Lightweight Fine-tuning of An Earth System Foundation Model for Sea Surface Temperature Forecasting

Rakib Hossain

December 8, 2025

Why AI Foundation Models for Weather?

Operational Numerical Weather Prediction (NWP) Systems:

- Complex physics-based models (e.g., IFS, GFS)
- Require extensive computational infrastructure
- High operational cost: millions per year for weather agencies
- Training and maintenance: domain expertise-heavy

AI Foundation Models (e.g., Aurora):

- **Order of magnitude cheaper** to train and run
- Inference: seconds on modern GPUs vs. hours on supercomputers
- Competitive forecast skill on standard variables
- Democratizes weather AI to smaller institutions

Trade-off: Aurora's 1.3B parameters are still substantial—full retraining prohibitively expensive

reference: Aurora: Bodnar et al., Nature vol. 641, no. 8065, pp. 1180–1187, May 2025, doi:10.1038/s41586-025-09005-y

Challenge: Adapting to Unseen Variables

The Problem:

- Aurora's original decoder outputs only standard variables (2m temp, wind, etc.)
- New physical processes (e.g., SST) require adaptation
- Full model retraining: ∼80 GB GPU memory, weeks of compute

Our Approach (inspired by Lehmann et al.):

- Freeze Aurora's encoder & backbone (1.3B parameters)
- Train only lightweight MLP decoder (∼300,000 parameters)
- Cost reduction: **orders of magnitude**
- Proof of concept: can Aurora's frozen representations generalize to unseen processes?

reference: Lehmann, Ozdemir, et al., "Finetuning a Weather Foundation Model with Lightweight Decoders for Unseen Physical Processes," arXiv:2506.19088, 2025. doi: 10.48550/arXiv.2506.19088.

Overview

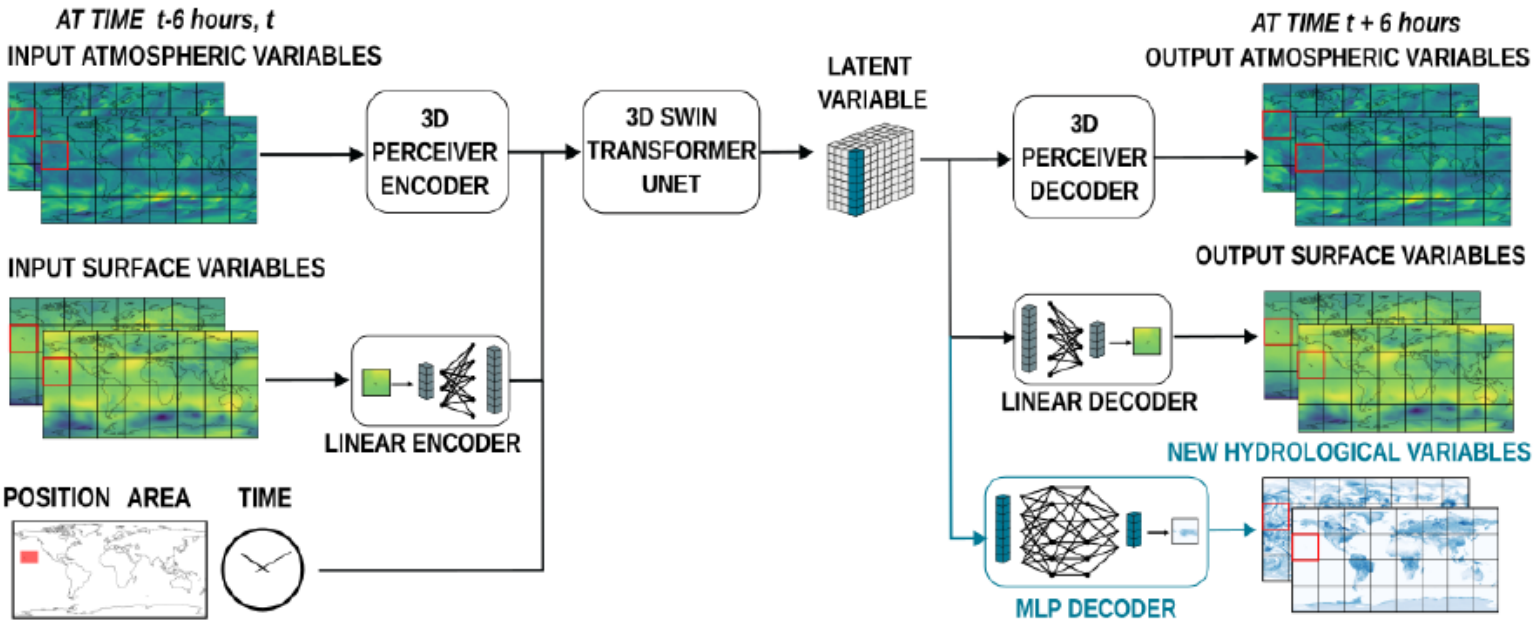
Goal: Predict sea surface temperature (SST) without retraining Aurora's 1.3B parameters

Approach:

- Freeze AuroraLite encoder and backbone
- Train lightweight MLP decoder on latent representations
- Data- and compute-efficient adaptation

Input: ERA5 fields (surface, static, atmospheric variables) over global grid
Target: SST at specific times and coordinates
Setting: Supervised learning with MAE loss

AuroraLite Architecture



Pipeline: Perceiver3D Encoder → Swin3D Transformer Backbone (frozen) → MLP Decoder. This was used by Lehmann et al.

reference: Lehmann, Ozdemir, et al., "Finetuning a Weather Foundation Model with Lightweight Decoders for Unseen Physical Processes," arXiv:2506.19088, 2025. doi: 10.48550/arXiv.2506.19088.

Perceiver3D Encoder

Input Types:

1. **Surface variables:** 2m temperature, 10m winds, mean sea level pressure
2. **Static variables:** land–sea mask, orography, soil type
3. **Atmospheric variables:** temperature, winds, humidity, geopotential (13 pressure levels)

Processing:

1. Normalization with precomputed statistics
2. Spatial cropping to align with patch size
3. Broadcasting static fields across batch and time

