Towards a Geospatial Foundation Model for Antarctica

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Abstract

Foundation models (FMs) have set off a new machine learning era by tapping into the vast pool of unlabelled data with the help of self-supervised learning techniques. Drawing on the success of FMs in the natural language domain, recent efforts in the GeoML community have focused on learning geospatial semantics from Earth observation (EO) data such as satellite imagery. The expanding field of 'machine learning for the cryosphere' (ML4Cryo) could benefit greatly from a reusable and versatile geospatial FM (GeoFM) to tackle tasks otherwise limited by the scarcity of labelled data in Antarctica, and thereby advance our understanding of this integral but vulnerable part of the climate science puzzle. However, existing pretrained GeoFMs and embeddings largely exclude the Antarctic region, and moreover, generic GeoFM pipelines are poorly suited to address the unique needs of the ice-covered continent. For example, optical images of the vast white ice surface fail to capture important non-stationary variations in the subsurface of the ice sheet, relevant to key polar modelling tasks. In this proposal, we outline the distinctive challenges that an Antarctic GeoFM needs to address, we discuss what benefits can be expected from such a model, and we suggest suitable datasets, diverse evaluation tasks, and training objectives, as a pathway towards a domain-informed spatial FM for Antarctica.

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1 Introduction

Foundation models (FMs) are shaping up to be the way forward in machine learning, leveraging task-agnostic knowledge representations distilled from abundant unlabelled data to tackle a broad range of downstream tasks. More recently, the concept of foundation modelling has been adopted by the GeoML community [1]–[9]. Geospatial foundation models (GeoFMs) are machine learning models pretrained on large amounts of geospatial data, such as *Earth observation (EO)* data, that encode comprehensive geophysical features of any given input location into a fixed-dimensional embedding vector. This foundational representation, learned during the self-supervised pretraining step — which only needs to be carried out once — enables the GeoFM to subsequently be fine-tuned to various spatial or spatio-temporal modelling tasks, even when limited labelled data is available. Recent studies have shown that GeoFMs are data-efficient and match or even exceed the performance of purpose-built models on high-impact tasks [1], [6], [10], yielding a desirable ratio of computational investment to value added. Notably, GeoFMs have been particularly successful in generalising to 'unseen' regions [6], [10] (i.e. region without labelled data), holding promise to specifically benefit under-resourced nations and regions, when data is insufficient to build supervised models from scratch.

While most studies evaluate GeoFM skill on climate-related tasks like flood mapping [1] or land cover and crop type classification [1]–[3], [6], applications to the ice-covered Antarctic continent have so far been widely overlooked, presumably due to its *distinct natural characteristics, separate datasets, and unique downstream modelling tasks*. Hence, in this proposal, we argue for a **specialised, domain-informed GeoFM for Antarctica**. To the best of our knowledge, SatCLIP [2], [11] is the only openly available GeoFM pretrained on EO data, that includes parts of Antarctica, even though other models claim 'global coverage.' Despite this lack of representation, the inhospitable polar region has a rich corpus of unlabelled, gridded *remote sensing (RS)* data, yet limited in-situ surface measurements [12] for supervised learning, which, in combination, make it a promising domain to benefit from a foundation model's accessibility as well as generalising capabilities.

The opportunity for machine learning to play a role in tackling high-leverage climate challenges in the polar regions has been highlighted by previous reviews [12]–[15], and demonstrated by successful 'machine learning for the cryosphere' (ML4Cryo) applications, such as Antarctic ice thickness super-resolution [16], [17], Arctic sea ice forecasting [18], snow stratigraphy classification [19], and ice flow prediction [20]. Spanning an area larger than Europe, Antarctica's ice sheet contains most of the world's freshwater, and therefore, progressing ice loss and rising sea levels are expected to have severe impacts on our Earth's hydrological cycle [21]. Antarctica's vulnerable cryospheric processes thus introduce significant uncertainties [13], [15] for future climate projections and actions [22]. Hence, Antarctica is a region of importance, that should not be overlooked by the GeoML community. *Meaningful, finely resolved, multi-scale, and interconnected spatial geophysical features*, extracted from the corpus polar-specific RS datasets, could boost scientific abilities to observe, understand and forecast the state of Antarctica, where labelled data is sparse, while **amortising computational costs** and data engineering efforts across future research projects.

