Earth Embeddings: Towards AI-centric Representations of our Planet

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Abstract

This paper presents a new perspective for the flexible and efficient representation of geospatial data, tailored to and empowered by AI: *Earth embeddings.* Earth embeddings provide a unified and accessible vector representation of local geographic characteristics. They fuse different geospatial data sources across time and space, compress highly-correlated raw geospatial data into one dense representation, can be used to guide interpolation between data observations, and can serve as a universal location token for foundation models. This provides a powerful alternative to existing geospatial workflows that rely on heterogeneous data, hard-to-acquire expertise, and significant computation by the user: embeddings instead provide convenient representations, easily adaptable for numerous downstream tasks. We posit that Earth embeddings redefine geospatial analytics, transforming it from fragmented, task-specific modeling into a coherent, generalizable framework for AI. We approach this from both the users' and developers' perspectives, outlining a path for how the rapidly developing technology of Earth embeddings can reshape the way we store, represent, and use geospatial data, evidenced by recent research charting initial directions. We call on Earth embedding users and developers to align methodological and applied development and deployment within an interdisciplinary, open-source oriented research community.

1 Introduction

Geospatial data are discrete snapshots acquired to capture information about the conditions and continuous dynamics of our planet. These data range from Earth observation or meterological imagery captured by hundreds of in-orbit satellites to human-generated social media posts and photos, tagged with geospatial metadata. At first glance, these data sources may appear completely different, but they share a fundamental commonality: all geospatial data are *indexed in space and time.* Just as a satellite image provides information about a particular geographic area at a particular point in time, so does a geotagged image or text description uploaded to point-of-interest databases like Open Street Map or social media platforms. Geospatial data are widely used to support modeling and decision making: Notable examples include disaster response [24], weather forecasting [31], transportation management [70], forest and wildfire management [62], water quality management [15], and disease spread modeling [7].

To process the ever-growing amounts of geospatial data, machine learning and artificial intelligence (AI) techniques have risen in popularity among geospatial practitioners, such as environmental scientists studying ecological changes [46], data scientists building flood maps at insurance

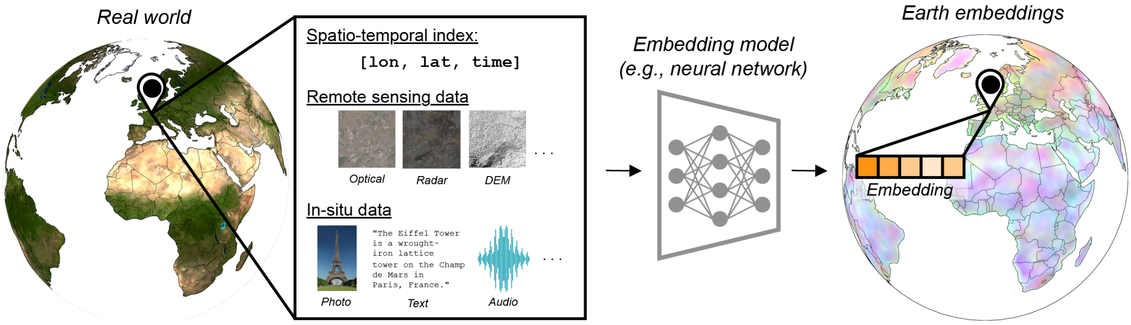

Figure 1: The Earth is observed by diverse geospatial modalities—such as satellite imagery, sensor networks, and geotagged social media posts captured at specific times and locations. These multimodal data streams serve as inputs to AI models that learn to represent the state of the Earth in compact, unified forms known as Earth embeddings. Earth embeddings encode information for all locations in a lightweight and flexible format, enabling downstream analyses across domains, from terrestrial ecosystems to ocean dynamics.

companies [26], or urban planners forecasting travel demand [19]. Enabled by the key strengths of AI methods to represent complex data in flexible and generalizable formats, ***Earth embeddings* are vector representations of geospatial data at specific locations in space and time** (see Figure 1) that allow us to capture the similarities and differences between locations according to their local features. They are produced by ***Earth embedding models***, which process data inputs into the vector shape of embeddings. The distinction between ***Earth embedding models*** which produce the ***Earth embeddings*** themselves is important throughout the paper, and we explain it in detail (and formally) in the box below.

Formal definition of *Earth embeddings*

Earth embedding vectors *emb* are produced by a family of embedding functions E that map continuous location inputs (i.e., longitude, latitude with optionally elevation, and time) into a d-dimensional vector space:

$$E : (location) \rightarrow emb \in \mathbb{R}^d \ . \tag{1}$$

E, also referred to as *embedding models*, come in two forms: First, as *explicit models*, extracting embeddings from raw data (e.g. satellite imagery) associated with a location ($emb \sim E_{explicit}(data_{location})$). Examples for this include vision models combined with a global satellite image database. Second, as *implicit models*, returning embeddings from only location inputs ($emb \sim E_{implicit}(location)$). Here, location-specific information is stored directly withing the weights of e.g. a location encoder network $E_{implicit}$. This distinction is explained in detail in Section 4.1.

AI embeddings represent specific concepts contained within the data they are based on; words or images and in the case of Earth embeddings: any geographic data. Over the past decades, fields such as natural language processing (NLP) and computer vision (CV) have developed specialized neural network architectures to efficiently embed text and image data, including methods specific to Earth observation images.

