



Elevation Data Integration Approaches for Deep Learning-Based 2-m Temperature Downscaling

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Workshop on AI-driven Data Engineering and Reusability for Earth and Space Sciences (DARES'25)

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Metrics | Training history | MAE Comparison | Output Comparison

Background → Weather Forecast

Numerical Weather Prediction (NWP) Models

- Deterministic modeling
- Solve differential equations to simulate atmospheric processes
- Rely on real-time observations and supercomputers

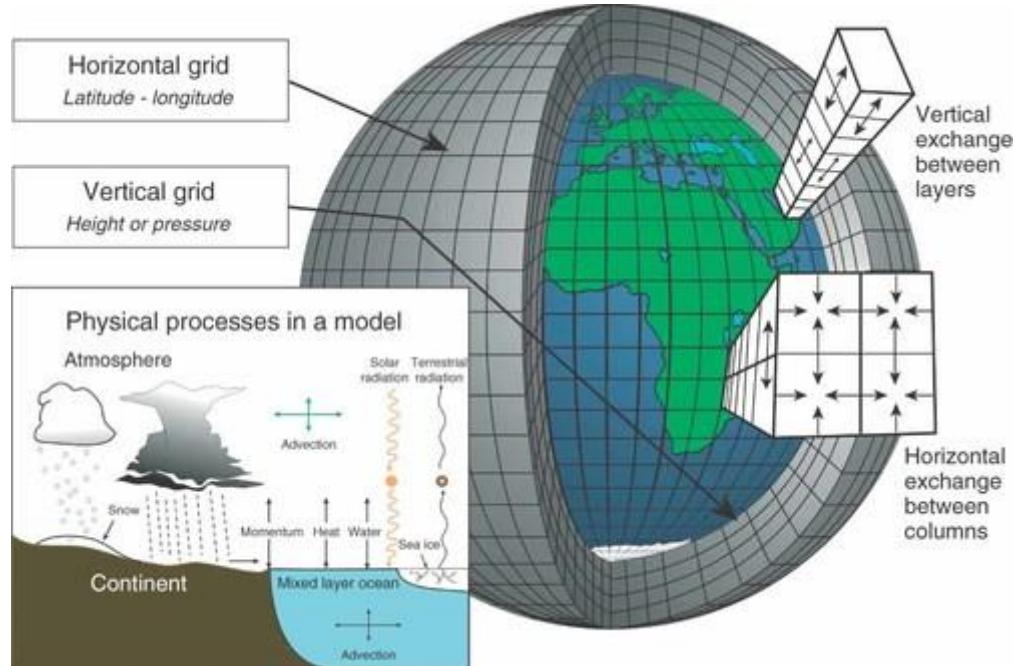


Fig. 1 [1]

Weather forecast trade-offs

- Time Range vs. Accuracy
- Global vs. Regional Focus
- **Spatial Resolution vs. Forecast Range**