2 Background: From embeddings to GeoFMs

Motivated by the relevance of spatial context to many modelling tasks of societal importance, such as those supporting the 17 United Nations Sustainable Development Goals (SDGs) [23], [24], encoding information contained in geospatial data into numerical representations, i.e. *Spatial Representation Learning (SRL)*, has been an active area of research in recent years [8], [25], [26]. SLR approaches can be classified based on the type of spatial data used: Location encoders [26] are methods that only use point data, i.e. coordinate inputs, to extract 'learning-friendly' representations with the help of neural networks. **TorchSpatial** [27] is a recently proposed comprehensive learning framework and benchmark for such direct location encoders. Other SRL approaches use georeferenced data such as polygons (e.g. representing postcodes), graphs (e.g. representing transport networks), natural images (e.g. picturing endemic species), or satellite images (e.g. depicting Earth's surface) to learn spatial representations [27]. We restrict the scope of the following overview to SRL approaches that leverage gridded remote sensing data, such as satellite imagery[1] or raster/gridded datasets from airborne geophysical surveys, because these type of data convey relevant information in the Antarctic context and are available at sufficient spatial coverage.

MOSAIKS [6] is a fully unsupervised embedding approach that extracts random convolutional features directly from global daytime RGB satellite imagery. The resulting MOSAIKS embedding vectors are available to download at a fixed grid resolutions of ~1km, allowing end users to simply interpolate these for any required location, and use these 8,192-dimensional vectors as features in statistical or machine learning models. While MOSAIKS offers an important solution that is highly accessible but static, many research groups have recently been working towards *foundation*

[1]We use the term *imagery* broadly to encompass multispectral satellite images as well as other types of remote sensing raster and grid data.

models. The difference is that foundation models are intended to be used as a pretrained model component of a machine learning model — usually the encoder — rather than as a fixed set of features. Therefore, foundation models additionally require the open-sourcing of the model and trained model weights that produce the latent embeddings, which allows the utilization of diverse fine-tuning strategies, see [1] for example, to effectively tune the model to the specific task, while exploiting the pre-learned spatial inductive bias. **SatCLIP** [2], [11] is a hybrid type of GeoFM that brings together a location encoder, taking coordinates as inputs, and an image encoder, taking RS imagery as inputs. The model simultaneously learns to align pairs of corresponding location embeddings and satellite image embeddings, through a contrastive pretraining objective analog to CLIP [28]. The resulting learned representations thus reflect both proximity on Earth's spherical surface as well as similarity of geographic features captured by the satellite imagery, like, for example, land cover types, dwellings or coastlines. As demonstrated by [2], this dual notion of nearness in the latent space enables SatCLIP to successfully generalise across tasks. An important distinction from other imagery-based GeoFMs is that during fine-tuning and at inference time SatCLIP only requires coordinate inputs, which makes it highly user-friendly and more accessible in practice.

Among the first methods to distil RS images into vector representations was Tile2Vec. **Tile2Vec** [3] proposes a self-supervised representation learning algorithm which can encode tiles of multispectral satellite data into vector embeddings. It uses a stationary distance hyperparameter to define isotropic 'neighborhoods', guiding the learning process with a triplet loss function, which requires triplets of a given tile, a neighboring tile and a non-neighbour tile. The triplet loss reduces embedding distance between a given tile and any neighboring tile, while enforcing distance between the given tile and any non-neighbour tile. IBM and NASA's joined GeoFM, **Prithvi** [1], relies on a Vision Transformer (ViT) backbone and uses a Masked AutoEncoder (MAE) learning strategy, both also used in **Clay** [29], to learn from the extensive Harmonized Landsat Sentinel (HLS) multispectral dataset. **SpectralGPT** [30] is another GeoFM, specifically designed for spectral RS imagery, utilizing a 3D generative pretrained transformer (GPT) architecture. Another recent method, **DOFA** ('Dynamic One-For-All'), presents an adaptive approach for harnessing multiple data modalities from a variety of sensors [31]. Meanwhile, other research groups have focused on adjacent topics, such as the creation of the **Geo-Bench** benchmark [4], [5]; leveraging large existing pretrained models via **continual pretraining** [7]; training GeoFMs on SAR data with the help of the **M3LEO** dataset [9], [32]; and learning scale-specific information with **Scale-MAE** [33]. Others have focused on encoding *additional temporal semantics* into GeoFMs, as demonstrated in **Presto** [34], a lightweight transformer trained on pixelwise time series; **SatMAE** [35], which uses temporal embeddings; and **EarthPT** [36], which employs autoregressive training.