The origin of "embeddings" in Natural Language Processing (NLP)

The concept of embedding spaces has its modern origins in natural language processing, where word embeddings techniques like Word2Vec [40] and GloVe [45] revolutionized the field by capturing semantic relationships between words. For example, in a word embedding space, the vector difference between "kitten" and "cat" is similar to the vector difference between "puppy" and "dog", illustrating how embeddings can capture meaningful semantic relationships. This idea of "distance" between words is also used in large language models (LLMs), which leverage embeddings to map similarity of words closer in embedding space.

Similar to how text or image embeddings capture semantic relationships, Earth embeddings map places and times that share similar properties closer together in embedding space. For example, an embedding of urban New York City may resemble that of urban Delhi more than that of rural Arkansas, reflecting functional rather than geographic similarity. Likewise, embeddings across time capture temporal variability—summer and winter embeddings in equatorial Costa Rica may be nearly identical, while those in highly seasonal Alaska may differ strongly—enabling quantitative comparison of environmental change and similarity across space and time.

Early versions of Earth embeddings are already enabling efficient, real-time monitoring of our planet and reducing barriers to accessing powerful geospatial analytics. Recent years have, for example, seen the publication of Earth embeddings based on satellite imagery [51, 29, 10], social media images [67], and demographic data [2]. The applications of Earth embeddings include image geo-localization [32], poverty mapping [57], detecting small-scale and artisanal mining [8], and satellite image super-resolution [44]. These applications also drive an increased commercial interest in the space, highlighted by a number of startups with Earth embeddings at the center of their product securing funding and e.g., Google Earth Engine launching their first Earth embedding product [5]. This leads to a rapidly growing, yet heterogeneous, ecosystem around Earth embeddings, with an increasing number of models and initiatives that share common objectives like data compression, fusion, interpolation, or increasing interoperability between models.

Current efforts to develop and apply Earth embeddings are often not coordinated and lack a clear, community-sourced research agenda. One sign of this is that existing Earth embedding models are implemented in fundamentally different ways: many recent efforts focus on developing geospatial foundation models (GeoFMs)—such as Clay [1], Prithvi [61], Galileo [64], Smarties [60], and DOFA [72]. Embeddings are more of a byproduct of these models, which are targeted at fine-tuning for specific downstream applications, such as image segmentation or classification. Recent foundation models, including Alpha Earth Foundation [5] and Tessera [16] focus explicitly on embeddings as a dedicated output and provide them as pre-computed *embedding databases*, either directly downloadable on e.g. Google Earth Engine, or available via an API interface. Simultaneously, a new class of pre-trained *implicit neural representation* models is emerging, such as GeoCLIP [67], SatCLIP [28], SINR [9], and Climplicit [14]. These models store geospatial information directly in their neural network weights, take location information (e.g. longitude, latitude and time) as inputs, and can be seamlessly integrated in existing deep models for geographic conditioning, image retrieval, or geo-sematic search and retrieval.

Earth Embeddings and Geospatial Foundation Models (GeoFMs)

Geospatial foundation models (GeoFMs) is the term used for large, multimodal deep learning systems developed for general purpose use and trained on diverse geospatial datasets [75] that ingest raw data (e.g. remote sensing imagery, climate records, socio-economic layers). Earth embeddings can be produced by many of these models, but are more a byproduct of GeoFMs, which are often meant to be finetuned for specific downstream tasks such as satellite image segmentation. They are one way–but not the only way–to produce Earth embeddings. In essence, GeoFMs are large-scale modeling and learning frameworks, whereas Earth embeddings constitute the interoperable, location-indexed data outputs that can be stored, shared, or queried independently of the model that created them.

While the increased attention and the emerging potential of Earth embeddings clearly demonstrate a need for further development, this conceptual heterogeneity in approaches impedes joint community building efforts and the organization of shared research directions that capture both the developers' and users' needs. Hence, harmonizing and formalizing Earth embeddings is necessary to unlock the emerging potential of Earth embeddings for both developers and end-users of

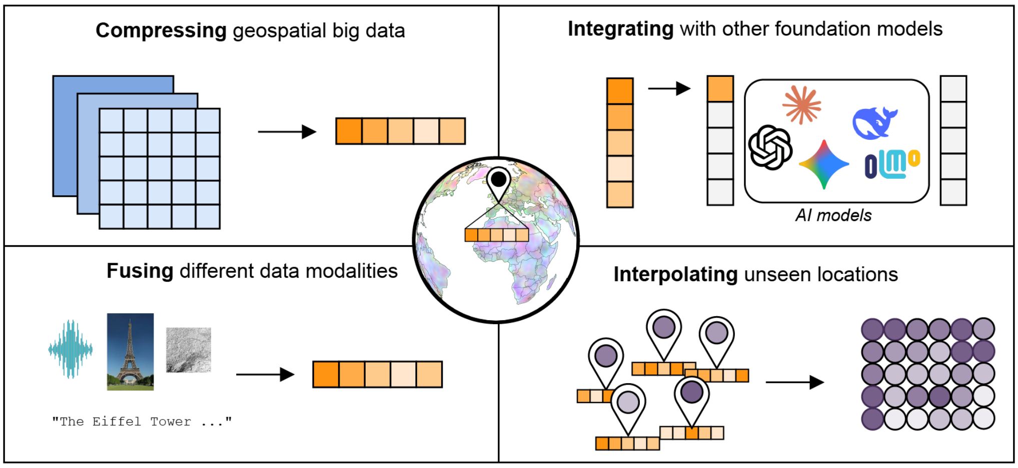

Figure 2: Earth embeddings provide different functions: (1) They compress high-dimensional data into a lower-dimensional vector format. (2) They fuse together different geospatial data modalities, from different types of images to text and tabular data. (3) They can interpolate to unseen spatiotemporal locations, where raw data is missing. (4) They are interoperable with other AI foundation models, such as LLMs, through aligned embedding spaces.

geospatial AI systems.

