SELF-SUPERVISED MULTI-MODAL WORLD MODEL WITH 4D SPACE-TIME EMBEDDING

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ABSTRACT

We present *DeepEarth*, a self-supervised multi-modal world model with *Earth4D*, a novel planetary-scale 4D space-time positional encoder. Earth4D extends 3D multi-resolution hash encoding to include time, efficiently scaling across the planet over centuries with sub-meter, sub-second precision. Multi-modal encoders (*e.g.* vision-language models) are fused with Earth4D embeddings and trained via masked reconstruction. We demonstrate Earth4D's expressive power by achieving state-of-the-art performance on an ecological forecasting benchmark. Earth4D with learnable hash probing surpasses a multi-modal foundation model pre-trained on substantially more data. Access open source code and download models at: `https://github.com/legel/deepearth`.

1 DEEPEARTH ARCHITECTURE

DeepEarth is a self-supervised multi-modal world model that learns unified representations of Earth observation data across space and time. As seen in Figure 1, the architecture processes multi-modal inputs (*e.g.* vision, language, sensor data) sampled around spatio-temporal events. The Earth4D encoder maps continuous space-time coordinates (*latitude*, *longitude*, *elevation*, *time*) to learnable positional embeddings, which are fused with embeddings from modality-specific encoders and processed as tokens in an autoencoder context window. Inspired by PerceiverIO (Jaegle et al., 2021), V-JEPA 2 (Assran et al., 2025), Galileo (Tseng et al., 2025), and AlphaEarth (Brown et al., 2025), DeepEarth learns to generatively reconstruct and simulate joint distributions of multi-modal data.

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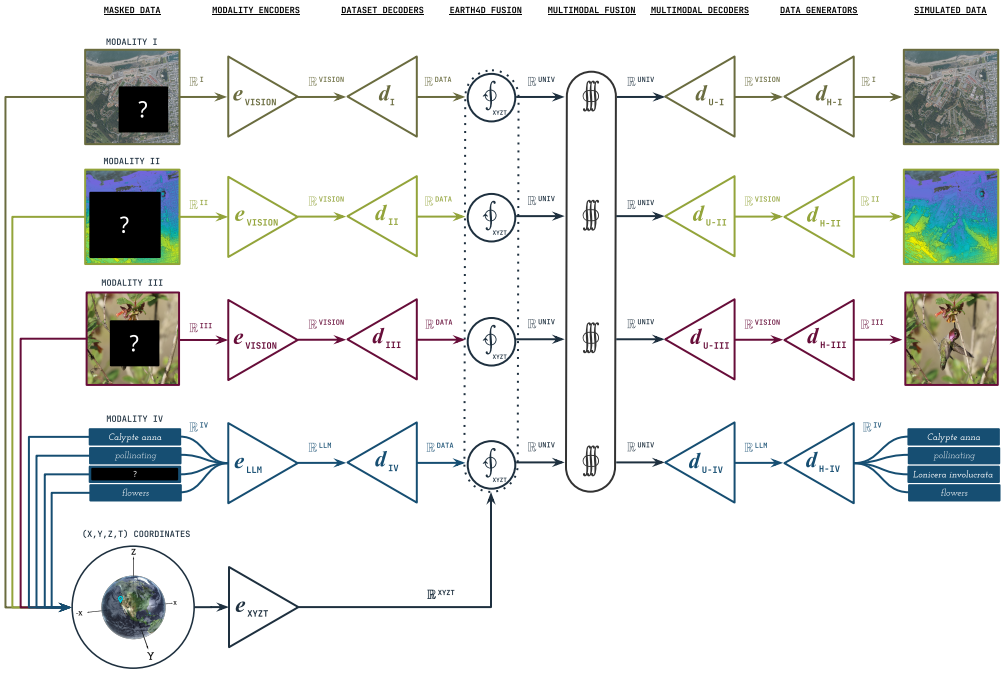

Figure 1: **DeepEarth Overview.** Masked multi-modal data (*e.g.* images, text) sampled around an event (*e.g.* pollination) are encoded and fused with Earth4D space-time embeddings. These universal tokens are jointly encoded, and then masked data is inductively decoded and simulated.

