOM, the Copernicus Global Embeddings Dataset, and LGND Clay Embeddings use GeoParquet for patch- or scene-level vectors and their metadata [37, 101, 220]. Earth Embeddings as Products and recent TorchGeo loaders expose several releases through similar query patterns [29, 125, 228], but they do not remove differences in coordinate reference systems, tiling grids, temporal support, numeric precision, or source-data provenance. A minimal metadata specification should record the encoder and source-data versions, spatial footprint, valid time, numeric

encoding, and processing history. OGC work on analysis-ready data and geodatacubes provides a precedent, although it does not yet define an Earth-embedding specification [324].

Storage remains a constraint even after inference has been centralized. A global land grid at 10m resolution contains approximately 1.5×10^{12} cells. At 64 signed 8-bit values per cell, one uncompressed annual layer contains about 96 TB of numeric values before masking, file compression, tiling overhead, and metadata. At a fixed grid and precision, increasing the vector width from 64 to 1,024 multiplies value storage by sixteen, while changing from annual to monthly output multiplies it by twelve. These estimates describe uncompressed value storage; actual archive sizes also depend on coverage, masking, compression, and file overhead. Compression studies also address different costs. Across 6 remote sensing foundation models and 4 classification tasks, post-hoc slimming retained more than 71% of relative accuracy at 1% of the original floating-point operations [218]; this reduces encoder computation, not vector storage. TESSERA v2 instead reports that a 16-dimensional prefix retains approximately 92% of the aggregate performance of its 128-dimensional vector while using one eighth of the value storage [102]. Quantization [216], ordered dimensions, and spatially coarser summaries may reduce distribution costs, but their effects should be tested separately for classification, continuous-variable regression, rare classes, and temporal change.

Precomputed layers reduce computation for users but do not eliminate the cost of training, global inference, hosting, and repeated updates. Current planetary releases depend on producers that can maintain large accelerator and object-storage resources [14, 34, 52], so long-term reliability depends on continued compute, storage, and maintenance. Google states that annual Satellite Embedding production will continue subject to source-data availability and that anticipated delivery changes will receive advance notice [217]. Comparable version, update, and deprecation policies are not yet documented consistently across the reviewed products. Stable archives and explicit maintenance responsibility are therefore prerequisites

for long-term access, including community or public-sector mirrors.

7.1.2. Temporal Coherence and Representational Stability

Temporal support differs substantially among released embeddings. Google Satellite Embedding and TESSERA provide annual summaries [14, 15, 34]; ESD retains within-year temporal information in each annual record [52]; and Major TOM and the Copernicus Global Embeddings Dataset associate vectors with individual source acquisitions [37, 220]. The current public LGND Clay collection instead provides monthly aggregated chip-level embeddings beginning in 2017 [101]. An annual release does not by itself establish how precisely within-year event timing can be recovered; acquisition-level collections retain individual observation dates but increase storage and processing costs. Generative models such as DiffusionSat support temporal generation, multispectral super-resolution, and inpainting [325]. No reviewed product reports that generated observations improve embedding stability.

Encoder updates create a separate compatibility problem. Let f_{old} and f_{new} denote two encoder versions. Reusing a downstream predictor trained on the old representation requires a map from the new space to the old one, for example

$$f_{\text{old}}(\mathbf{x}) \approx \mathbf{A}f_{\text{new}}(\mathbf{x}). \quad (21)$$

If a linear map $\mathbf{A}$ is accurate on the relevant data, an existing predictor g_{old} can be evaluated as $g_{\text{old}}(\mathbf{A}f_{\text{new}}(\mathbf{x}))$. Orthogonal Procrustes analysis provides one way to estimate a linear alignment [326], but it does not guarantee preservation of task-relevant information. A nonlinear adapter, regeneration of historical embeddings, or retraining of the downstream predictor may be needed when linear alignment is inadequate.