This article provides this harmonization with concrete calls-to-action mapping out a research agenda for Earth embeddings. We posit that Earth embeddings will emerge as the dominant format of geospatial data in the AI age, enabling efficient deployment in critical use cases and connecting the current heterogeneous landscape of geospatial data modalities and formats. In the remainder of this paper, we present a unifying framework on Earth embeddings, defining their central functions in section 2. We then outline specific application use-cases and goals for methodological development, capturing both user and the developer perspectives in sections 3 and 4. Finally, in section 5, we describe existing considerations and future steps to facilitate effective community building to advance a coherent, AI-native foundation for the next generation of geospatial analysis.

2 The Central Functions of Earth Embeddings

Current Earth embedding approaches are designed to serve one or more of four central functions, as illustrated in Figure 2:

1. **Compression:** Earth embeddings can be interpreted as data compression, as they distill high-dimensional, location-specific, multi-modal data such as satellite images or geotagged text data into a smaller vector format [18]. While this compression loses some information and varies with training method, geospatial data's redundancy and spatio-temporal patterns make it easier to compress effectively. Some work in this area exists already, for example on the compression of climate data within deep networks [22]; however, dedicated compression models are needed, as current embedding models produce correlated embedding vectors [65] with a comparatively low intrinsic dimension [49].

2. **Fusion:** Earth embeddings fuse different geospatial data modalities–e.g.,images and text data–into a joint embedding space, leveraging their shared location and time information. For example, Earth embeddings trained on multi-modal geospatial data may represent both an optical satellite image and social media posts associated with a given location. This allows them to provide a more holistic location representation for general-purpose use. For instance, current multi-modal remote sensing foundation models like MMEarth [43], DOFA [72], Galileo [64], or Smarties [60] fuse multiple data sources into feature embeddings representations at one location.

3. **Interpolation:** Some Earth embeddings–those obtained via location encoders–are available in continuous space and time. They are based on *neural implicit representations* (see section 4.1), which learn a smooth surface in embedding space by interpolating between seen training locations. As such, any location (in continuous space and time) may be queried from location encoder models like SatCLIP [29], SINR [9], or GeoCLIP [67], even if it was not present in the training data. This returns an Earth embedding representing an interpolation of nearby locations with available training data.

4. **Interoperability:** Earth embeddings can be used to inject geospatial contextual information into other AI foundation models. They can be seen as interoperable "location tokens" (Figure 2), allowing users to interact with Earth embeddings using text prompts directly, asking queries such as "What are similar locations to the location (lon, lat)?" and to augment current text-based assistants and foundation models efficiently with location information. An analogous approach is to exchange pre-trained implicit embedding models that are becoming increasingly integrated in other deep frameworks, for instance for image synthesis [55] of geography-aware super-resolution [44], to facilitate interoperability between models through a joint location context.

3 User Perspectives: Earth Embeddings Unlock New Use-cases and Expedite Existing Ones

Earth embeddings provide users with a compact way to access the multifaceted contextual information encoded in geospatial data. From a user's perspective, Earth embeddings function as a versatile input that can be easily plugged into existing or new workflow, often reducing data-processing demands while improving model performance. Because general-purpose Earth embeddings are designed for broad downstream use, they allow practitioners to enhance familiar tasks and explore entirely new applications (Figure 3). Below, we outline key ways in which users can employ Earth embeddings for prediction, conditioning, simulation, and search:

1. **Direct prediction:** Earth embeddings can be used as the input to predictive models that learn spatially distributed outcomes, in much the same way that raw data would be input into AI models. Examples include temperature, species presence, or population density prediction across space [12, 9, 29, 2, 71]. Earth embeddings also have shown to be competitive or even outperform hand-crafted specialized features with random forests in applications like tree species identification [23]. Since Earth embeddings already represent (often major) data pre-processing, they often allow for learning with smaller predictive models that one would need if using the raw data (e.g. satellite data, text data) as input [51]. Additionally, in contrast to traditional geospatial analytics and GeoAI workflows, Earth embeddings remove the need to query databases of raw data, which can significantly ease storage and accessibility requirements.

2. **Geographic conditioning:** Earth embeddings can serve as "geographic priors" which provide geospatial context to downstream applications. Earth embedding models can be integrated as auxiliary module in an existing workflow, conditioning GeoAI models to the specific area of interests (e.g., continents), resulting in location-aware prediction models [64, 74, 67]. Strategies employing Earth embeddings for geographic conditioning have been used to improve classification of animal images [33, 37] and to generate synthetic remote sensing imagery [55, 44, 27]. Earth embeddings can also serve as auxiliary data in settings with limited labels and in the face of domain shift [48], helping to boost performance. These successes are particularly inspiring as research into novel GeoAI architectures and training procedures that incorporate Earth embeddings as auxiliary contextual information is still in its infancy.