2 EARTH4D ARCHITECTURE

Following Grid4D (Jiawei et al., 2024), Earth4D extends NVIDIA's multi-resolution hash encoding (Müller et al., 2022) to four dimensions (Figure 2) by concatenating features from one spatial (*xyz*) and three spatio-temporal (*xyt*, *yzt*, *xzt*) grids. Implemented as a standalone PyTorch module with massively parallelizable CUDA kernels, Earth4D is suitable for integration into larger models.

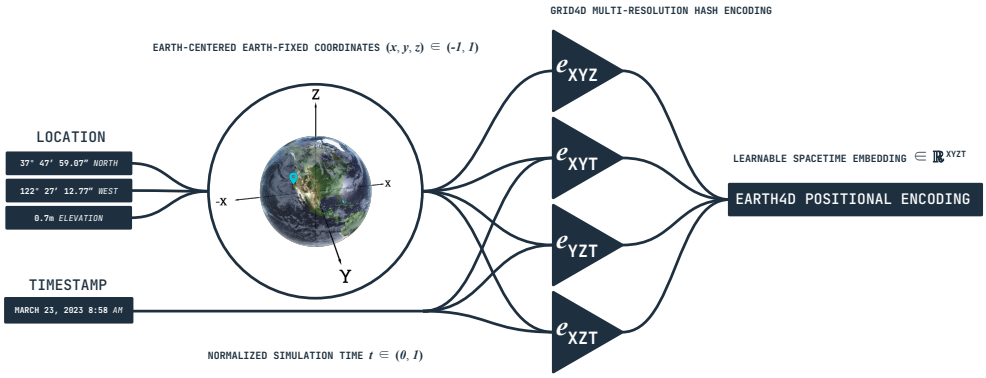

Figure 2: **Earth4D Space-Time Positional Encoding.** A planetary-scale 4D encoder with fully decomposable spatio-temporal representation. Four grids (*xyz*, *xyt*, *yzt*, *xzt*) are each learned in 3D space and computed in parallel. Each grid has multiple resolution levels (Appendix A), enabling deep learning of complex joint distributions in multi-modal data across space-time scales.

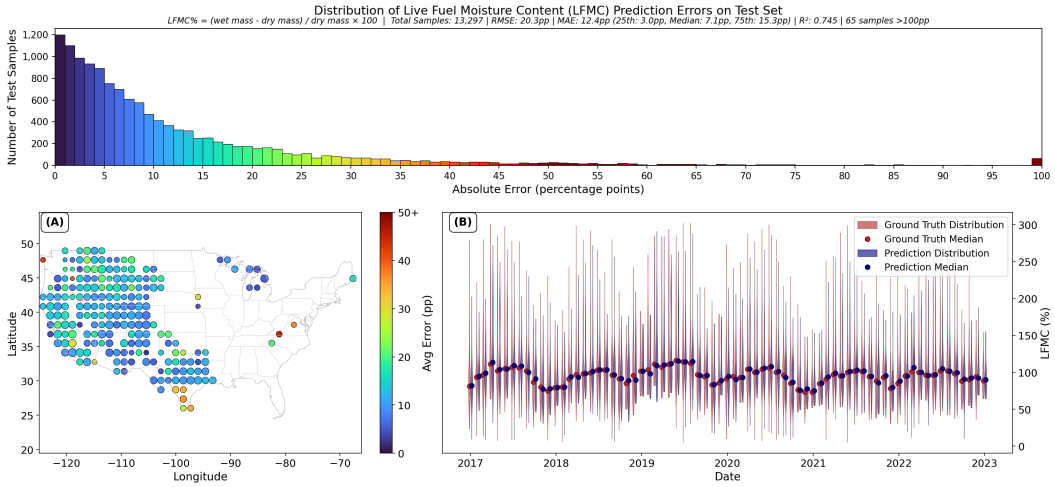

Figure 3: **Earth4D LFMC Prediction Performance.** *(Top)* Distribution of absolute errors in percentage point predictions across 13,297 test samples, showing median error of 7.1pp. *(A)* Geographic error distribution across CONUS shows low error in well-sampled regions. *(B)* Temporal predictions closely track ground truth LFMC measurements across seasons (2017–2023).