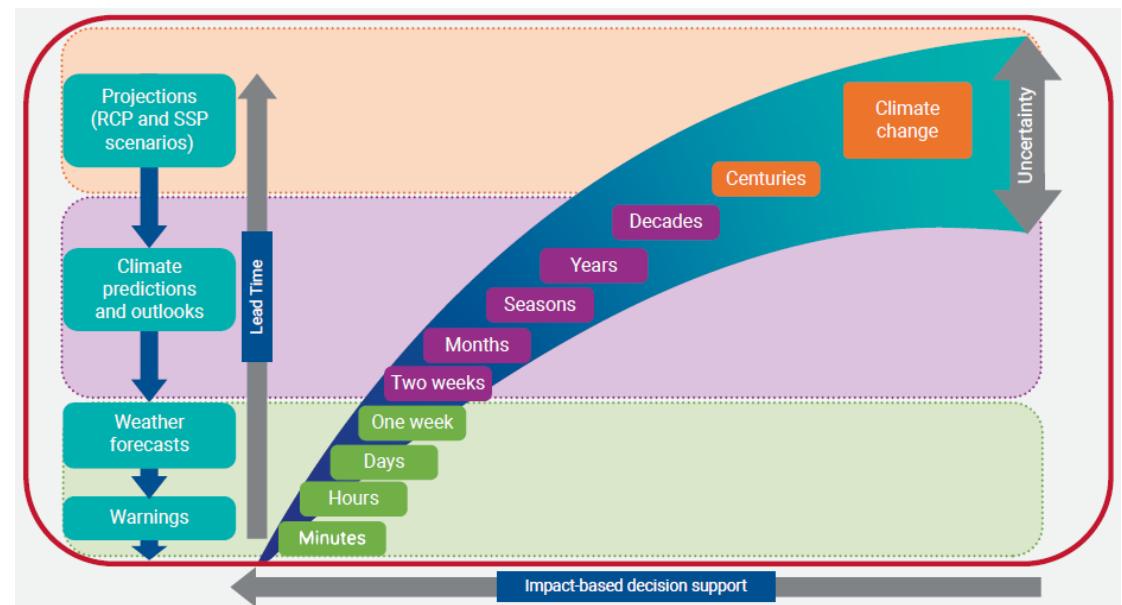


Fig. 2 [2]

Background → Problem Statement

When Forecast Models Use Low Spatial Resolution?

1. Global Weather Models

- Cover the **entire Earth**
- Typical resolution: **10–50 km grid spacing**

2. Climate Models

- Forecast **decades to centuries ahead**
- Typical resolution: **50–200 km grid spacing**

Why High Spatial Resolution is important?

Could guide more confident decision-making in sectors like:

- Agriculture
- Energy
- Transportation
- Environment and Disaster Management
- Etc.

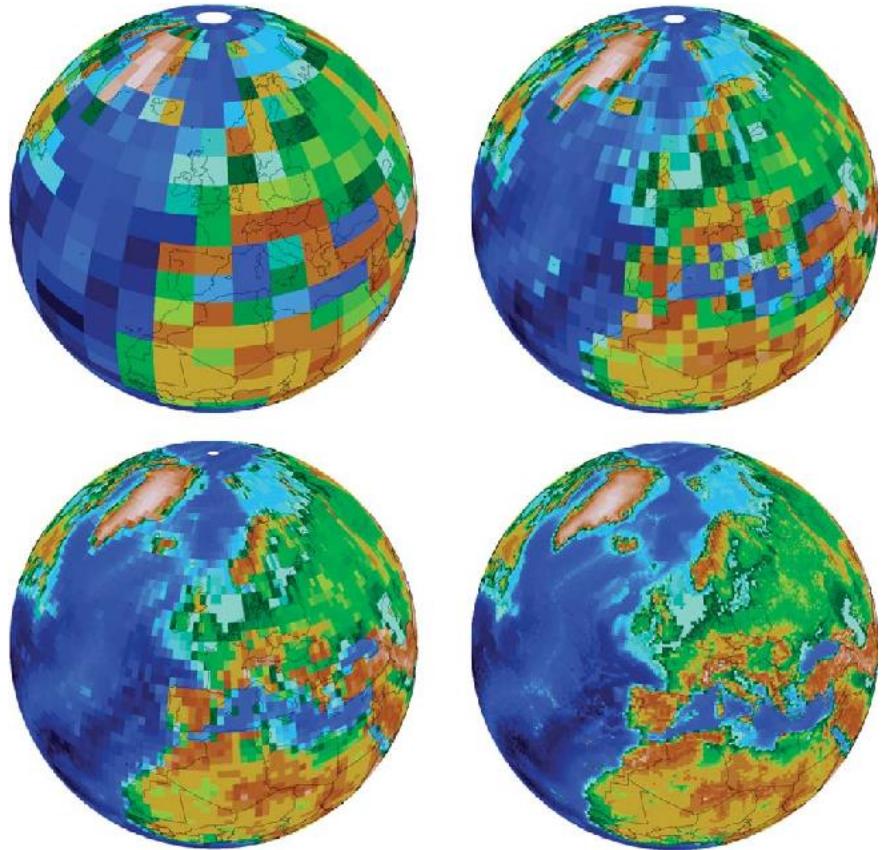


Fig. 3 [3]

Background → Previous work

1. **Publication:** A deep learning approach for spatial error correction of numerical seasonal weather prediction simulation data [4]
 - Seasonal predictions
 - CAE with Evidence transfer
2. **MSc Thesis:** Use of Deep Learning methods and land cover/use data to improve the spatial resolution of Numerical Weather Prediction (NWP) simulations.
 - Comparison of CNN-based models
 - Gradual downscaling
 - Integration of elevation
3. **EU Projects:**
 - **NEVERMORE:** Development of models and tools for simulating and assessing the impacts and risks of climate change
 - **MOUNTADAPT:** Production of adaptation solutions to reduce climate change impacts on health in mountainous regions