Despite enormous progress in the area of Earth Observation FMs over the past years, pretrained GeoFMs — except for **SatCLIP**, which covers lower-latitude parts of Antarctica — do not include the Antarctic continent, let alone address its unique needs.

3 Four reasons why Antarctica needs a specialised GeoFM

In this section we present four arguments, visualised in Fig. 1, on why generic GeoFM pipelines are poorly suited to address the unique needs of Antarctica in the context of spatial representation learning and geospatial foundation modelling, and how requirements can be met instead.

(A) BEYOND SURFACE IMAGERY - Whereas optical satellite imagery contains non-trivial information for climate and sustainability-related modelling tasks worldwide, its utility for Antarctica is limited, due to the ice sheet's vastly indistinguishable reflective surface, see Fig. 1. However, **additional polar-specific gridded data products** — such as ice thickness, subglacial bed elevation, gravity anomaly, surface mass balance, or ice velocity data — developed by domain experts mostly from airborne or spaceborne EO data, carry valuable complementary information relevant to domain-specific downstream tasks, such as ice sheet modelling, or mapping of subglacial lakes, that, for instance, also depend on the geometry of the subsurface.

(B) NON-STATIONARITY - Antarctica's geophysical features and associated climate phenomena exhibit spatially non-stationary behaviour: For example, East Antarctica's ice mass, resting on elevated bedrock, has been rather stable, while West Antarctica, located on the other side of the Transantarctic Mountain range, which conversely is characterised by a bedrock base lower than sea level in many places, has been losing mass [37], [38], see Fig. 1. Unsupervised learning objectives like the triplet loss function used to train the Tile2Vec embedding [3] materialises assumptions about stationary and isotropic similarity, which conflict with Antarctica's patterns of geophysical variation. A GeoFM for Antarctica thus needs to **accommodate non-stationarity and anisotropy** in its design and learning objective, to be able to represent sharp discontinuities of physical properties.

(C) POLE OF IGNORANCE - The polar regions are also referred to as the 'poles of ignorance' to allude to our lack of understanding but also to the lack of available data. The orbits of most EO satellites, including Sentinel-2 which was used to train SatCLIP [2], or Landsat 8 and 9 used to train Prithvi [1], do not reach high polar latitudes > 83°, due to orbital mechanics (see Fig. 1). Thus, Antarctica is often not represented in commonly used near-global satellite datasets, but is rather observed through polar-targeted airborne or spaceborne RS missions. These separate datasets underscore **the need for polar-specific data sources** to pretrain an Antarctic GeoFM since they provide revealing high-coverage unlabelled data. Nonetheless, harsh ground conditions and months of darkness contribute to Antarctica's inaccessibility, limiting access to e.g. in situ data for supervised learning. This makes it a suitable domain to benefit from a GeoFM's strengths, for instance in informed interpolation and robust extrapolation, when geared toward the Antarctic data context.

(D) COORDINATE REPRESENTATION - Conventional coordinate systems, such as the latitude-longitude grid, or other common 2D map projections, are poorly suited to represent distance and area in geolocated data from the polar regions. As shows in Fig. 1, true distance between degrees of longitude diminishes towards the South Pole. Higher dimensional coordinate representations can better represent the spherical nature of Earth's surface and thereby combat these distortions, but even projections like the Double Fourier Sphere are not optimised for the far South [10]. Location encoder like [10] are **suitable to represent Antarctica's unique geolocation**, so that learned spatial representations can capture the complexities of the physical world.