Output: Sequence of latent tokens representing 3D atmospheric state and history

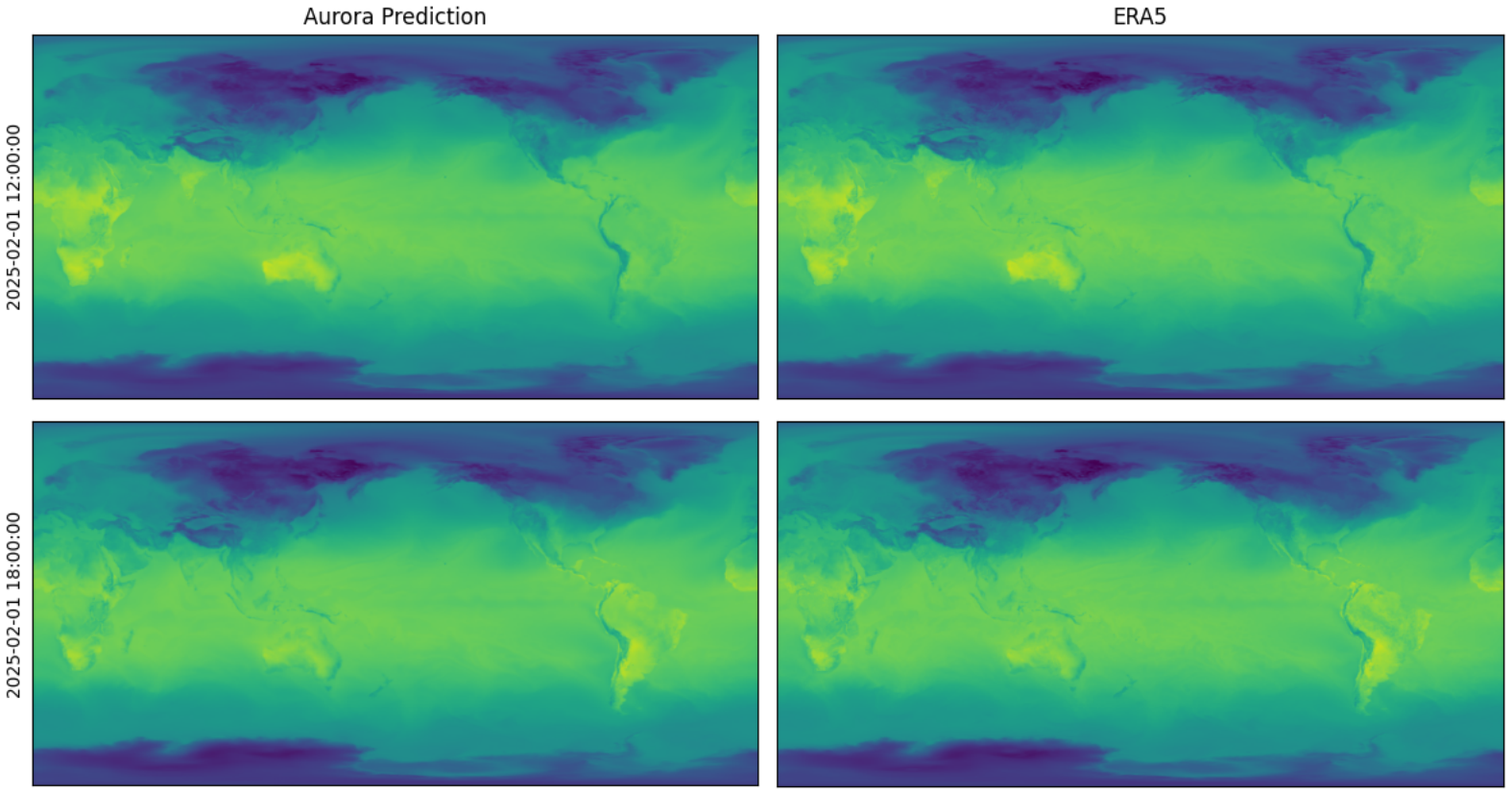
MLPDecoderLite

Architecture:

1. Input: latent_decoder + lat/lon metadata
2. Per-variable MLP head:
    1. Input dimension: D_{embed} (encoder embedding $\times 2$)
    2. Hidden layers: $512 \to 512 \to 256$
    3. Output dimension: P^2 (patch-wise predictions)
3. Unpatchify to full resolution
4. Denormalize to physical units

Scale: $\approx 300,000$ parameters for a decoder

Baseline - 2m Temperature (Aurora Native)



Lead Time	RMSE (K)	Correlation
Step 1 (+6h)	0.6450	0.9995
Step 2 (+12h)	0.8337	0.9992
Average	**0.7393**	**0.9994**

Methodology - Inference

SST Inference Workflow

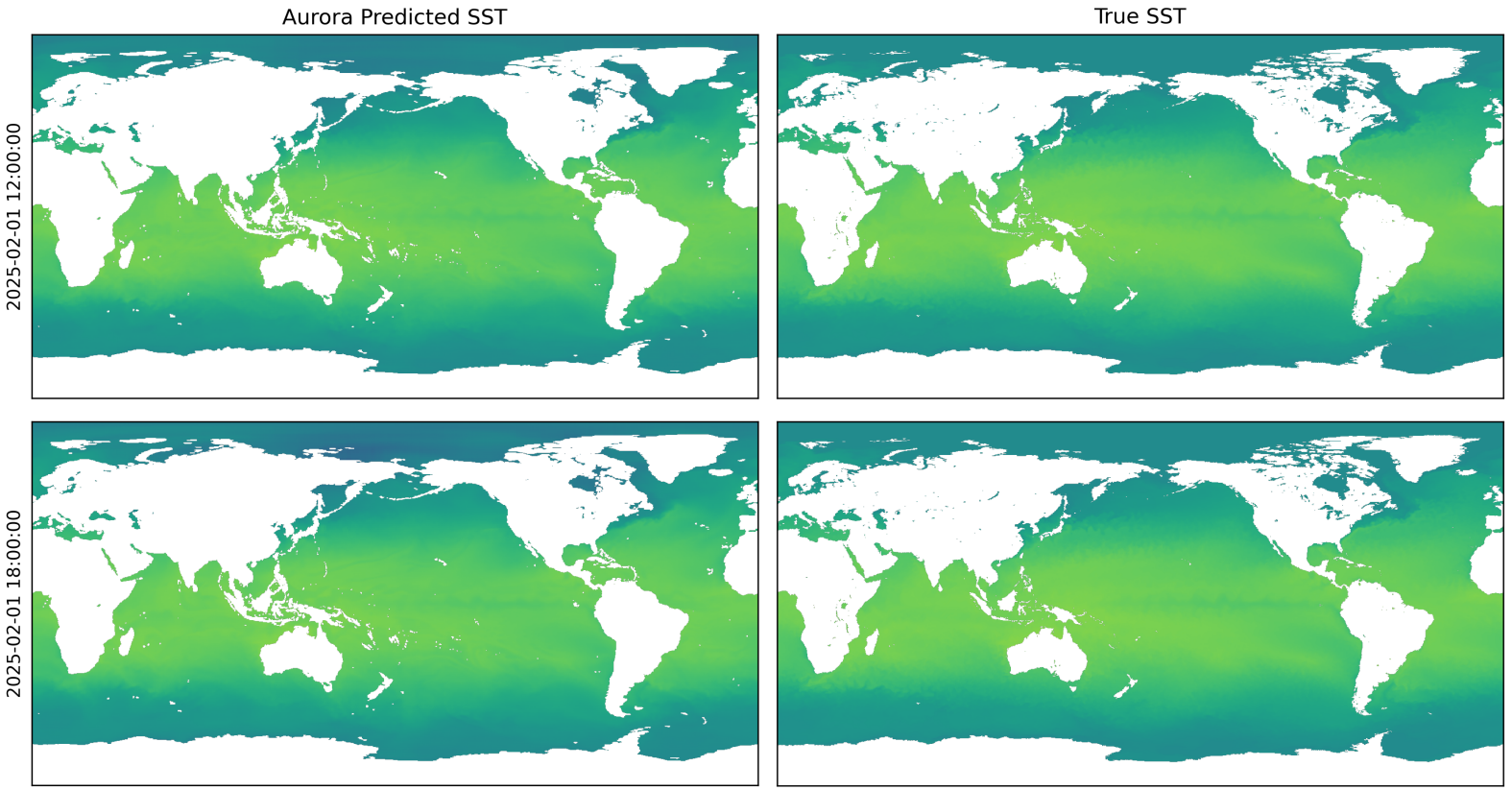
Step 1: Fill missing SST values using spatial median
Preprocess ERA5 SST data to handle missing/invalid values.