Earth4D's hash encoding compresses spatial features into a fixed memory budget, but different coordinates can map to the same memory location (collisions). We integrate learned hash probing (Takikawa et al., 2023), an end-to-end differentiable system that learns optimal memory allocation patterns for the data. This yields substantial performance improvements across tasks (Appendix B).

3 Earth4D Experimental Validation

3.1 Live Fuel Moisture Content Prediction

Dataset. Live Fuel Moisture Content (LFMC) measures the percentage of water in vegetation relative to its dry weight, a critical indicator for wildfire risk assessment. We evaluate Earth4D on Globe-LFMC 2.0 (Yebra et al., 2024), a global ecological forecasting benchmark containing field measurements across diverse plant species, geographic regions, and temporal periods.

Baseline Model. We compare against Galileo (Johnson et al., 2025; Tseng et al., 2025), a pre-trained Vision Transformer processing multi-modal remote sensing data (Appendix C).

Architecture. Earth4D encodes (x,y,z,t) into a 192D vector, concatenated with a learnable species embedding initialized randomly (no prior knowledge). An MLP then predicts LFMC %.

Results. Earth4D achieves MAE 12.1pp and R^2 0.755, surpassing Galileo (MAE 12.6pp, R^2 0.72) using only (x,y,z,t) coordinates and species embeddings (Table 1).

Model	Data Inputs	MAE (pp)	RMSE (pp)	R^2
Galileo (Pre-Trained)	(x,y,z,t) + Species Type + Remote Sensing	12.6	**18.9**	0.72
Earth4D (Learned Hashing)	(x,y,z,t) + Species Name	**12.1**	19.9	**0.755**

Table 1: **State-of-the-Art Ecological Forecasting Benchmark.** Earth4D surpasses the pre-trained Galileo foundation model without satellite imagery, weather data, or topography.

3.2 RGB Aerial Imagery Reconstruction

We evaluate Earth4D's ability to infer RGB pixels from (x,y,z,t) inputs with objective $(x,y,z,t) \rightarrow (r,g,b)$. Using USGS 3DEP LiDAR (Stoker & Miller, 2022; Sugarbaker et al., 2014) and USDA NAIP imagery (USDA, 2003–present) paired by Allred et al. (2025), we train on 5.8M coordinate-color pairs from Houston coastal wetlands (Figure 4).

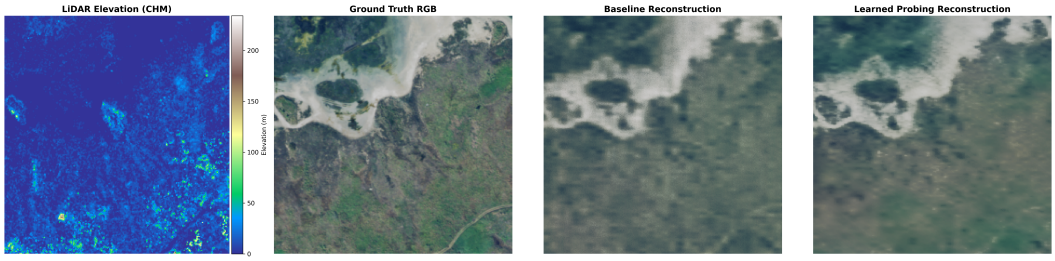

Figure 4: **RGB Reconstruction from LiDAR Elevation.** Houston coastal wetlands, 2018. *Left to right:* LiDAR height, ground truth, baseline, learned probing (18% lower loss).

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APPENDICES

A EARTH4D RESOLUTION SPECIFICATIONS

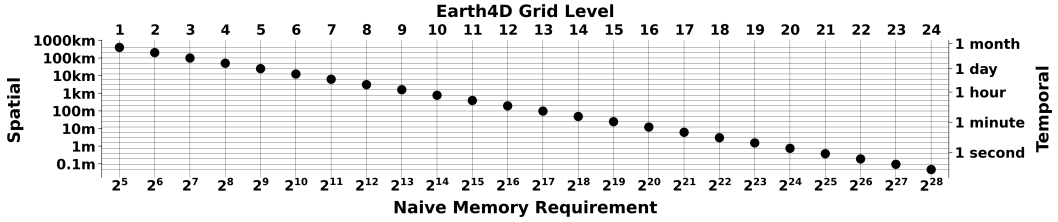

Figure 5: **Earth4D Space-Time Scales.** Default 24×24×24 levels for each *xyz*, *xyt*, *yzt*, *xzt* grid. Each level stores up to 2^{22} entries, with each entry storing a 2D feature. Requires 724M trainable parameters (∼11 GB GPU memory during training). Parallelizable across levels and spatio-temporal boundaries. Outputs 192D per (x, y, z, t) coordinate from 4 grids × 24 levels × 2D feature per level. Hashing saves memory vs. naive requirement, e.g., $(2^{28})^3 = 10^{25}$ at level 24.