Version changes also affect longitudinal analysis. If adjacent annual layers are generated by different encoders, an observed difference can reflect either surface change or representation drift. Regenerating the complete historical archive with each encoder removes this ambiguity but is costly and changes previously published results. Each layer should record the encoder, source archive, preprocessing configuration, and inference date, and mixed-version time series should not be treated as homogeneous without explicit compatibility tests.

7.1.3. Interpretability, Uncertainty, and Trustworthiness

Embedding dimensions do not correspond directly to named physical variables, which limits the explanations that can accompany scientific or policy decisions. A downstream predictor can identify influential dimensions, but this does not by itself show which observations, environmental processes, or preprocessing choices produced the signal. Interpretation must therefore distinguish statistical predictability from physical meaning.

Current released embedding layers do not expose calibrated, location-specific uncertainty estimates. This differs from uncertainty in a downstream prediction, which depends on labels, the prediction model, and the deployment distribution. Encoder ensembles can measure representation disagreement, but ensemble spread is not automatically calibrated uncertainty and repeated global inference is expensive.

Nearest-neighbor distance in a reference feature space has been used for out-of-distribution detection [327]; applied to Earth embeddings, it would flag vectors far from a reference collection but would not distinguish a previously unseen surface from sparse sampling. AlphaEarth's von Mises-Fisher bottleneck does not provide a released confidence value for each location: its concentration parameter is fixed during model construction [14]. Confidence measures intended for comparison across products will require held-out geographic and temporal tests together with calibration against observed downstream errors.

Task accuracy alone is insufficient for claims about reliable use. REOBench measures sensitivity to 12 image-corruption types across 6 tasks [241], while EarthShift evaluates changes in geography, time, scale, sensor, and data source and reports average out-of-distribution degradation of 15–20% across 8 geospatial foundation models and 11 tasks [328]. Although these studies evaluate model features, their protocols can also test released embeddings. Reliability claims also require documentation of data gaps, supported temporal and spatial scales, version history, and validation outside the regions used to fit downstream predictors.

7.1.4. Geographic Equity and Representational Bias

Planetary coverage does not imply uniform representation quality. Pretraining collections use different spatial sampling strategies: MMEarth balances 1.2 million locations across 14 biomes [62], whereas SSL4EO-S12 samples approximately 250,000 locations around the world's 10,000 most populated cities and removes most patch overlap [96]. Kaur et al. [329] report that the geographic and spectral composition of pretraining data affects downstream performance, with the preferred sampling strategy depending on the model and target distribution. Coverage maps and sample counts should therefore be accompanied by distributions over biome, sensor conditions, acquisition time, and relevant target populations.

MMEarth-Bench reports lower performance under geographic transfer across five environmental tasks and 12 modalities [330]. EarthShift finds that robustness varies by shift type, with relatively small temporal losses and larger losses under sensor and geographic shifts [328]. Comparisons across climate, data availability, and socioeconomic conditions require the same tasks, spatially separated labels, identical downstream protocols, and enough observations in each group to separate representation quality from label noise and target prevalence.

Observation conditions also vary geographically. Persistent cloud, seasonal snow, illumination geometry, topographic shadow, and sensor revisit patterns alter which measurements are available at a location [331]. These factors can create distribution shifts, but their effect on embedding quality must be measured rather than inferred from geography alone. Multimodal products may reduce dependence on any single sensor, and a recent comparison found that combinations of AlphaEarth, TESSERA, GeoCLIP, and SatCLIP improved on the best individual embedding in four of six evaluated tasks; the gains remained task- and location-dependent [179]. Regional evaluation should therefore report source availability and test both individual and combined embeddings under the same labels and splits.