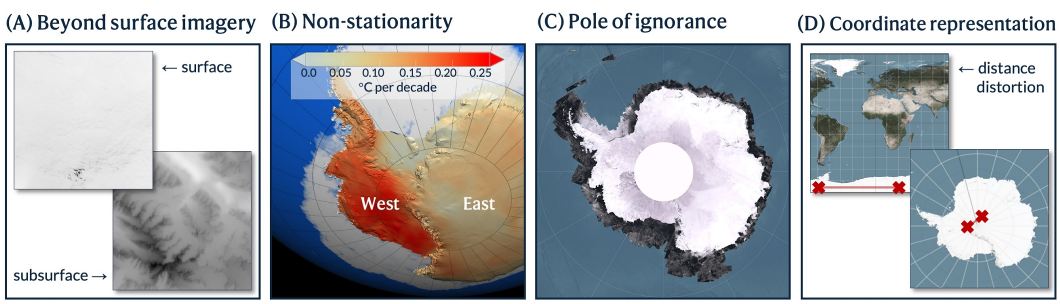

Figure 1: Visualisations supporting the four arguments (A), (B), (C), (D) made in Section 3 for why Antarctica needs a specialised, domain-informed GeoFM. (A) shows how optical imagery of the ice surface contains little variation, while the bed topography exhibits rich detail. (B) visualises the 1957 to 2006 temperature trend as an example of spatially non-stationary climate phenomena in Antarctica. Note the sharp change over the Transantarctic mountains dividing West and East. (Image credits: NASA/Goddard Space Flight Center Scientific Visualization Studio.) (C) shows the data gap around high latitudes in Sentinel-2 data. (Image credits: Copernicus.) (D) illustrates how the equirectangular projection, plotting latitude and longitude directly as x and y coordinates, misrepresents distances within Antarctica. (Image credits: Daniel R Strebe.)

4 Proposing a GeoFM for Antarctica

Due to its unique geophysical characteristics (A), (B), bespoke datasets (C), particular location on Earth (D), and motivated by its acute scientific importance discussed above, we argue for the development of a **domain-specific Antarctic GeoFM**. Currently, modellers often only use coordinates to provide deep learning and statistical models with a sense of spatial context. This not only misrepresents true Euclidean distances ((D)), but it also neglects valuable geospatial insights, e.g. about what regions are geophysically similar in terms of e.g. topographic roughness or presence of ice streams, which are hidden within polar RS datasets. A pretrained encoder, or even just a learned embedding, will provide a practical and accessible SRL tool to machine learning practitioners and domain scientists, who would otherwise likely not be able to incorporate large amount of EO data into their modelling pipeline. Thus, a great advantage of GeoFMs is that they consolidate computational efforts, they provide practical numerical abstractions that can boost diverse modelling tasks particularly for cross-regional generalisation, thereby speeding up scientific progress and discovery.

Most GeoFMs we review in Section 2 require the input of satellite imagery of a predefined format during fine-tuning and inference, to match the format used during pretraining. While this allows the pretrained network to adapt to, for instance, more recent satellite observations directly, it requires greater data acquisition and data engineering efforts. In contrast, the framework of the hybrid SatCLIP model only requires coordinate inputs, which makes it an appealing approach, combining location encoding and image encoding, see Figure 2. Since essential information about the Antarctic continent comes from multiple rather than a single dataset, managing these diverse datasets can pose inhibiting challenges for practitioners. Furthermore, as we elaborate in Subsection **??**, most of these datasets are the results of complex expert-led data processing, and thus only get updated infrequently, so that recency across all inputs is hard to achieve, and may even counteract temporal alignment between datasets. Therefore, we believe that a location-encoding GeoFMs framework like **SatCLIP** exhibits the greatest ease of use, which we deem critically important for the successful implementation of an Antarctic GeoFM, that should also be accessible to practitioners who have limited experience in working with satellite data.

Hence we propose to adopt the **contrastive learning framework** from SatCLIP [2], [39] and tailor it to the demands of Antarctica. Figure 2 illustrates how such a model, and Antarctic GeoFM based on SatCLIP, can be trained (top) and then fine-tuned for diverse downstream tasks (bottom). The contrastive learning framework is well suited to accommodate Antarctica's non-stationary nature discussed in (B), by simultaneously learning a *joint embedding* from a location encoder as well a multi-channel image encoder. The locations encoder can thereby be chosen to be congenial to Antarctica, as mentioned in (D). Likewise, the image encoder within this modular framework can be chosen to comprise of properties relevant to processing multi-channel remote sensing data, such as rotation-invariance [40], awareness of scales [33], or interaction between particular channels. Furthermore, we expect that training a separate model for Antarctica will benefit the model's ability to **learn nuances within the multi-modal RS data**, rather than just capturing the stark contrast between ice-covered and ice-free surfaces in a global, optical model. To encapsulate Antarctica's complex geophysical features, the training data for a GeoFM should contain a stack of gridded datasets (i.e. a data cube or tensor), including variables unique to the cryosphere (A), typically contained in specialist datasets (C). We suggest a collection of such datasets in Subsection **??** below. Next, we list relevant evaluation tasks in Subsection 4.2, and we elaborate on selecting evaluation baselines compatible with Antarctica's 'pole of ignorance' (C) in Subsection 4.3. Subsection 4.4 contains remarks on determining suitable coordinate representations (D), as well as ideas for ablation studies more broadly.