Step 2: Run Aurora inference using SST as 2m temperature
Feed the preprocessed SST into the frozen AuroraLite model as if it were 2m temperature input.

Step 3: Mask land grid points in model prediction
Apply land-sea mask to remove predictions over land regions (keep only ocean predictions).

Step 4: Compare masked predictions with original SST
Evaluate model output against ground truth ERA5 SST over valid ocean pixels.

Sea Surface Temperature - Inference



Lead Time	RMSE (K)	Correlation
Step 1 (+6h)	1.4204	0.9952
Step 2 (+12h)	2.3195	0.9880
Average (ocean)	**1.8699**	**0.9916**

Data

Training: ERA5 Reanalysis 2020–2021, 6-hour intervals
Validation: Jan–Aug 2022
Total Dataset Size: 445 GB

Data Configuration:

1. Grid: 720 lat $\times$ 1440 lon
2. History: 2 time steps (current timestep and immediately previous timestep)
3. Pressure levels: [50, 100, 150, ..., 1000] hPa (13 levels)
4. Sequential batching: 22 timesteps ($\approx$ 5.5 days)

Target: Single 2D SST field per time step

Methodology - Training

Loss: Mean Absolute Error (MAE)
Optimizer: Adam with learning rate $\eta = 3 \times 10^{-4}$

Validation: Jan–Aug 2022, evaluated every 22 timesteps

Sequential Pass: Gradients accumulated over sequential data to capture seasonal patterns