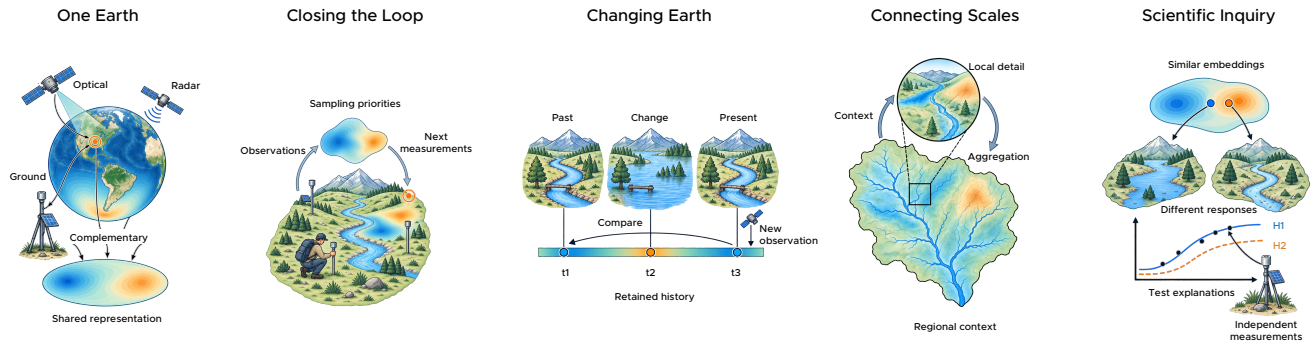


Figure 14: Earth embeddings for observing and understanding a changing Earth.

7.2. Future Perspectives

Beyond the potential research directions outlined above, future work should consider five broader perspectives on Earth embeddings, as illustrated in Fig. 14. These perspectives explore how representations could connect observations, accumulate geographic knowledge, and support scientific investigation.

7.2.1. One Earth

Earth observations provide partial measurements of a common, evolving world. Their differences reflect both the properties being measured and the spatial support, timing, and physical sensitivity of each observation. This suggests learning representations of the underlying geographic state rather than organizing them solely around individual sensors. That state is a collection of spatially and temporally varying properties, only some of which can be inferred from a given set of observations. Multi-view representation learning provides a theoretical basis for identifying shared latent factors under explicit assumptions about partial observability [332]. For Earth embeddings, the research question is which properties can be estimated consistently across observations and which require complementary measurements. A common representation should preserve both shared and source-specific information, rather than force every modality into an identical description. Testing correspondence under missing observations and across scales would establish which information remains comparable. The existence of one Earth motivates this direction, but does not establish a unique or universally sufficient latent vector.

7.2.2. Closing the Loop

Embeddings could help determine what should be observed next. Combined with existing field measurements, they could describe where current samples are representative, where predictions remain uncertain, and where additional measurements are likely to improve inference. Information-based sensor placement already provides methods for selecting observations that reduce uncertainty at unmeasured locations [333]. Extending this principle to Earth embeddings would produce a spatial field of expected observation value, from which sampling probabilities or sensor locations could be chosen subject to cost, accessibility, and geographic coverage. Each new batch of measurements would update the predictive model and the next sampling decision. The selected locations should account for information shared among candidate sites, rather than simply take the largest individual uncertainty values. Field trials should compare this strategy with spatially balanced and conventional

sampling at matched budgets, using independent observations for evaluation. Such a feedback between representation and measurement could improve data collection in poorly sampled regions while avoiding repeated sampling of already well-characterized conditions.

7.2.3. A Memory of a Changing Earth

Long-term use requires representations that accumulate observations without losing the ability to compare the past. Two locations with similar present conditions may have followed different trajectories, and those histories can matter for subsequent change. Future embeddings should therefore distinguish persistent background from short-lived variation and retain the timing and sequence of informative changes. This calls for updates that incorporate new observations while preserving historical comparisons, rather than treating each annual release as an unrelated description. Backward-compatible representation learning offers a method for retaining comparability during encoder updates, although its demonstrated use in visual retrieval does not establish temporal validity for Earth observation [334]. Separating real change from encoder drift will require overlap observations, stable references, and tests of both change sensitivity and historical consistency. Selective updates could also reduce repeated computation, provided that observations omitted from an update do not conceal important changes.