3. **Data synthesis & simulation:** Earth embeddings can be integrated in generative models to synthesize and simulate Earth processes and can serve as a building block for improved simulators of dynamical processes on the Earth. This forward-looking use case for Earth embeddings aims to incorporate not only observational data, but to also integrate scientific knowledge about physical processes, such as atmospheric dynamics. While no such systems exists to date, Earth embedding conditional generative models such as [55] may be expanded into simulators,

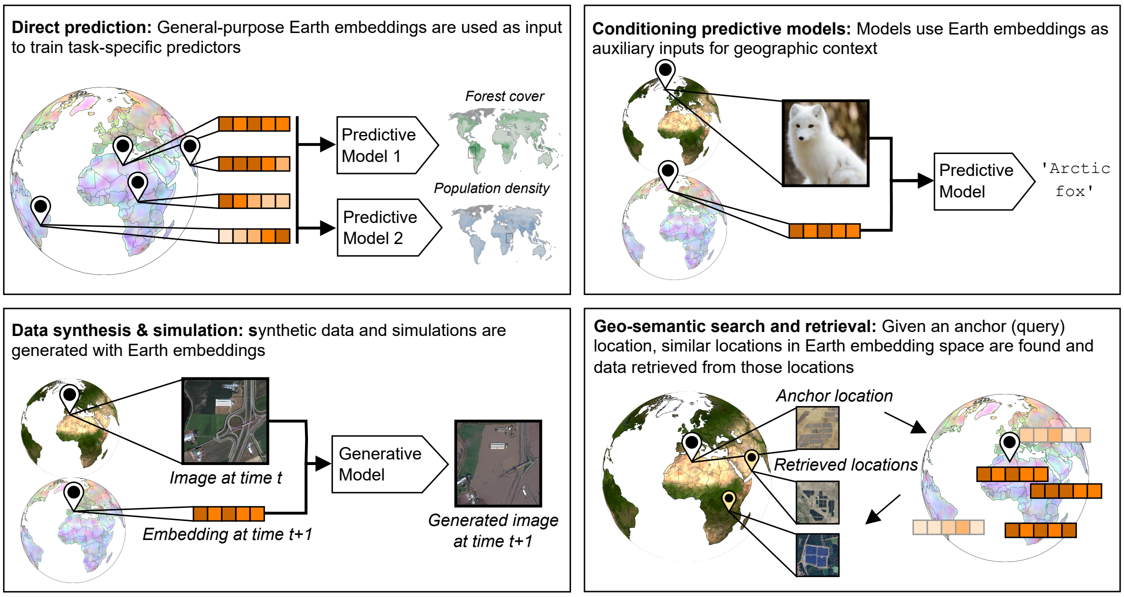

Figure 3: Earth embeddings can be used for diverse applications: For example, **a)** Earth embeddings may be passed through a learned prediction model to generate wall-to-wall dense predictions of forest cover, population density, or other outcomes across the globe. They **b)** may be used as auxiliary or conditioning context in other predictive tasks, such as animal species classification. Similarly, they **c)** could be used as contextual input to a generative model, enabling image synthesis reflecting certain ground conditions, such as flooding. Lastly, **d)** Earth embeddings can be used to query similar locations (i.e. find other locations with solar farms) around the world by matching similar Earth embeddings. As Earth embeddings are lightweight, integrating them in existing models in any of these examples can be done quickly, without any need for processing or analyzing raw data.

while spatio-temporal location encoding methods may be tested for forecasting and scenario generation [6, 14, 22].

4. **Geo-semantic search and retrieval:** Earth embeddings can also be used for fine-grained, semantic search. They enable a "queryable Earth", acting as a lookup table for efficiently identifying specific concepts of interest, such as solar farms, at scale: Knowing the Earth embedding of a satellite image containing a solar farm, we can conduct a similarity search among all other available Earth and return locations with high similarity scores [34]. Furthermore, Earth embeddings aligned with text embedding spaces allow for text-based queries and retrieval [73, 67, 38, 11]. Due to their small size, Earth embeddings can even unlock global search, which is computationally infeasible with e.g. raw satellite imagery.

While general-purpose Earth embeddings are not tailored to any specific application or use case, they are fundamentally constrained by the raw data they are based on. SatCLIP Earth embeddings [29], for example, which are based on multi-spectral satellite imagery, may only represent phenomena that are captured by large-scale overhead imagery, such as climate zones or forest coverage, but not, for example, ocean currents. Conversely, GeoCLIP [67] embeddings are based on ground Flickr images, and naturally capture patterns that are visible from a street-view. Futhermore, both SatCLIP and GeoCLIP–as examples of implicit neural representations (detailed in section 4.1)–provide large-scale, low-resolution embedding fields, while explicit feature extraction approaches like AlphaEarth Foundations [5] or Tessera [16] provide much higher resolution embeddings, as they process the underlying geolocated raw data.