Hyperparameters: All fixed; validation used only to monitor convergence

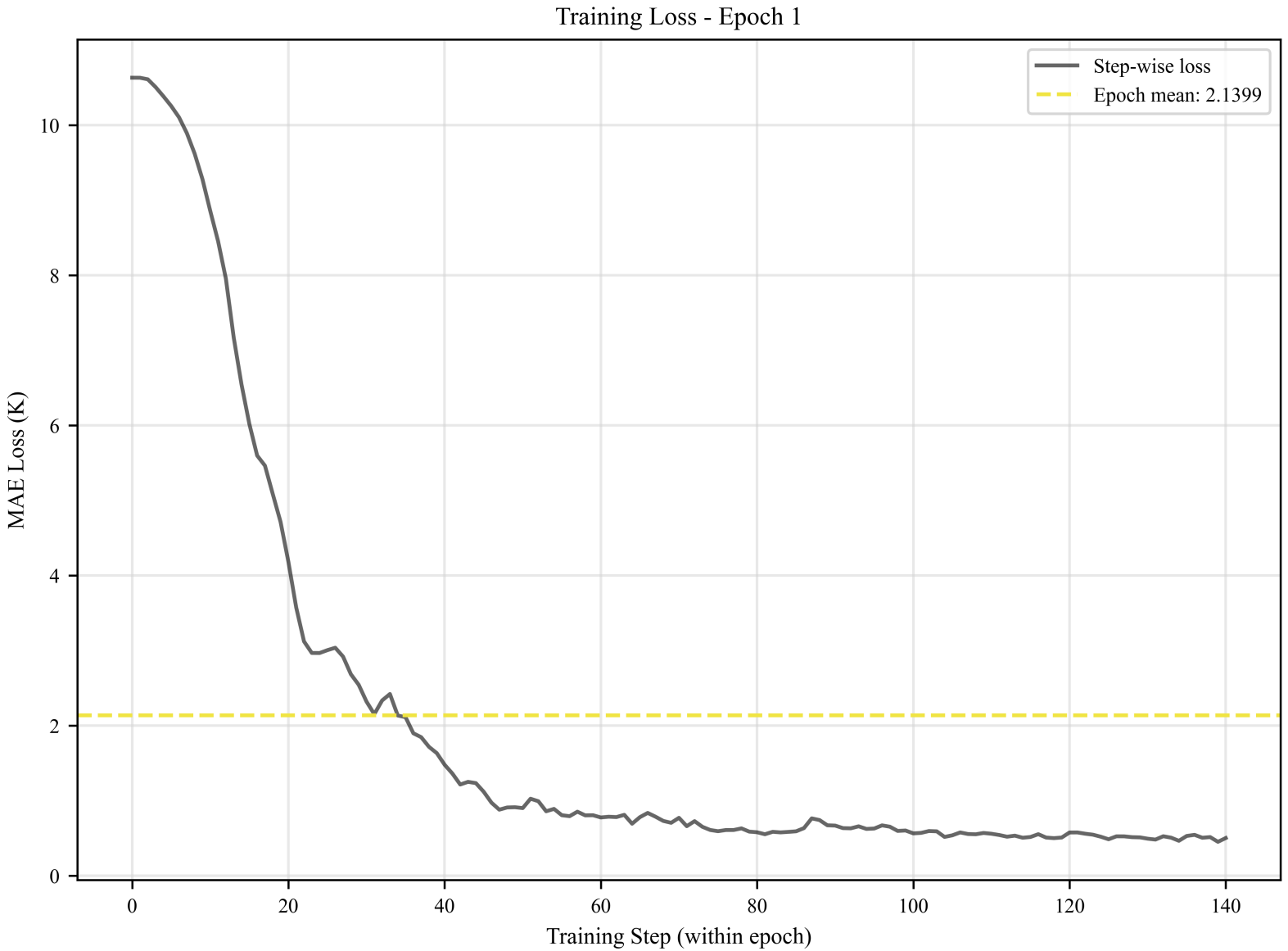
Computational Resources

Hardware: Requested on Fir Cluster of Research Alliance Canada

1. GPU: 1× NVIDIA H100
2. CPU: 12 cores
3. RAM: 288 GB system memory

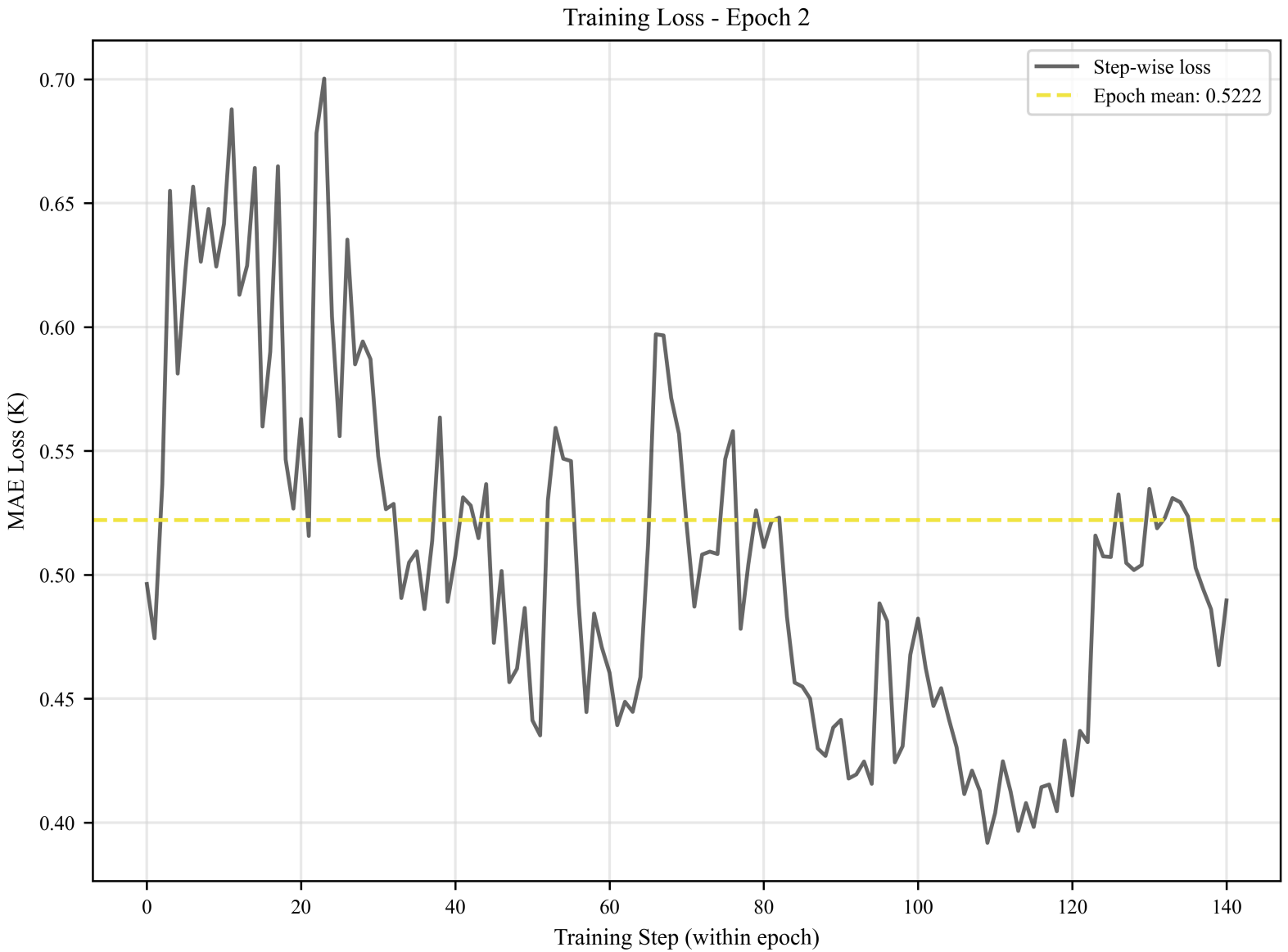
Runtime: ˜3 days for 2 epochs

Training Loss - Epoch 1



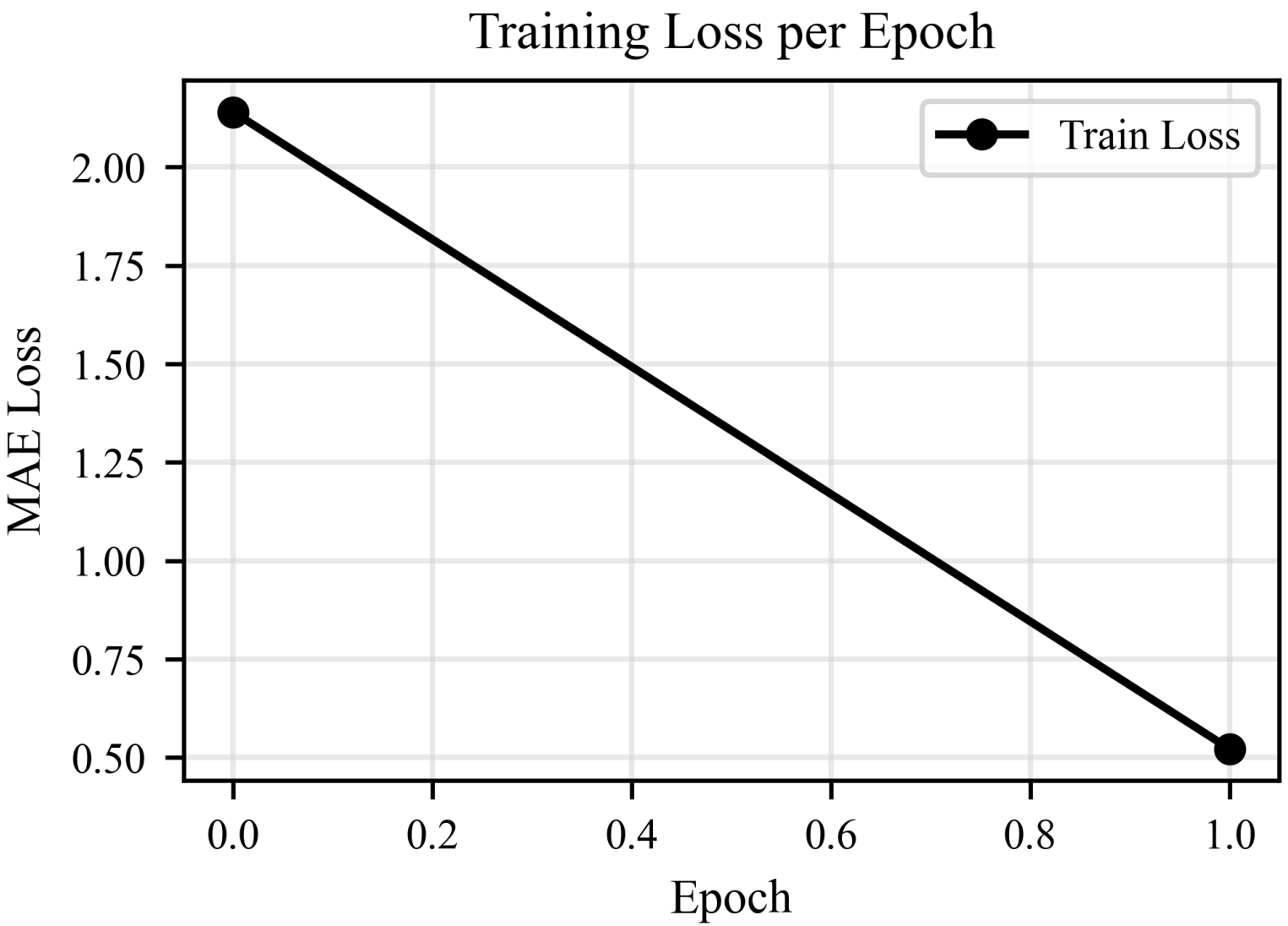
Epoch 1: Train Loss 2.1399 $\rightarrow$ Val Loss 0.7272

