

# 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.), *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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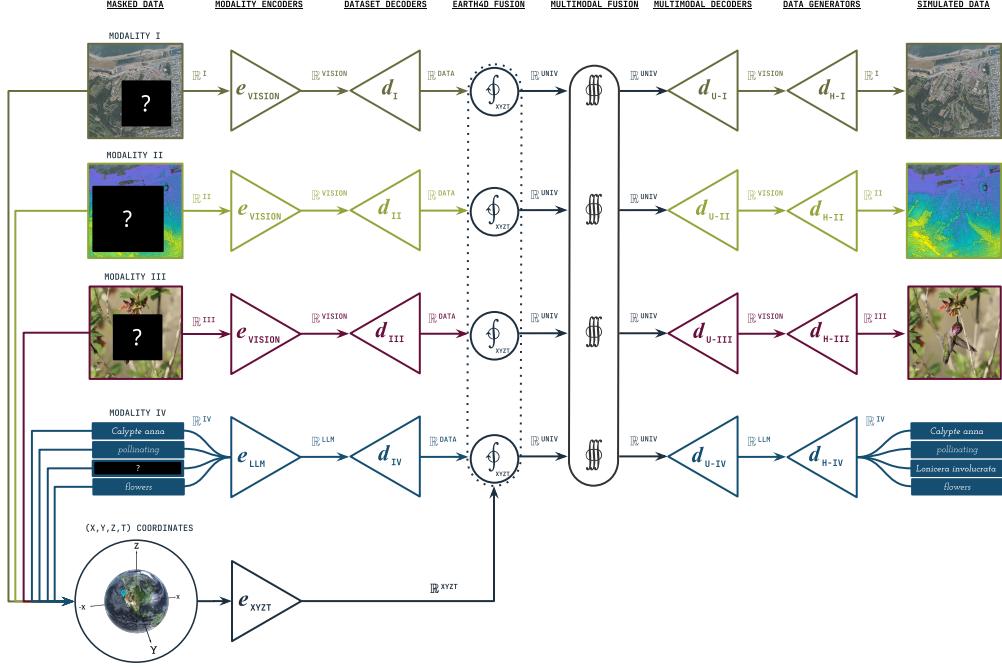


Figure 1: **DeepEarth Overview.** Masked multi-modal data (e.g. images, text) sampled around an event (e.g. pollination) are encoded and fused with Earth4D space-time embeddings. These universal tokens are jointly encoded, and then masked data is inductively decoded and simulated.

## 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.

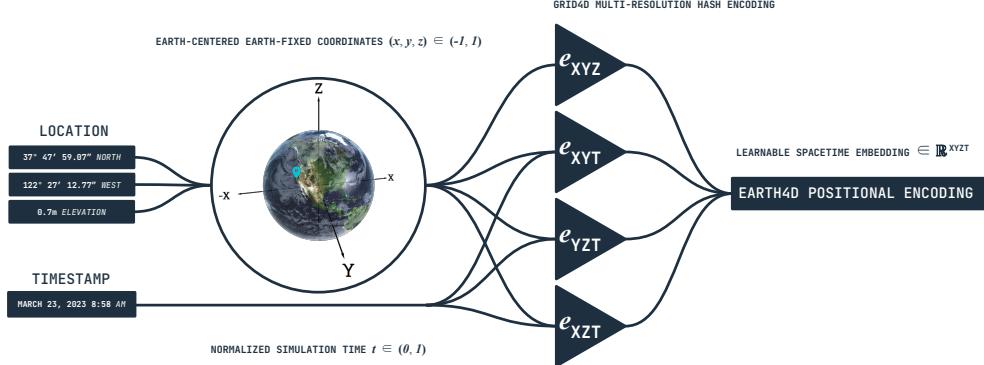
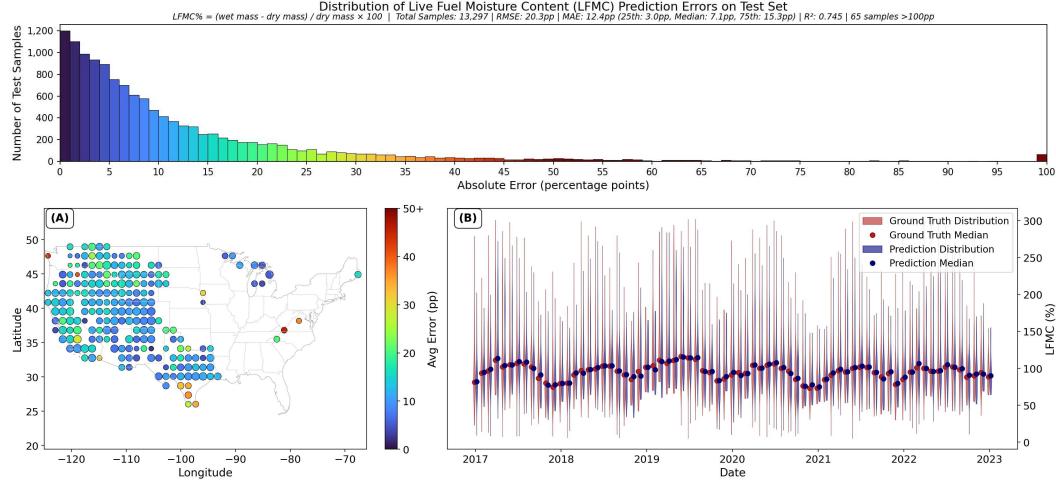


Figure 2: **Earth4D Space-Time Positional Encoding.** A planetary-scale 4D encoder with fully decomposable spatio-temporal representation. Four grids ( $xyz$ ,  $xyt$ ,  $yzt$ ,  $xzt$ ) are each learned in 3D space and computed in parallel. Each grid has multiple resolution levels (Appendix A), enabling 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	<b>18.9</b>	0.72
Earth4D (Learned Hashing)	$(x, y, z, t)$ + Species Name	<b>12.1</b>	19.9	<b>0.755</b>

**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; Sugabaker 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).