With strong evidence that Earth embeddings can improve existing GeoAI workflows and unlock new use-cases, it is critical to align research directions with user needs. We synthesize several steps along this path, highlighting how the user and research community can work together to improve the responsible and effective application of available Earth embeddings models and data products in the call to action below:

Call to action: Advancing analyses and applications with Earth embeddings. While Earth embeddings show clear potential to push the frontier of geospatial analysis, there are several bottlenecks hindering their broader adoption into unexplored areas of use. Here we highlight the most pressing application-centric research gaps for advancing the utility of Earth embeddings for public and private sector use:

- **Evaluating and benchmarking Earth embeddings:** In order to advance the capabilities of Earth embeddings, we must be able to comprehensively measure and benchmark their performance on a wide range of use-cases. Expanding on current benchmarks that measure the capacity of Earth embeddings to capture specific quantities (e.g. forest cover or population densities) [66, 71], more varied types of evaluations are needed. Future evaluation frameworks could test Earth's embeddings' ability to capture interactions of different planetary processes, such as the connection between climate change and human migration, or their utility for search and retrieval. In contrast to many existing GeoAI benchmarks that are primarily for image inputs, good benchmarks for Earth embeddings will focus on challenges of prediction when location and time references are used as inputs [50]. This could include evaluation suites that assess: spatial interpolation and extrapolation, performance under different degrees of spatial bias in the labels, and performance across spatiotemporal scales.

- **Explainable and interpretable Earth embeddings:** Embeddings obtained by current deep networks often lack interpretability [52]. That is, we don't know which part of an Earth embedding represents a given ground condition, such as a tree or a building–or if the embedding captures these ground conditions at all. This impedes our ability to use Earth embeddings to understand interactions or explore drivers of variations, such as seasonal versus geographic distances. Black-box methods complicate decision making [53]–a general challenge with modern AI. As such, improving Earth embedding interpretability (e.g., understanding which input modality contributes to which part of the Earth embedding) can help to make them more attractive for integration into decision-support and real-world deployment settings. Data provenance and metadata reporting standards are further key factors in supporting interpretability efforts.

- **Learning planetary processes with Earth embeddings:** It has long been a dream of geospatial researchers to create a digital version of our planet, a "digital twin" [21]. Earth embeddings may offer a step towards this dream: as they learn to fuse and compress multi-modal geospatial data into an succinct representation of the planet within their vectors, Earth embeddings contain information necessary to understand the interconnections and dependencies of different planetary processes–from seasonal weather to bird migration and land-use change. For example, the Climplicit Earth embeddings that implicitly encode climate data [14] are shown to be competitive models for ecological tasks like species distribution modeling and and plant trait regression, underscoring the relatedness of data from seemingly very different domains.

4 Developer Perspective: Learning to Embed our Planet with AI

From a developer's perspective, the central challenges of Earth embeddings are how to learn and serve them effectively. Developers must choose between fundamentally different strategies for generating embeddings–explicit feature extraction or implicit neural representations–as well as between delivery interfaces such as embedding models or embedding databases. This section provides a unified conceptual view of these design choices, outlining how Earth embeddings can be built, stored, and accessed, and outlines objectives for future methodological advances.

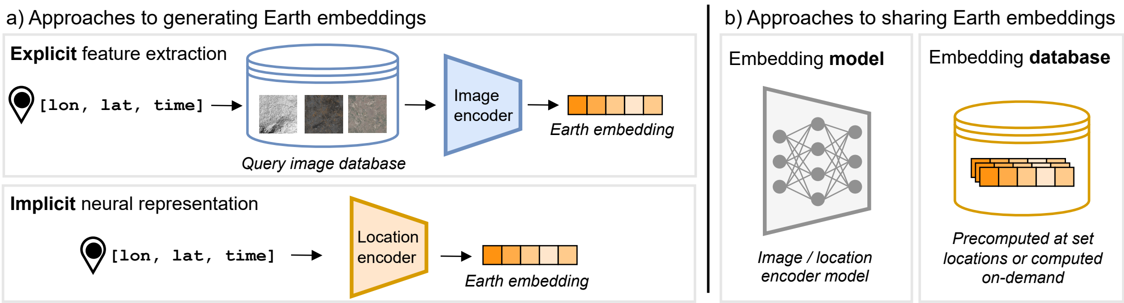

Figure 4: There are different methods for obtaining Earth embeddings (left side) and interfaces for accessing them (right side). Explicit encoding approaches embed data from geospatial databases (indexed in space and time) using e.g. a GeoFM. The resulting pre-computed embeddings can be stored in a new embedding database which can be accessed using location queries at inference time. Both the GeoFM used for producing embeddings and / or the resulting embedding database may be released. The implicit encoding approach directly encodes geospatial information within the weights of a location encoder network. The location encoder serves both at "model" and "database" and, once released, can also be queried simply using location queries.

4.1 Earth Embedding Models: Explicit Feature Extraction versus Implicit Neural Representation

To capture the characteristics of a given input location, Earth embeddings capture information from geospatial data sources such as satellite imagery and social media data. The Earth embedding models producing them can be split into two categories, outlined in Figure 4: encoding data sources explicitly (fig. 4, left-top) or implicitly via neural network weights (fig. 4, left-bottom).