Training Loss - Epoch 2

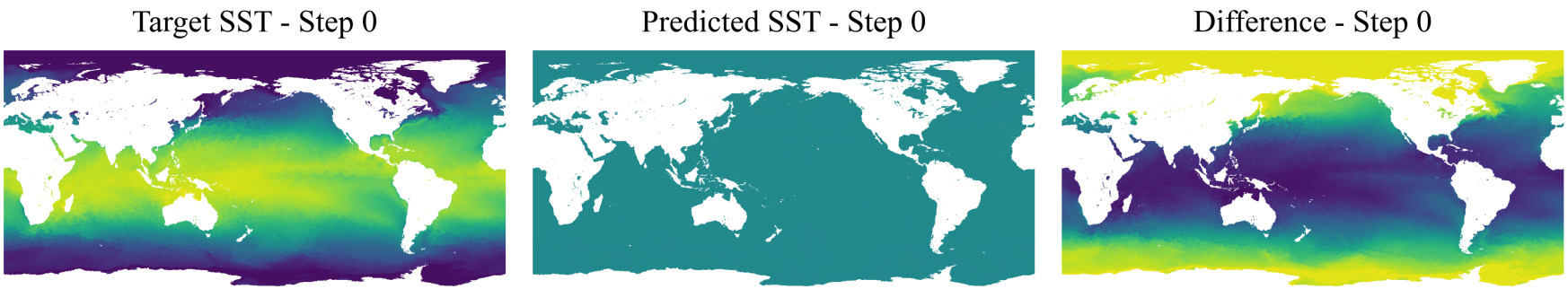


Epoch 2: Train Loss 0.5222 $\rightarrow$ Val Loss 0.6218

Training Loss Over Epochs

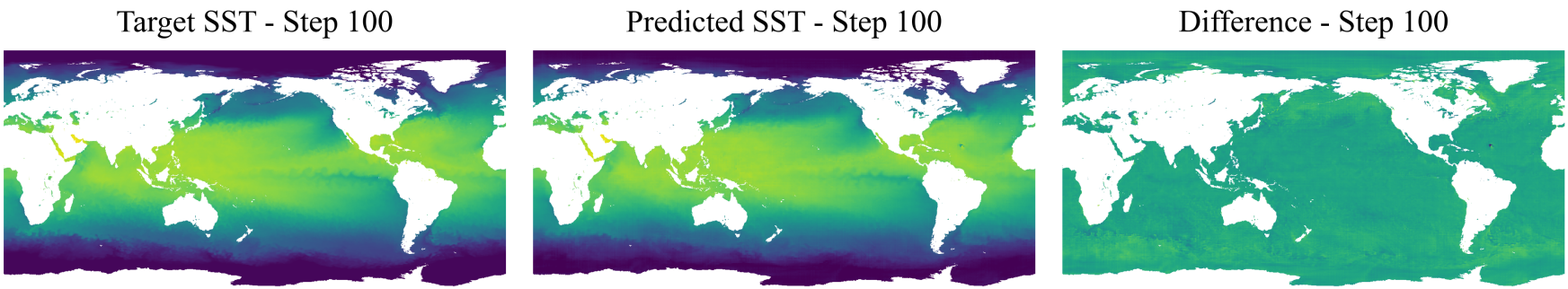


Training Progression - Step 0



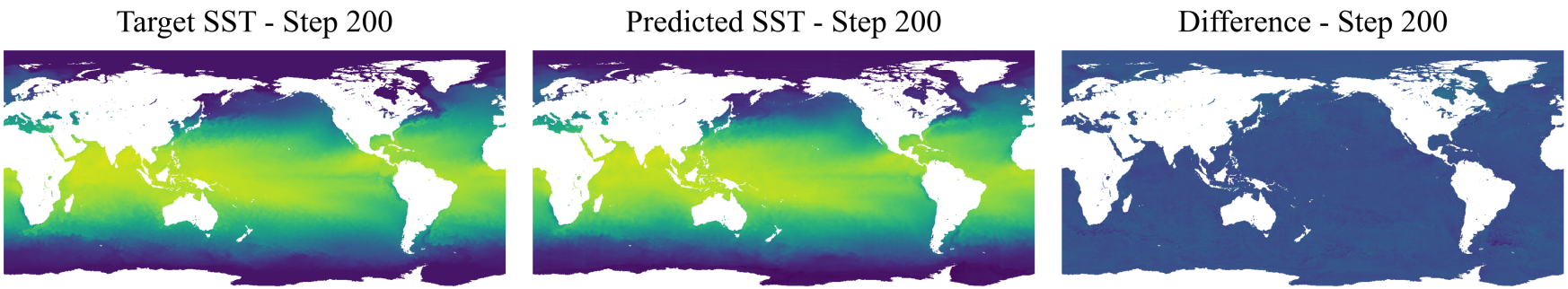
Initial training state: raw predictions before convergence

Training Progression - Step 100



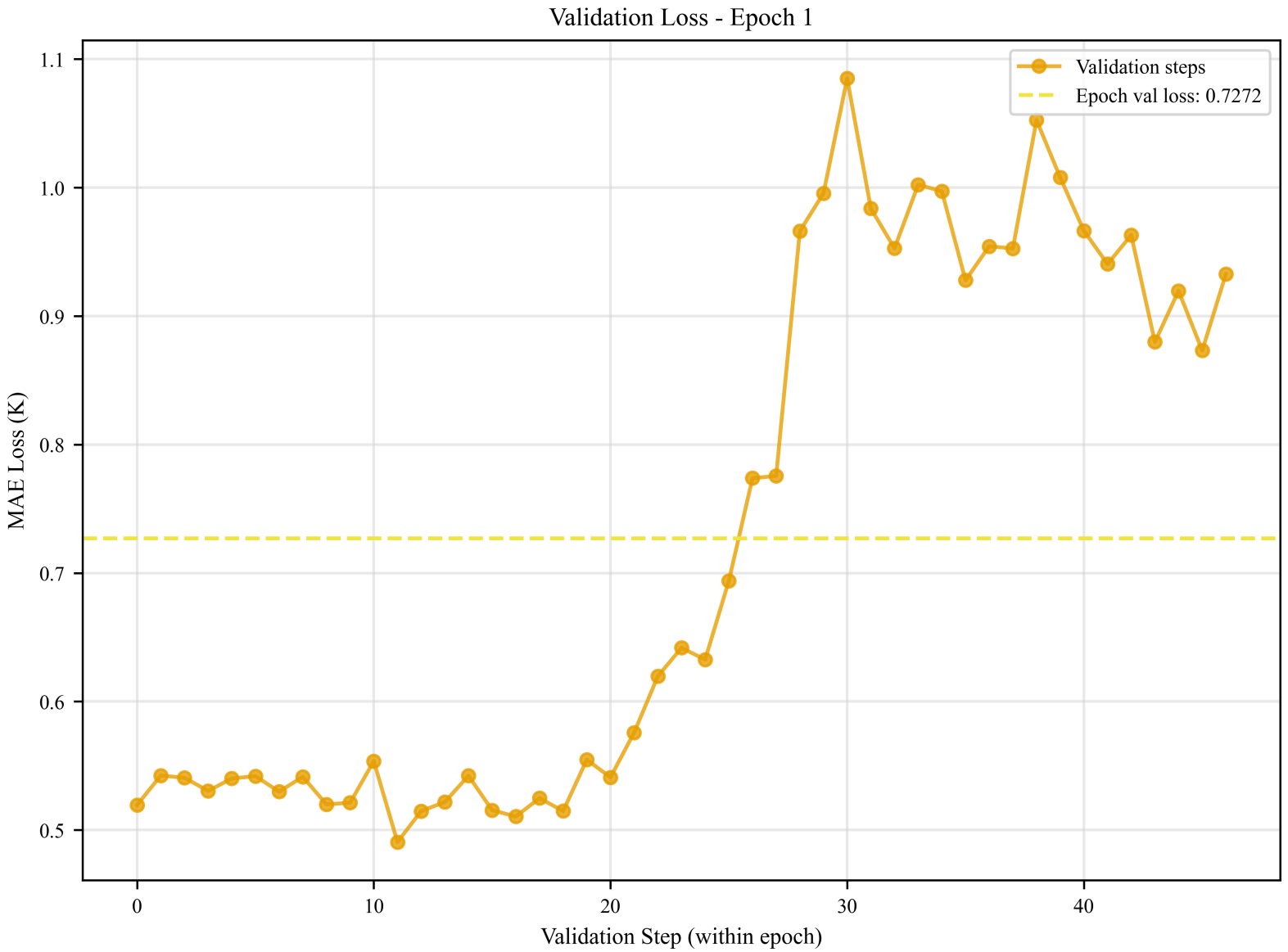
Early training: spatial structure begins to emerge