4.1 Training data

To learn comprehensive and detailed semantics about Antarctica, as addressed in (A) and (C), training data should contain a stack of foundational, gridded datasets of Antarctica's surface and subsurface. An non-exhaustive overview of suggested datasets for pretraining is provided in Table 4.1. The Reference Elevation Model of Antarctica (**REMA**) [41], [42] contains a Digital Elevation Model (DEM) of the Antarctic (ice) surface at very high horizontal and vertical resolution. MEaSUREs **BedMachine** Antarctica [37], [43] is the latest model of subglacial bed elevation and ice thickness, combining measurements with a mass conservation approach, that enforces physically consistent interpolation in coastal areas. It also contains an ice/ocean/land mask. Alternatively, the gridded bed topography and ice thickness dataset BedMap3, integrating the most recent ice-penetrating radar measurements, is expected to be released soon [44]. MEaSUREs **Phase-based ice velocity** map [45], [46], covering the years between 2007 and 2018, combines data from various Synthetic Aperture Radar (SAR) satellite missions to present time-averaged ice velocity at the surface of the ice sheet. The regional atmospheric climate model, **RACMO** Antarctica [47], is a spatio-temporal model of the Antarctic ice sheet's near-surface climate, including surface mass balance (SMB) and surface energy balance (SEB). Antarctic SMB consists to 91% of precipitation (i.e. snowfall), and thus