Explicit feature extraction methods aim to directly embed geospatial data into a vector representation. There is a breadth of research on feature extraction of Earth observation and spatio-temporal data, most recently using neural network architectures and learning objectives from computer vision or time series analysis [64, 5, 16, 10, 51]. Since the raw data that these models encode is always geolocated, their embeddings are inherently linked to specific locations and times (e.g. the spatial extents and time stamp of images), as a function of the content of the inputs. An early explicit embedding approach, MOSAIKS [51], demonstrates that embeddings of satellite imagery extracted with random convolutional features can be used for direct prediction of a variety of economically and environmentally-relevant downstream tasks. Similarly, deep learning models trained with self-supervised contrastive learning trained on BigEarthNet [59] or SSL4EO [68] can be also seen as explicit embedding models that extract deep embedding features from Sentinel-2 satellite imagery. Most recently, multi-modal foundation models like DOFA [72], Smarties [60], or MMEarth [43] can extract joint embeddings from multiple remote sensing and meteorological modalities. These larger models are still often open-source but are typically resource-intensive to deploy. As such, embeddings are increasingly pre-computed and made available via embedding databases like AlphaEarth [5], Tessera [16], or MajorTom [10], which we detail in section 4.2. Embedding vectors produced by explicit embedding models are fine-grained and typically produced at high native resolution of the underlying data. This makes them well-suited for geo-sematic search and retrieval and detailed direct prediction of visual tasks like land cover and land use classification, but less-suited for geographic conditioning and data synthesis. Explicit feature extraction approaches can produce embeddings at either the patch level (i.e. representing a whole image or image patch), such as Clay [1] or MMEarth [43] or the pixel level, such as AlphaEarth [5]. This difference further informs their specific applicability for downstream use.

Implicit Neural Representations are an alternative approach that store Earth embeddings within the weights of deep networks. They are based on location encoder networks [35]–models that take geographic coordinates as inputs and inspired by approaches in computer vision [58, 41].

They can be trained in a supervised fashion to reproduce a given location-specific value (e.g. temperature) and effectively interpolate between training points. Typical applications include the estimation of sea ice thickness [6], housing prices [54, 37], or species presence probabilities [9, 33, 20]. SINR [9] has demonstrated that even in a supervised setting, features from intermediate layers encode general semantic information following topographic and biome-specific boundaries– and, as such, could serve as Earth embeddings.

When trained in a self-supervised fashion through geolocalization, location encoder models return embedding vectors that capture the patterns that make a particular location unique, which makes these embeddings potentially effective for a wide range of applications. Examples of recent studies include GeoCLIP trained on geolocating ground-based Flickr images [67], or SatCLIP [28] and CSPNet [36] trained on overhead satellite imagery. These models are usually light-weight, open-source and can be easily downloaded and integrated into existing workflows. They typically provide embeddings at a lower resolution suitable for general geographic conditioning, data synthesis and direct prediction of larger-scale direct prediction tasks like air quality or disease mapping, but are not optimal for retrieval or fine-grained tasks like land cover classification.

Hybrid approaches combine explicit feature extraction with implicit neural representations. A straightforward but effective approach is concatenating high-resolution explicit feature embeddings with low-resolution implicit embeddings. Such an approach, for example, won the NeucoBench challenge [66] at the 2025 CVPR Earthvision workshop. A more complex strategy involves a retrieval augmented generation (RAG). For example, the RANGE model [12] dynamically queries suitable high-resolution explicit image features using implicit embeddings as query. These examples highlight that hybrid approaches can achieve good results in practice, though possibly at the cost of additional methodological complexity.

4.2 Earth Embedding Interfaces: Embedding Models versus Embedding Databases

For widespread adoption, the interface through which users access Earth embeddings determines how easily these embeddings can be used and integrated into downstream applications. This holds regardless of whether embeddings are produced by "explicit" or "implicit" approaches (section 4.1). Two conceptually distinct interfaces have emerged: releasing embedding models (fig. 4, right-top) directly and releasing embedding databases (fig. 4, right-bottom). Each enables different forms of access, affords different degrees of flexibility and scalability, and introduces its own constraints.

Embedding models deliver the model as code and parameters. More specifically, the user must download the model implementation with its trained parameters and infer the embeddings for given coordinates on an appropriate device (optimally, using a GPU). For the implicit approach, only the coordinates are needed as input, while an explicit feature extraction model additionally requires the imagery (or other applicable data) at the corresponding the location to be collected, loaded, and pre-processed into model-compatible inputs. This complexity requires users to bring some familiarity with the principles of deep learning and the underlying data and software implementations, as well as sufficient resources, in terms of the computation time, memory, and type of device. When these requirements are met, this interface offers flexibility: the explicit embeddings can be extracted from any raw self-compiled dataset, while implicit embeddings can be queried for any new point location. The underlying model can be analyzed through interpretable methods like Grad-CAM [56] and altered by fine-tuning it to a given use case, which often increases the final downstream accuracy. Sharing pre-trained models is a common practice across the machine learning community with open-source code and open-licensed parameters available to download on public platforms like GitHub or HuggingFace. Examples for this approach include implicit approaches like SatCLIP [29], Climplicit [14] and GeoCLIP [67], or explicit approaches like AnySat [3], MMEarth [43], Galileo [64], and MOSAIKS [51].

Embedding databases deliver the pre-computed model outputs as a database of static embedding vectors corresponding to locations, which can be built on existing geospatial data infrastructure and served from storage or over a network protocol. The storage format could be as simple as tabular data on disk or as sophisticated as global-scale backend systems like Google Earth Engine, and in the same fashion the protocol could provide a simple exchange of coordinates for vectors or a sophisticated set of options over spatiotemporal regions of interest. Creating and hosting Embedding databases require storage capacity or network bandwidth, which can incur substantial costs on the developer's side, which we detail more in section 5. However, for the users' side they come with the clear advantage in that they do not require deep learning expertise or computation of the underlying model by the user. This makes embedding databases applicable to a broad user base of scientists and practitioners from a diversity of disciplines. However, this accessibility comes with limitations: given the static nature of the pre-computed embeddings, it is not possible to run, alter, or inspect the underlying model or its parameters themselves. While Embedding databases are easy to adopt, extending them is often impractical or impossible. Embeddings-as-data is an emerging interface, popularized by AlphaEarth [5] built on prior pioneering works like MOSAIKS [51] and Major TOM [10]. In practice, embedding databases are mainly relevant for explicit feature extraction models that are often large and computationally expensive to run, while implicit embedding representations are comparatively small and served as embedding models.