Training Progression - Step 200



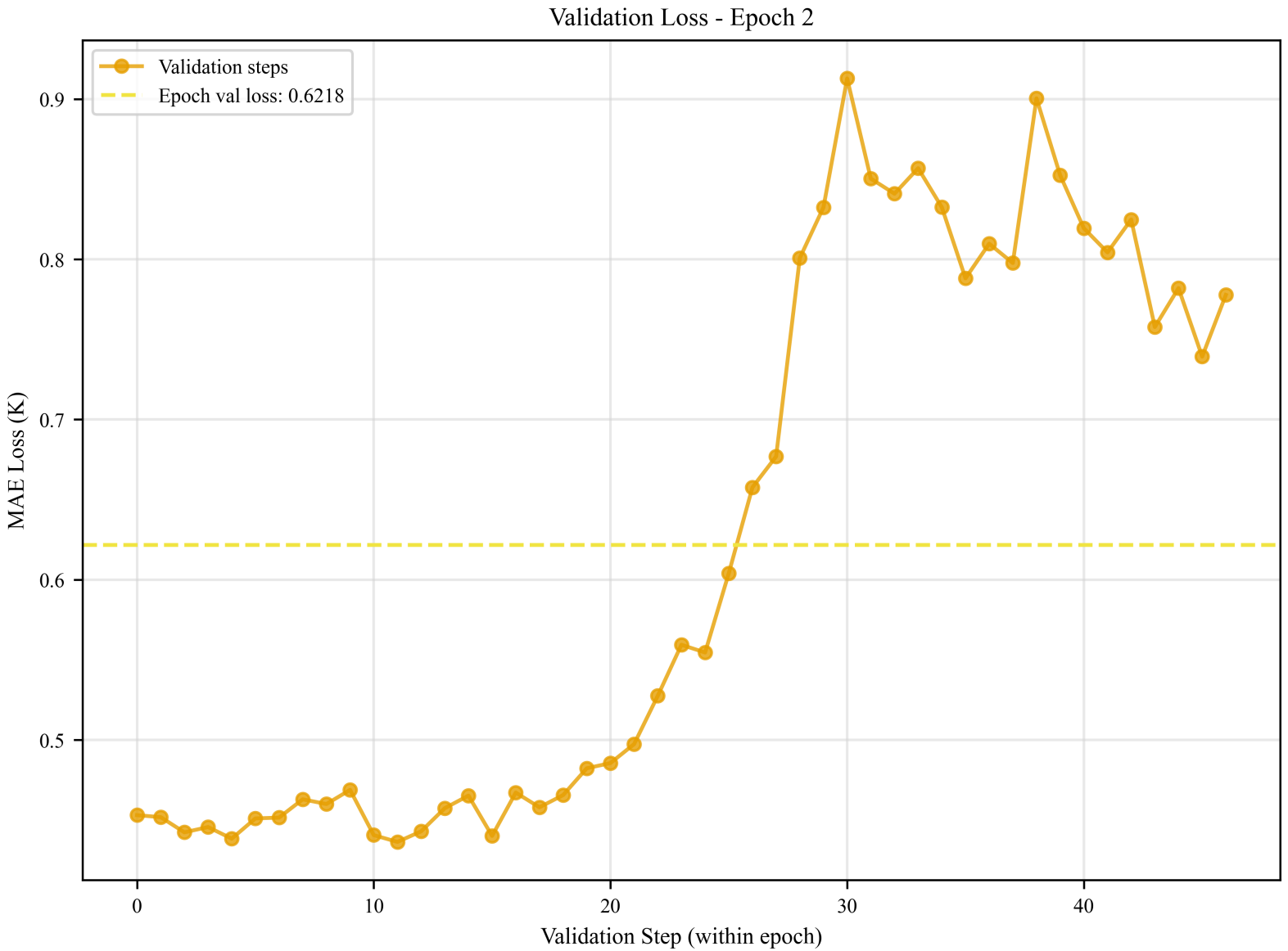
Convergence: model captures realistic ocean temperature patterns

Validation Loss - Epoch 1



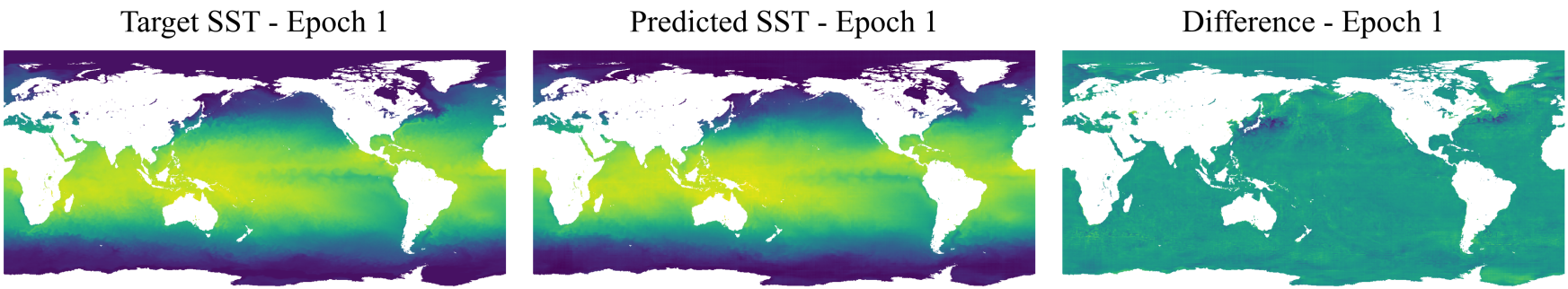
Performance better on data from Jan - Apr

Validation Loss - Epoch 2



Validation loss decreses at each point, yet same pattern

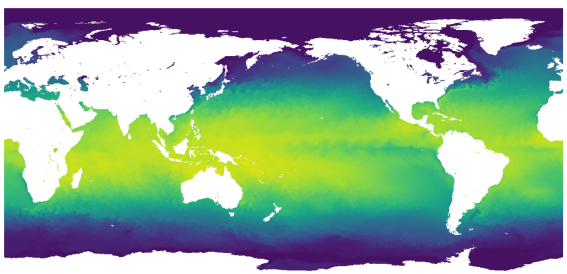
Validation Predictions - Epoch 1



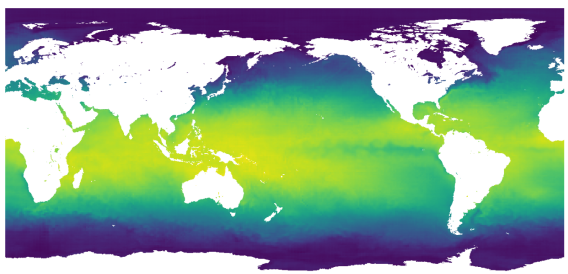
Early epoch: model already captures significant SST structure