7.2.4. Connecting Scales

Geographic understanding depends on how local properties combine into larger structures and how broader conditions influence local behavior. Embeddings could provide a common basis for these comparisons if they preserve spatial organization as well as local content. Averaging vectors may summarize composition while discarding adjacency, connectivity, and arrangement; areas with similar average properties can consequently behave differently. Scale-aware pretraining already addresses relationships among observations at different resolutions [12], while pooling studies show that spatial aggregation affects downstream performance [178]. A further direction is to learn how local representations compose into regional descriptions while retaining the interactions relevant to the question. For example, describing a catchment requires the organization of terrain and vegetation, not only their average attributes. Comparisons between directly encoded regions and aggregated local representations could test which properties survive changes in spatial support. This would connect resolution

choices to geographic reasoning rather than treat resolution only as a storage or mapping parameter.

7.2.5. Embeddings for Scientific Inquiry

Beyond estimating known quantities, embeddings could help researchers identify regularities, investigate anomalies, and formulate hypotheses for independent testing. Dimension-wise associations with environmental variables provide one starting point for interpretation [315], but scientific use also requires examining how such associations change across conditions. Disentangled and physics-informed learning offer ways to introduce explicit assumptions [335–337]; their value depends on whether those assumptions fit the observations and research question. Hybrid approaches combining learned representations with physical process models provide a broader basis for this direction [338]. For instance, contrasting responses among otherwise similar regions could identify missing observations or competing process explanations worth investigating. Embeddings would organize the comparison, while independent measurements, process constraints, and study design would determine which explanations remain plausible. Evaluation should therefore examine whether representations help discriminate hypotheses and guide follow-up observations, alongside predictive accuracy. In this setting, Represent, Relate, and Reason describe a continuing exchange between what is observed, how observations are connected, and what can be learned from them.

8. Conclusion

Earth embedding research now includes reusable image encoders, coordinate-based models, and precomputed vector collections [14, 34, 38, 70, 101]. Released products allow users to download or query vectors without repeating feature extraction over large image archives, but their value depends on the information retained and the scale of the intended analysis. Community benchmarks and application studies report performance that varies with the task, available labels, region, and evaluation protocol [122, 177, 184, 236, 278, 291, 312]. Our experiments similarly found that geometric similarity did not determine predictive accuracy and that retaining more PCA components of flattened patches did not consistently improve prediction. Reliable reuse therefore requires clear data specifications, stable access, and evaluation of transfer and compatibility across updates [29, 328, 330].

This survey examines Earth embeddings through three connected questions: what they represent, how they relate geographic information, and how they support reasoning. We review their data and learning foundations, compare models and released products, and examine design choices, access infrastructure, benchmarks, and applications. Experiments complement this review by comparing embedding geometry, classification, regression, and sensitivity to dimension. Together, these analyses connect the development of embeddings with their practical use and the geographic information they make available for further study.

Open challenges concern interoperability, spatial and temporal detail, interpretability, updating, geographic equity, infrastructure, evaluation, and trustworthy use. Beyond addressing these limitations, future research can investigate

how complementary observations describe one Earth, how embeddings inform new observations, how successive representations preserve a history of change, and how information connects across scales. Their role in scientific inquiry also deserves attention: embeddings could help identify patterns and formulate hypotheses for testing with independent measurements and process knowledge. These directions would extend their contribution from reusable features for prediction to representations that support continuing observation and scientific investigation.

CRedit authorship contribution statement

Yongchuan Cui: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Software, Visualization, Writing - Original draft. **Keli Shi:** Investigation, Validation, Writing - Review & Editing. **Shunlin Liang:** Conceptualization, Supervision, Validation, Writing - Review & Editing.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

Data availability

The data sources used in this survey are described and cited in the article. Additional materials supporting the comparative analyses are available from the corresponding author upon reasonable request.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used GPT-6 solely to aid or polish writing and to generate graphical elements for schematic figures. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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