Methodology → Integration strategies

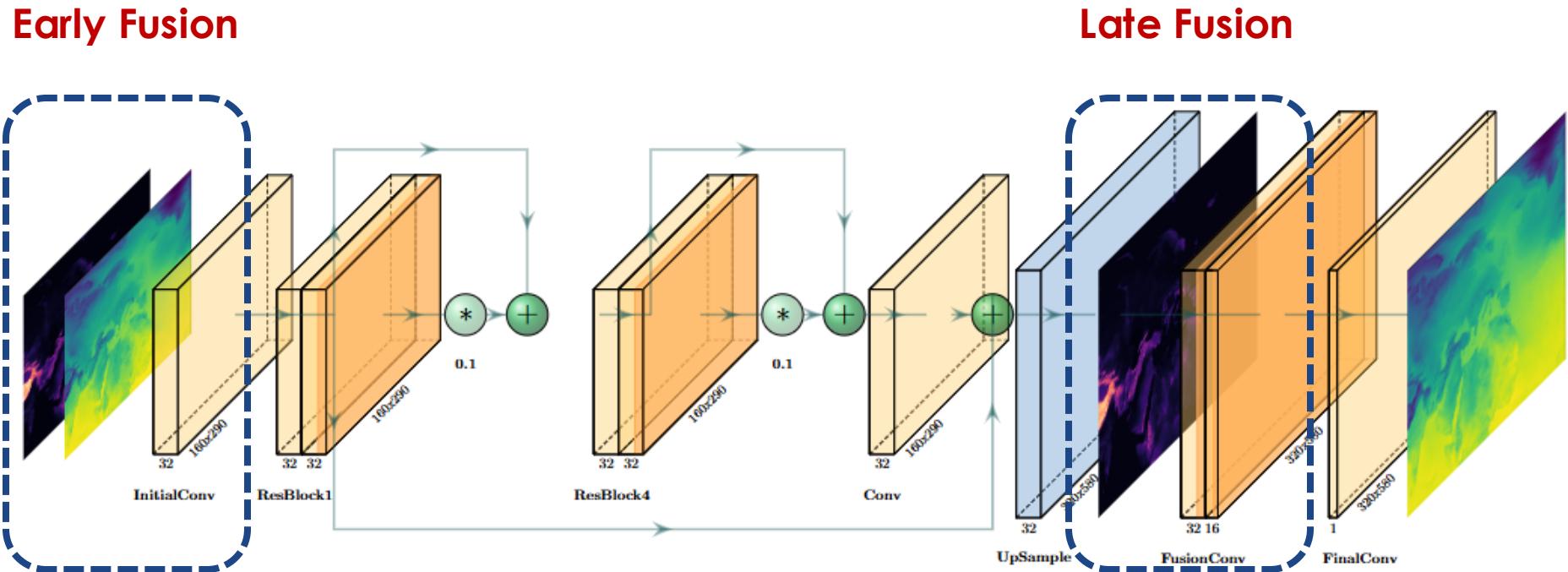


Fig. 4

Methodology → Elevation-derived features

Elevation

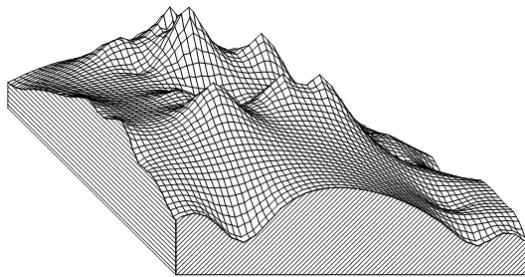


Fig. 5 [5]

Slope

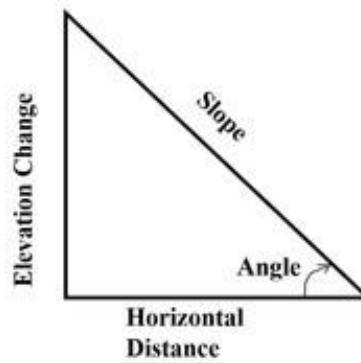


Fig. 6 [6]

Aspect

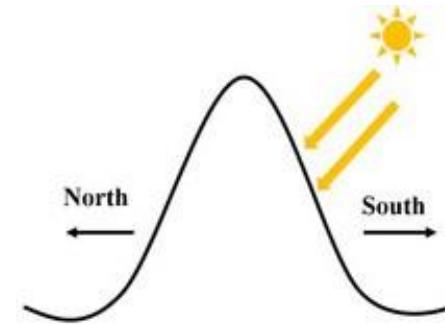


Fig. 7 [6]