Validation Predictions - Epoch 2

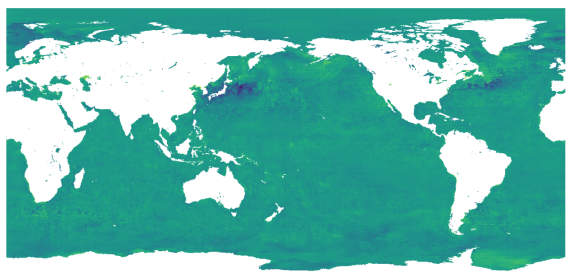
Target SST - Epoch 2



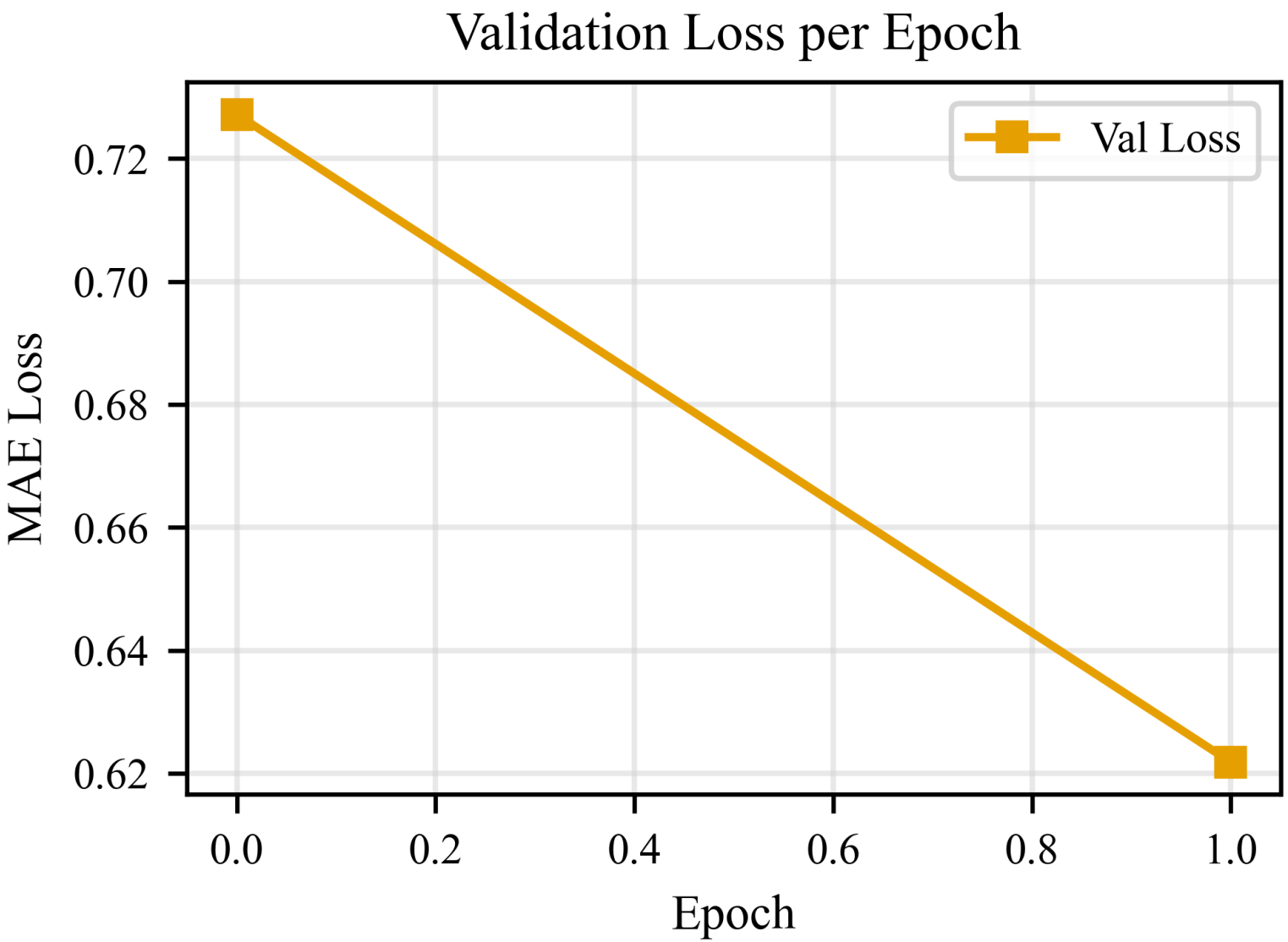
Predicted SST - Epoch 2



Difference - Epoch 2



Validation Loss Over Epochs



Validation loss trajectory showing tendency of model convergence

Spatial Consistency Regularization

Gradient Penalty Loss:

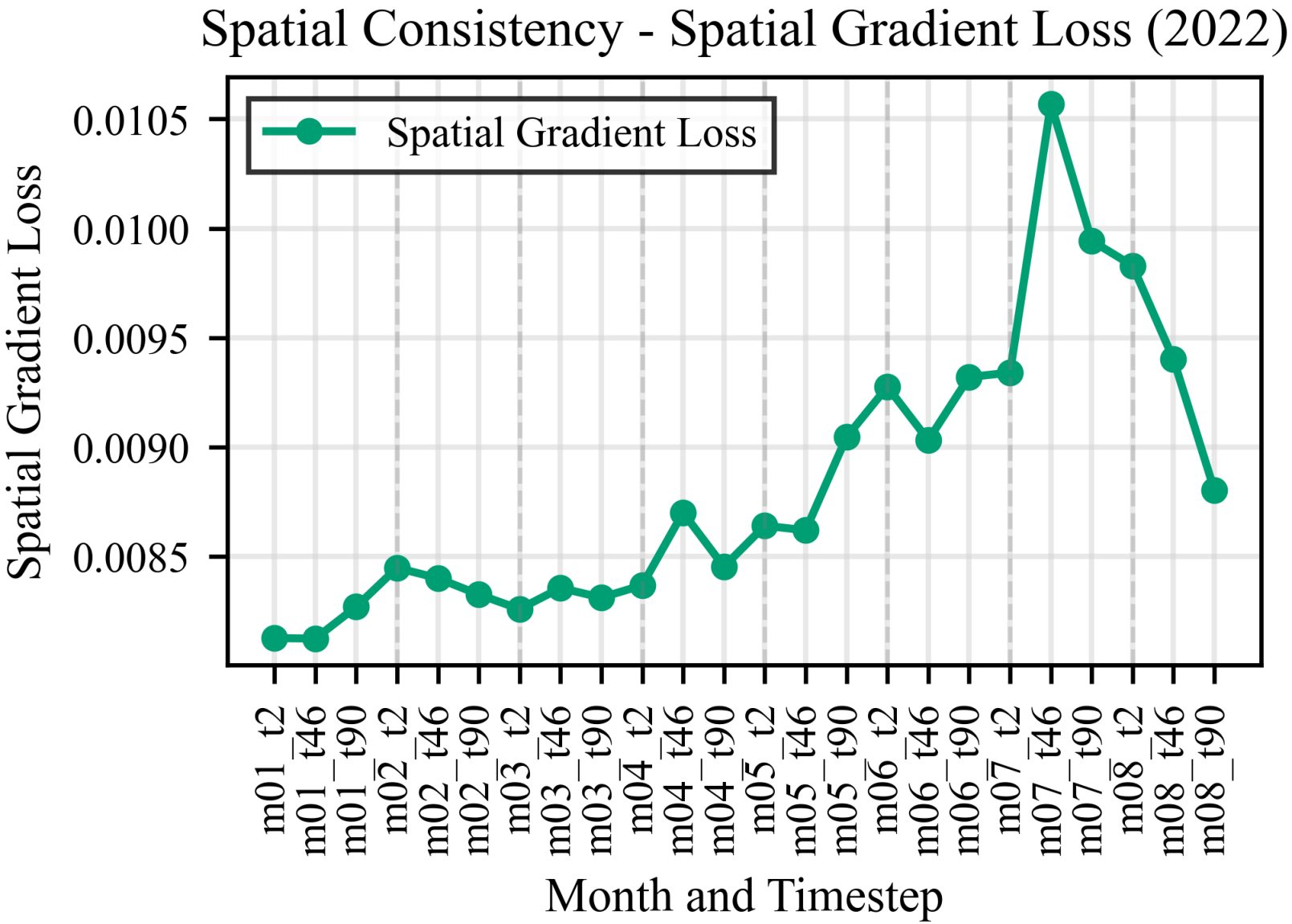
$$\Delta_{\text{lat}} = \frac{1}{N} \sum_{i,j} |\text{SST}_{i+1,j} - \text{SST}_{i,j}|^2 \tag{1}$$