Call to action: Challenges and opportunities for improving Earth embeddings. There are several open methodological challenges that motivate future research to improve the utility of Earth embeddings:

- **Model capacity:** The embedding model capacity required for producing effective yet informative Earth embeddings remains an open research problem: Current implicit encoding models (i.e., location encoders) are few-layer multi-layer perceptrons with relatively few parameters. This leads to limitations in their capacity for storing geospatial patterns. Future advances could, for example, take inspiration from natural language processing, where transformers with several blocks of positional embeddings and feed forward layers have proven highly effective in storing large amounts of text data [25]. Similarly, it is unclear whether explicit feature extraction models (e.g. GeoFMs) have reached sufficient capacity to model the full breadth and expressivity of Earth data. An alternative approach to solve this challenge could involve hybrid approaches between precomputed embedding databases and implicit neural embedding representations: for instance, Dhakal et al. [13] used location encoders with pre-combined embedding fields for more fine-grained embedding retrieval.

- **Spatio-temporal heterogeneity:** Current Earth embedding models have statically defined parameter spaces, with the same number of parameters for every point in space and time. Geospatial information, however, can be complex in one location, but sparse in another. For example, while a satellite image over New York City and over the Pacific Ocean might be of the same size, the former is much more information dense than the latter. Future Earth embeddings models should be able to reflect this by varying their capacity based on location, otherwise, a globally trained model might smooth over a specific heterogeneous region leading to poorer local performance. Similarly, different sensors and data modalities might be more or less important in different areas of the world. For example, radar data might be more important in areas with high cloud coverage or in arctic regions during winter, when sunlight is scarce. Adaptations in positional embeddings or distinct deep network architectures might be taken from advances such as adaptive coordinate networks in computer vision [39].

- **Data curation and scaling:** The training and downstream usage of Earth embedding models need to be explored with respect to their data–and how additional data improves performance or not. These analyses should be conducted along the different dimensions of geospatial data: space, time and modality. Beyond intuitive guidelines, such as that Earth embeddings should be trained on data covering all regions of the world and all months of the year, the marginal benefits of e.g. adding one more spatial location, one more timestep, or one more sensor or modality are emerging as a research question [47] but remain largely unanswered. The discussion on data importance and scaling laws is directly related to that of *spatio-temporal heterogeneity* above, as it might be important to "overrepresent" heterogeneous areas in the training data compared to homogeneous areas [4], or to re-sample or re-weight the different dimensions according to better align with the spatial regions, temporal intervals, and input modalities of interest.

- **Learning objective:** The learning objectives used to train models that produce Earth embeddings remain largely unexplored. To date, location encoder approaches have largely relied on supervised training and CLIP-style contrastive learning (e.g., geolocalization). Models used for explicit embedding generation, often large-scale convolutional or transformer models, often simply adapte learning objectives from other machine learning areas (e.g. computer vision, NLP). Future work should focus on exploiting the unique characteristics of geospatial data, such as spatial autocorrelation or temporal dynamics, for designing dedicated learning objectives. There exist several promising proof-of-concept studies in this direction [69, 30, 28].

5 Community Perspective: Fostering the Earth Embedding Ecosystem

As Earth embeddings mature, a broader ecosystem is emerging around them–one that depends not only on scientific progress, but also on how models, data, and infrastructure are shared and sustained. Two key aspects shape this ecosystem that includes users and developers: the openness of embedding resources and the practical costs of producing and maintaining them. A collective effort is needed to maintain open-accessibility and cultivate the impactful applications required to justify and sustain the costs associated with creating and maintaining embedding models and databases.

Open source code, embedding models, and embedding datasets enable the broad adoption of Earth embeddings. Whatever the modeling approach and interface, the options for adoption and extension are gated by how closed or open a project is. The Marin foundation model project and community (`http://marin.community`) define a trichotomy of degrees: open-weight (with weights but no code or data), open-source (with weights, code, data), and open-process (with weights, code, data, process details, and participation). Existing Earth embedding releases, both models and databases, mostly choose open-weight or open-source release. Major TOM [10] is uniquely open-process at this time, with its public standard and path to contributing. We encourage more similar open-process efforts to accelerate progress on Earth embeddings. Other projects releasing both the embedding model and embedding dataset include MOSAIKS [51], Tessera [16], Clay [1], or Presto [63]. AlphaEarth [5] constitutes a more restrictive open-output policy, releasing the embedding dataset but opting not to share the underlying model used to generate the embeddings. Our perspective is that sufficiently open sharing is a prerequisite for community-driven advancement of Earth embeddings, affording more rapid progress for research and development of the embeddings and for their applications