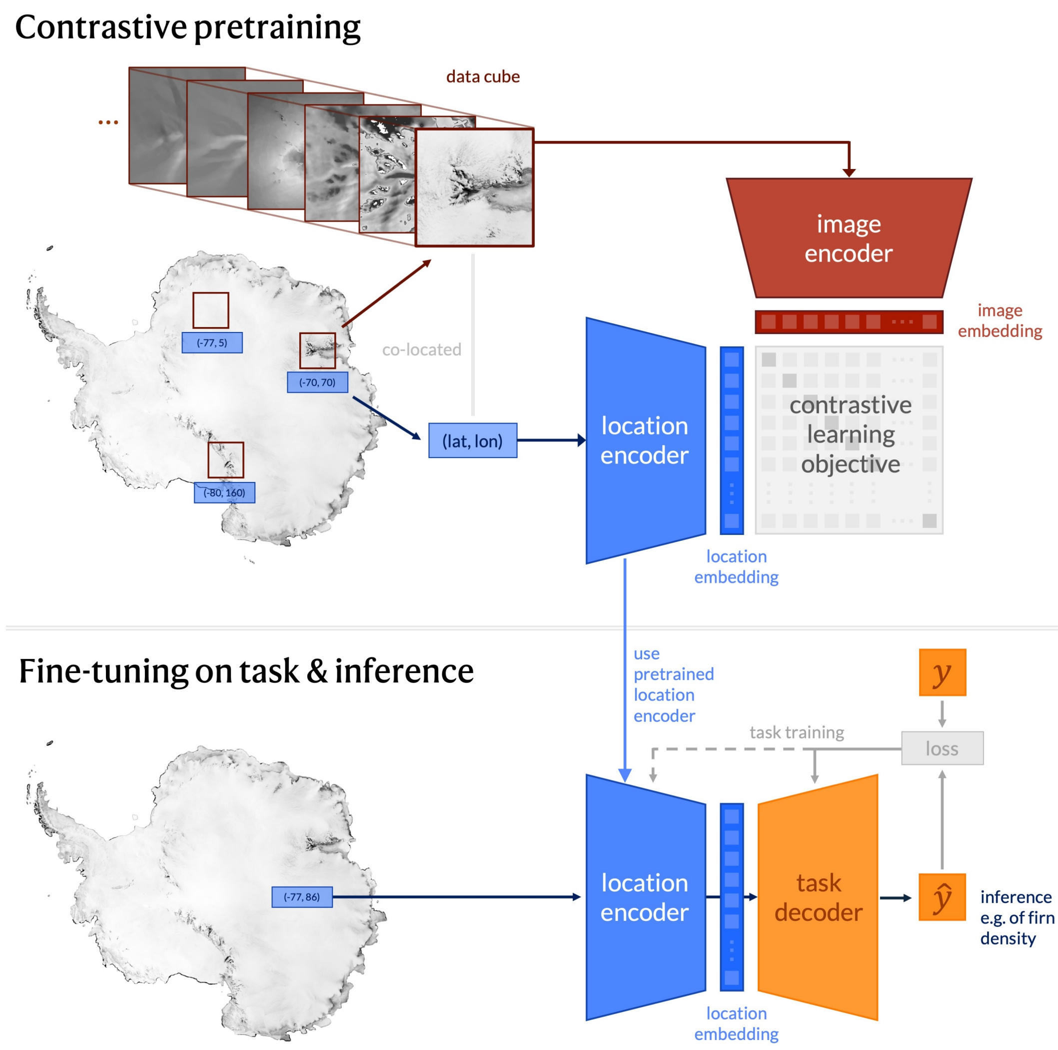

Figure 2: Illustration of the proposed modelling framework for an Antarctic GeoFM based on SatCLIP [2], [39]. The top shows the contrastive pretraining, taking in pairs of coordinates and co-located data cubes, which aligns embeddings learned by a location encoder with the respective embeddings learned by an image encoder. The bottom shows how the pretrained location encoder can be used for diverse downstream tasks via fine-tuning. Note that the model only requires coordinate inputs at fine-tuning and inference time.

RACMO describes the most important contributor to mass gain, however at lower resolution than the aforementioned datasets. An alternative dataset for average annual surface mass balance is [48], and while the data is available on a 1 km resolution grid, the effective resolution is only 100 km, thus providing less detail than RACMO. The next version of RACMO, RACMO2.4, is expected to be released soon [49]. Another large-scale geophysical variable, gravitational anomaly, is measured by the GRACE/GRACE-FO satellite missions. Models like **COST-G** adjust these measurements for glacial isostatic adjustment, i.e. the process of land, once pushed down by greater/smaller overlying ice masses, rising and falling, to infer spatio-temporal ice mass change [50], [51].

The **RADARSAT-2** SAR image mosaic [52], [53], produced by the Antarctic Mapping Initiative as part of the International Polar Year 2007–2008, provides a continent-wide dataset of Synthetic Aperture Radar (SAR) C-band backscatter coefficients. Such radar backscatter data can be very useful, particularly when combined with other data types, to reveal characteristics of the ice surface, such as surface roughness, crevasses, and melt zones, but it can also detect properties such as snowpack

Table 1: Overview of suggested datasets for pretraining an Antarctic GeoFM.

VARIABLE	DATASET	CITATIONS	RES.
Surface elevation	REMA	[41], [42]	< 10 m
Ice thickness (or bed elevation)	BedMachine	[37], [43]	500 m
Ice surface velocity	Phase-based ice velocity	[45], [46]	450 m
Surface mass balance [*temporal mean*]	RACMO	[49], [61]	27 km
Ice mass balance [*temporal mean*]	GRACE(-FO) COST-G	[50], [51]	50 km
SAR backscatter	RADARSAT-2	[52], [53]	100 m
Surface morphology & Snow grain size	MODIS MOA	[55], [56]	250 m
Optical (VIS, NIR, SWIR)	MODIS composite	[54]	200 m
Optical (VIS, NIR)	LIMA	[57]	15 m

density of the shallow subsurface [54]. MEaSUREs MODIS Mosaic of Antarctica (**MODIS MOA**) [55], [56] provides a full-coverage surface morphology map as well as a map of inferred snow grain size, nominal to 2013-2014. Surface morphology is derived from processing Band 1 MODIS data and provides insight into surface shape and reflectivity of the snow and ice. Tollenaar, Zekollari, Tuia, *et al.* [54] recently released a 7-band **MODIS composite** dataset for Antarctica, nominal to 2008-2010, covering the visual (VIS), near infrared (NIR), and shortwave infrared (SWIR) parts of the electromagnetic spectrum. The Landsat Image Mosaic of Antarctica (**LIMA**) [57] also contains optical satellite imagery of Antarctica, and while the dataset comes at a higher resolution than MODIS composite, it does not cover latitudes below 82.5° south, since the data was obtained from the Landsat satellite, as discussed in Section (C). The cloud-free LIMA mosaic was created by combining 1100 individually selected Landsat-7 ETM+ scenes from 1999 - 2003, adjusting for differences in sun angle and brightness saturation in regions of high surface reflectivity, and increasing the resolution to 15 m with the use of pan-sharpening. While LIMA does not provide full spatial coverage of the Antarctic continent, it provides a cohesive, high-resolution, and true-colour representation, that may be used together with other datasets, to achieve a detailed representation of geophysical and optical properties.