$$\Delta_{\text{lon}} = \frac{1}{N} \sum_{i,j} |\text{SST}_{i,j+1} - \text{SST}_{i,j}|^2 \tag{2}$$

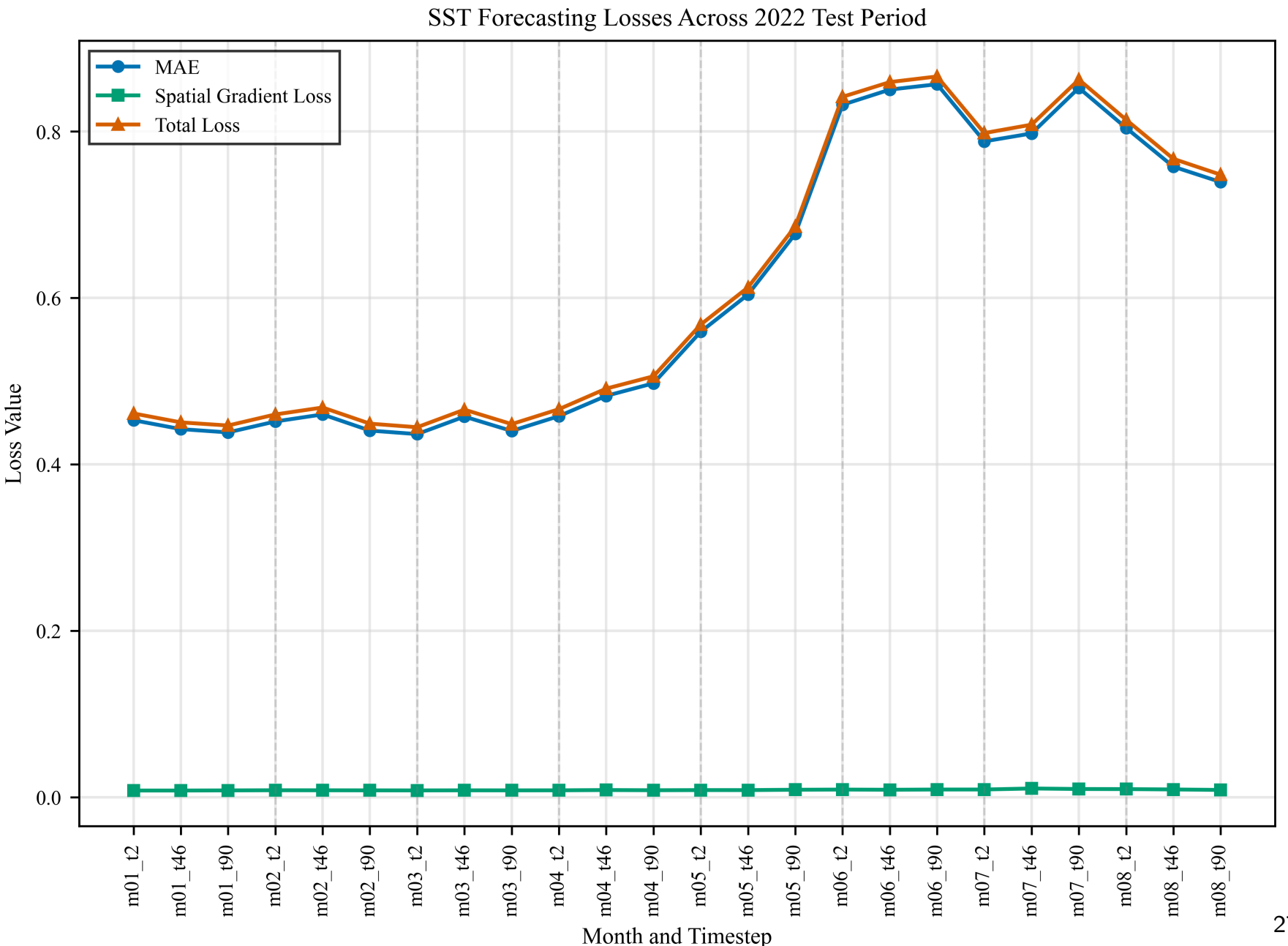
$$L_{\text{gradient}} = \lambda \left(\Delta_{\text{lat}} + \Delta_{\text{lon}} \right), \quad \lambda = 0.05 \tag{3}$$

These gradients enforce physical smoothness: SST should vary smoothly across space, preventing unrealistic sharp discontinuities in temperature fields. It was only used for testing.

Spatial Consistency Check



Spatial Consistency-based Validation



Key Results

Forecasting Performance:

1. We can conclude that without explicitly seeing SST data during training, the Aurora Model can predict SST.
2. However the model has generalized better on SST data from January to April compared to May to August.
3. We can see the model already maintains spatial consistency (SST does not rise or fall from one coordinate to another rapidly). Yet in this case we see better performance in first 4 months.

Scopes of improvement:

1. Finetune on at least 8-10 years of data.
2. Validate on more years. Both of the tasks will require much more resources and time.

Takeaway: Foundation models + lightweight decoders enable practical adaptation to new variables with minimal compute

Acknowledgements

1. This slide demonstrates my endeavours to explore Aurora model. https://github.com/mridul0837/aurora-sst-forecasting
2. This work is a part of course project done for COMP6936: Advanced Machine Learning Course of MUN instructed by Dr. Jingrong Wang. Link to the full course project by all groupmates: https://github.com/Aiden0609/MLProject-G1-F2025
3. Special thanks to the Research Alliance Canada for all the resources.

Thank You!

For any questions, please feel free to contact:

Email: mdrh@mun.ca

LinkedIn: md-rakib-hossain-mridul

GitHub: github.com/mridul0837