B Learned Hash Probing and Ablation Studies

B.1 Hash Collision Simulations

Scenario	Spatial	Temporal	Description
Uniform Random	Global	Full	Uniform Earth surface sampling
Continental Sparse	North America	Full	Sparse continental coverage
Moderate Spatial Cluster	10km × 10km	Full	City-scale clustering
Moderate Temporal Cluster	1k locations	Distributed	Temporal sampling at fixed locations
Moderate Spatiotemporal	1km × 1km	1 hour	Neighborhood-scale event
Extreme Spatial Single	10m × 10m	Full	Building-scale dense clustering
Extreme Spatial Multi	10 × (10m × 10m)	Full	10 dense clusters worldwide
Extreme Temporal Single	Global	1 hour	Global snapshot
Extreme Temporal Multi	Global	10 × (1 hour)	10 temporal snapshots
Time Series	10k locations	100 steps	Regular temporal sampling

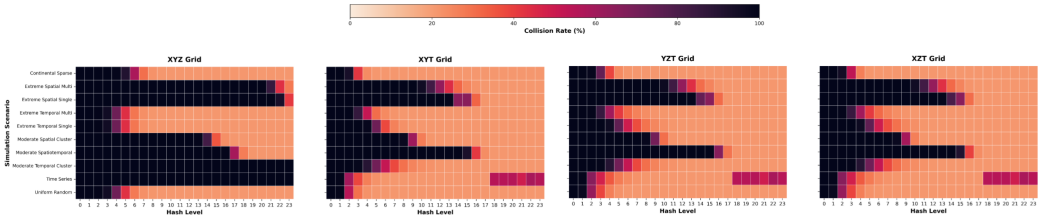

Figure 6: **Earth4D Hash Collision Analysis.** *(Table)* 10 (x, y, z, t) point distribution scenarios that were simulated to analyze hash collisions in Earth4D memory. *(Graph)* Shows results for 1M point simulations across all 24 levels.

B.2 Performance Improvements

Standard multi-resolution hash encoding without learned probing obtains RMSE 26.0pp, MAE 16.6pp, and R^2 0.58 (800M parameters, 2^{22} hash capacity). Integrating learned hash probing (Takikawa et al., 2023), which learns to select optimal hash table indices from a candidate set, yields RMSE 19.9pp, MAE 12.1pp, and R^2 0.755—a 27.1% MAE reduction and 30.2% R^2 improvement. Extreme compression to 5M parameters (99.3% reduction, 2^{14} hash capacity) achieves MAE 15.0pp/R^2 0.668, outperforming the 800M baseline by 14.7% in R^2 with 4× training speedup and 93% memory reduction. On RGB reconstruction, learned probing reduces validation loss by 18%. These gains result from collision reduction (33% at 1M points) and learned shared features across memory indices, allowing the model to discover meaningful spatio-temporal patterns.

C Benchmark Specifications

C.1 Galileo Baseline Model

Galileo (Johnson et al., 2025; Tseng et al., 2025) is a Vision Transformer (Dosovitskiy et al., 2021) (5.3M parameters) pre-trained by the Allen Institute for AI. It processes Sentinel-2 optical imagery (Drusch et al., 2012), Sentinel-1 SAR (Torres et al., 2012), VIIRS night lights, ERA-5 weather (Muñoz Sabater, 2019), TerraClimate soil/water data (Abatzoglou et al., 2018), SRTM topography (Farr & Kobrick, 2000), (x,y,z,t) coordinates, and species type. We use the Allen Institute for AI's exact Globe-LFMC 2.0 (Yebra et al., 2024) train/test split (76,467/13,297) to directly compare against this benchmark.