The computational costs of embeddings are another major factor to consider. While embedding databases lower barriers for adoption and use, they introduce substantial and often underappreciated costs up front. This makes precomputation infeasible for most research groups, with the dominant expense in large-scale inference being not GPU compute but the data pipeline and storage. To illustrate this, and to allow for comparisons with compute and storage needs of existing geospatial data paradigms, let us consider the following example: A single NVIDIA V100 GPU can process an *embedding model* like a U-Net with an EfficientNet-B7 backbone at roughly 900,000 km^2 per hour using 4.7 m PlanetScope imagery—enough to process all land on Earth in about seven days for an estimated compute cost of only $514 on Microsoft Azure. Yet the corresponding imagery totals approximately 108 TB uncompressed, requiring co-located compute and storage to maintain high utilization, and generating roughly 432 TB of 64-dimensional embeddings (assuming 1 byte per dimension). Storing these embeddings in commercial cloud storage would cost around \$8,000 per month (\$2,000 per 100 TB of Azure Blob "hot" storage as of September 2025), or nearly \$100,000 per year—far exceeding compute costs within days of operation. In comparison, an *embedding database* like AlphaEarth [5] faces similar challenges: maintaining multi-year, global-scale precomputed embeddings at 100 m resolution implies storage in the hundreds of terabytes (about 475 TB for five time steps), that can cost approximately \$9,500 per month even without redundancy. These calculations are a rough estimate, but explain the underlying challenges behind why precomputed embeddings remain rare outside of major corporations or space agencies and point to a key research challenge: developing efficient compression, caching, and dynamic delivery schemes that reduce the dependency on massive static storage, or rethinking embedding delivery as on-demand computation where compute acts as a substitute for long-term storage.

Call to action: Building an accessible, interdisciplinary and impactful Earth embedding community. Broad institutional support for Earth embeddings depends on community efforts to establish them as a distinct geospatial data modality that requires its own infrastructure scaling efforts. In particular, the interfaces used to access Earth embeddings and the computational requirements for storing them dictates who is able to develop, use, and analyze them. We envision an open ecosystem that includes researchers and model developers, users, and data providers. We identify the following community objectives to support building the Earth embedding ecosystem accessibly, efficiently and with a diverse user-developer community at its center:

- **Interdisciplinarity:** We need durable structures that put domain scientists, AI researchers, product engineers, and data stewards in communication with each other from the start. Such structures include funding for cross-appointments and exchange residencies, co-designed benchmarks drawn from real decision contexts, and community sprints where method design, labeling, and evaluation are co-developed. Priority should go to use cases proposed by practitioners outside AI, with dedicated resources for inclusive participation from underrepresented communities and institutions.
- **Traceable computational infrastructure:** We need shared, sustainable infrastructure that makes access to Earth embeddings affordable and transparent. Rather than storing massive datasets permanently, we should promote on-demand generation where possible. Tracking the resources used is essential so that the costs of producing and distributing embeddings can be fairly shared among those who benefit from them. One key aspect to consider is implementing traceability of the computed embeddings to commercial downstream applications to fund the expensive but optimally open-source and open-access infrastructure.
- **Embedding standards and interfaces:** We need shared techincal standards that link embedding models and embedding datasets, across both explicit feature embeddings and implicit neural representations. These standards should define how embeddings are described, versioned, and shared, with consistent metadata on location, time, provenance, and quality. Crucially, standardized protocols for how models and databases exchange geospatial context in a common format would allow different systems to exchange embeddings, making it easier to combine embeddings for specific downstream tasks and to move seamlessly between model-based generation and precomputed databases.
- **Reporting and documentation:** We envision "Embedding Cards"–a combination model cards [42] and data sheets [17]–that report training data coverage, objectives, known failure modes, spatial/temporal biases, uncertainty calibration, and safety/privacy considerations. Releases should include exact recipes: code, configs, hashes, container images, and seeds—and make use of evaluation suites spanning scale transfer, domain shift, and interpolation/extrapolation (see the Call to action box for users in section 3).

6 Conclusion

AI is rapidly transforming the geospatial analytics landscape and Earth embeddings are emerging as a central data format within this evolution. Earth embeddings allow us to compress and process the vast amounts of Earth data more efficiently, improving existing geospatial analytics and unlocking new applications.

This perspectives paper harmonizes a rapidly evolving and heterogeneous field and establishes Earth embeddings as an emergent research domain at the intersection of geospatial sciences and AI. We formalize Earth embeddings within a clear technical definition, harmonizing research over the past several years. We define functions and properties of Earth embeddings and outline current and emerging use cases. From these, we derive open research challenges centered around concrete actions items for the scientific community:

- We call on the community to tackle **application-centric** research challenges, ranging from better evaluations for Earth embeddings to making them more interpretable. The goal of this line of work is to *improve accessibility and enable new use cases for practitioners.*
- We call on the community to tackle **methodological** challenges for improving and scaling future-generation Earth embeddings. Work on encoding our planet is in its infancy and methodological development is essential for *enabling more efficient, expressive and adaptable* Earth embeddings.
- We call on the **community of users and developers** to center considerations around *interdisciplinarity, infrastructure, standards, reporting and documentation* to support the development of Earth embeddings that are accessible and effective.

The research agenda we outline is fundamentally interdisciplinary: Earth embeddings will rely on feedback from domain scientists, e.g. in ecological, geological, oceanographic, and atmospheric sciences, that incorporate Earth embeddings into their analyses and from data practitioners applying Earth embeddings in their workflows and products. This research agenda is also far-reaching and ambitious: We believe that Earth embeddings are an important component in enabling real-time Earth monitoring and that they can help to unlock a deeper understanding of planetary processes. We hope that our perspectives and proposed research avenues can help inform the directions Earth embeddings research and development will take in the years to come, focusing on maximizing their utility for scientific discovery and deployment in critical use cases.

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