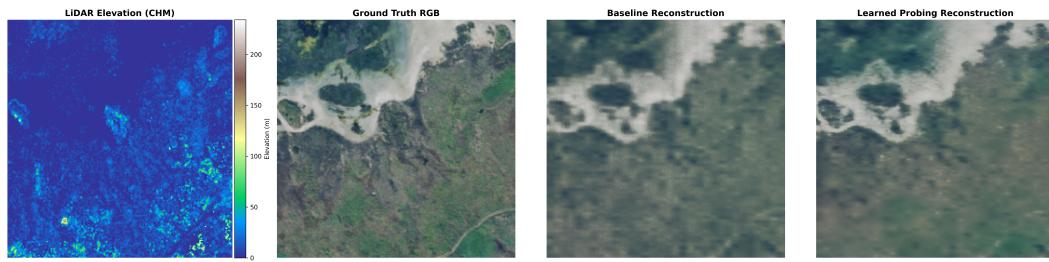


Figure 4: **RGB Reconstruction from LiDAR Elevation.** Houston coastal wetlands, 2018. *Left to right:* LiDAR height, ground truth, baseline, learned probing (18% lower loss).

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## APPENDICES

### A EARTH4D RESOLUTION SPECIFICATIONS

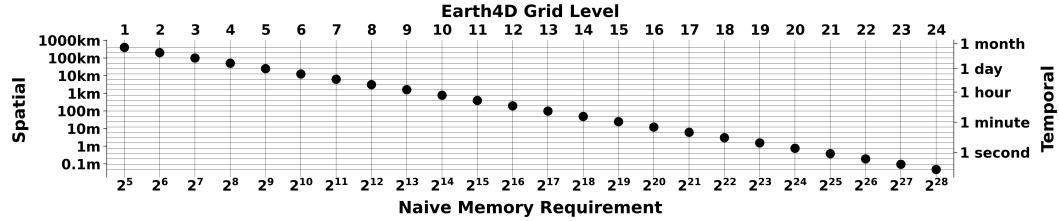


Figure 5: **Earth4D Space-Time Scales.** Default  $24 \times 24 \times 24$  levels for each  $xyz$ ,  $xyt$ ,  $yzt$ ,  $xzt$  grid. Each level stores up to  $2^{22}$  entries, with each entry storing a 2D feature. Requires 724M trainable parameters ( $\sim 11$  GB GPU memory during training). Parallelizable across levels and spatio-temporal boundaries. Outputs 192D per  $(x, y, z, t)$  coordinate from 4 grids  $\times$  24 levels  $\times$  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
<i>Uniform Random</i>	Global	Full	Uniform Earth surface sampling
<i>Continental Sparse</i>	North America	Full	Sparse continental coverage
<i>Moderate Spatial Cluster</i>	10km × 10km	Full	City-scale clustering
<i>Moderate Temporal Cluster</i>	1k locations	Distributed	Temporal sampling at fixed locations
<i>Moderate Spatiotemporal</i>	1km × 1km	1 hour	Neighborhood-scale event
<i>Extreme Spatial Single</i>	10m × 10m	Full	Building-scale dense clustering
<i>Extreme Spatial Multi</i>	10 × (10m × 10m)	Full	10 dense clusters worldwide
<i>Extreme Temporal Single</i>	Global	1 hour	Global snapshot
<i>Extreme Temporal Multi</i>	Global	10 × (1 hour)	10 temporal snapshots
<i>Time Series</i>	10k locations	100 steps	Regular temporal sampling

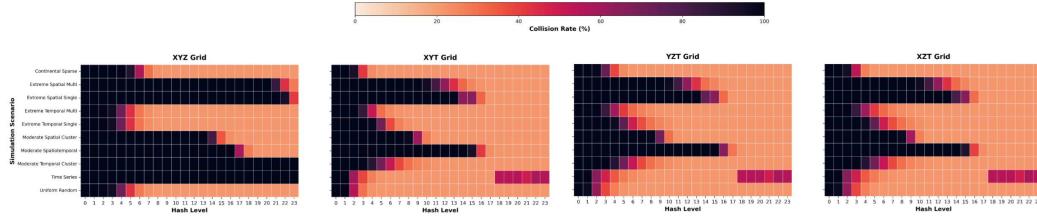


Figure 6: **Earth4D Hash Collision Analysis.** (Table) 10 ( $x, y, z, t$ ) point distribution scenarios that were simulated to analyze hash collisions in Earth4D memory. (Graph) Shows results for 1M point simulations across all 24 levels.

### 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.