Datasets from Table 4.1, or additional datasets, for example from the Quantarctica data package [58], can then be combined into a multi-channel 'image' tensor (i.e. a data cube), where every channel represents a 2D map of a geophysical variable or a spectral channel. Since the datasets suggested in Table 4.1 have diverse natural resolutions (see RES. column), approaches like interpolation or SetConv [59], [60] may be applied to reach a unified internal resolution, trading off nominal data resolutions with increased computational and storage demand at higher resolutions. Given the data paucity of Antarctica, *minor temporal mismatch* between datasets is unavoidable. However, the goal of a GeoFM is to represent a recent snapshot of Antarctica's diverse geophysical properties in space, as best as possible. Spatio-temporal data like ice sheet mass balance and surface mass balance, can be time averaged over a period that best corresponds to remaining spatial datasets, to create a spatial dataset for a common reference period, and to increase robustness to measurement errors with averaging.

4.2 Evaluation Tasks

Downstream evaluation tasks should be tailored to the cryospheric domain, yet diverse, to rigorously test the efficacy of an Antarctic GeoFM against existing solutions with respect to model skill, data efficiency and computation. We refer the reader to Barry and Gan [21] for an overview of the components of the Antarctic ice sheet, as part of the terrestrial cryosphere, and to Liu [14] for a compact review of deep learning applications. Evaluation tasks may cover spatial as well as spatio-temporal modelling problems, spanning segmentation, classification and regression. The following selection presents a non-exhaustive list of potential evaluation tasks, as well as references to related studies:

(I.) Ice sheet modelling [62]

(II.) Surface albedo modelling [63]

(III.) Surface air temperature modelling [59]

(IV.) Basal friction inference [64]

(V.) Firn densification modelling [65]

(VI.) Supraglacial lake mapping [66], [67]

(VII.) Blue ice area mapping [54]

(VIII.) Crevasse segmentation [68], [69]

(IX.) Vegetation classification [70]

4.3 Baselines

Most pretrained GeoFMs do not currently cover Antarctica: MOSAIKS embeddings [6] are not available for Antarctica, EarthPT [36] is only trained on a small part of the UK, Clay [29] explicitly excludes the polar regions, and Prithvi [1] was only pretrained on US data. More general location encoders that go beyond the remote sensing domain, as those SatCLIP [2] compares against, use datasets like YFCC100M (the 'Flickr' dataset used in GPS2Vec [71]) or INaturalist (used in CSP [72]), that barely represent earth's far south.

Therefore, **SatCLIP** [2], to our best knowledge, represents the only pretrained baseline that covers considerable parts of Antarctica. SatCLIP was pretrained on a uniformly sampled collection of ESA's Sentinel-2 multispectral data, the S2-100K dataset. Less than 3.6% of S2-100K however cover Antarctica, thus underrepresenting the continent's relative global landmass of 9.5%. While SatCLIP attains near-global coverage, no satellite images south of - 83.7° latitude are contained due to 'the pole of ignorance' resulting from the Sentinel-2 orbit, discussed in Section (C). Although Klemmer, Rolf, Robinson, *et al.* [2] investigate the performance of SatCLIP across continents, they do not include Antarctica, a continent larger than Europe or Australia, in their analysis, likely because tasks like median income prediction have little meaning in an inhabited region. While we suggest SatCLIP to be used as the main baseline for the Antarctic GeoFM, it remains to be evaluated whether regions in the extreme south, particularly the area around the South Pole not reflected in its training data, are nonetheless effectively represented by SatCLIP's learned embedding. Hence, models trained on a subset of the selected Antarctic data modalities, as well as location embeddings like [10], may serve as additional baselines. To meet the goals for an Antarctic GeoFM to be versatile and reusable, the GeoFM should be compared against state-of-the-art models for each respective evaluation task, as done by the Prithvi team [1].

4.4 Ablations

Ablation studies could examine the benefit of using various **pretrained image encoders** via continual pretraining [7], to create an Antarctic GeoFM with competitive skill across diverse downstream tasks. SatCLIP [2] uses image encoders pretrained specifically on EO datasets, namely SSL4EO [73], and subsequently fine-tunes the last layer of model weights. Because SSL4EO [73] does not contain any data from Antarctica however, as imagery was sampled to cover the world's 10,000 most populous cities and its surroundings, it remains an interesting research question, whether pretraining on satellite imagery of populated areas [40] nonetheless helps the image encoder to adapt to rotation-invariant, non-object-centric, yet scale-sensitive RS/satellite data of unpopulated Antarctica.

Similarly, ablations could provide further insight into the impact that the choice of **coordinate representation**, which is then passed into the **location encoder**, has within the context of contrastive learning. Whereas Spherical Harmonics (SH) combined with Sinusoidal Representation Networks (SirenNets), proposed by [10] and used in SatCLIP [2], were developed to represents earth's spherical shape, and thus represent the polar regions better than many prior methods, a comparison to the simple 2-diemsnional but domain-specific NSIDC Polar Stereographic Projection should be conducted. Investigating whether the concatenation of established vector representations with relative location representations, which could contain the shortest distance to the coastline, or to a research station, can boost the performance on evaluation tasks, constitutes another interesting research direction.

Arithmetic analysis of trained embeddings as showcased in [3], as well as zero-shot and few-shot experiments on out-of-distribution regions [2], [3], [6], will add to a rigorous evaluation.

Furthermore, ablations on subsets of training data would provide information about the value that these satellite modalities supply to solve downstream tasks of scientific priority. This could guide **planning and decision-making for future investments into satellite missions and Antarctic science** by governments and research organisations.

5 Limitations

The suggested training datasets and evaluation tasks listed above are focuses on the continent of Antarctica, and are thus limited to the terrestrial cryosphere [21]. We focus on Antarctica because it holds the largest ice mass of our planet [21] and because of Antarctica's critical role in the context of climate change [12], [13], [22]. Most arguments and ideas presented also transfer to Greenland, which typically has corresponding data products, e.g. of the bed topography, ice velocity or gravity. Furthermore, components of the proposed model may also be extended to the marine cryosphere, comprised of sea ice, ice shelves and icebergs, and even the southern ocean, where bathymetry data, describing the ocean floor, could complement satellite imagery of the ocean.

Future work may also look into incorporating **temporal information**, as addresses in **Presto** [34], **SatMAE** [35], or **EarthPT** [36], towards a 'spatio-temporal FM' which can represent seasonally varying components. As of now, it is unclear whether there is sufficient spatio-temporal data available to train such a time-aware model for Antarctica. Hence, in this proposal we advocate for a GeoFM to represent a temporal snapshot of Antarctica's spatial information. The integration of multiple datasets will introduce minor temporal mismatch between training datasets, but also between the resulting pretrained GeoFM and tasks, as also encountered in [6].

The **open source** nature and accessibility of any future Antarctic GeoFMs is paramount, to honour the Antarctic Treaty, Article III, and more broadly to enable continuous, collaborative development, and of course scientific use in application-driven machine learning research [40].

6 Proposal conclusion

"Technology won't solve our problems but we won't solve our problems without technology."

GeoFMs are large, generalist representation learners, trained on the distinct class of satellite and EO data [40], that can tackle diverse high-leverage climate modelling tasks and even generalise to data-deficient regions. The important practical advantange of GeoFMs is that by encoding complex spatial and location features beyond simple coordinate representations, they avoid the need to train expensive models from scratch every time, and they relieve the need for modellers to deal with large RS datasets directly. In this proposal we motivate the need for a **domain-informed Antarctic GeoFM**, we outline four specific challenges such a model needs to address, and how we envision these to be implemented in the GeoFM development. With this proposal we intend to launch the collaborative development of an expressive GeoFM for Antarctica, to accelerate future application-driven research [74] at the intersection of machine learning and cryospheric sciences, that can advance our understanding of Antarctica and its critical role in climate change.

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