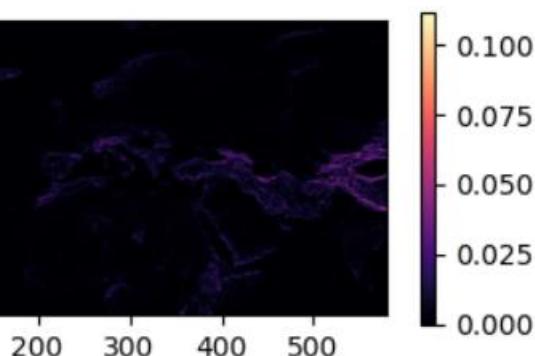
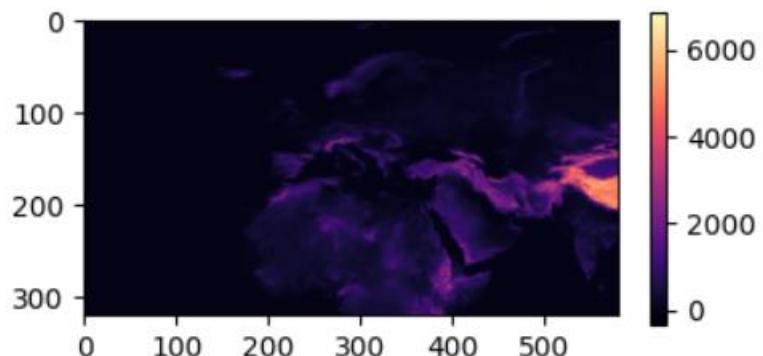
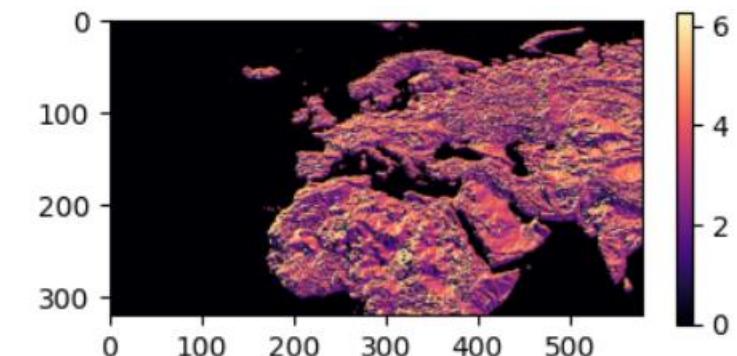


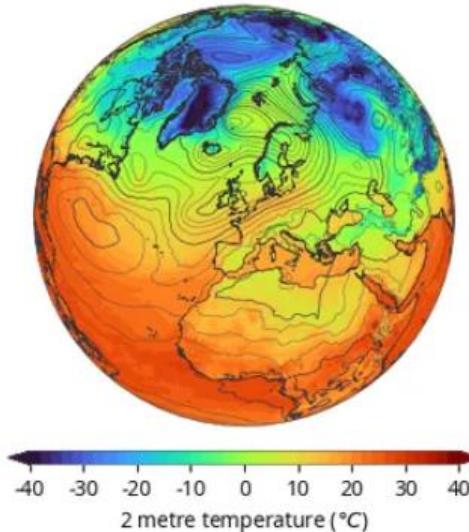
Fig. 8



Experimental Setup → Dataset & pre-processing

ERA5 reanalysis Dataset [7]

Data type	Gridded
Projection	Regular latitude-longitude grid
Horizontal coverage	Global
Horizontal resolution	Reanalysis: $0.25^\circ \times 0.25^\circ$ (atmosphere), $0.5^\circ \times 0.5^\circ$ (ocean waves)
Temporal coverage	1940 to present
Temporal resolution	Hourly
File format	GRIB
Update frequency	Daily



Pre-Processing Steps

- Upscaling:** Bicubic interpolation to match target resolution (from $0.25^\circ \times 0.25^\circ$ to $0.5^\circ \times 0.5^\circ$)
- Normalization:** Z-score standardization
- Shuffling:** Randomize data order to remove temporal bias
- Splitting:** 70% training, 15% validation, 15% testing

- Variable:** 2-meter air temperature (T2m)
- Period:** 2000 – 2020
- Temporal resolution:** 6-hourly (00:00, 06:00, 12:00, 18:00 UTC)
- Spatial domain:** Latitude **80° N to 0°**, Longitude **60° W to 85° E**

“A model-agnostic input approach with no model or temporal bias.”

& elevation data from the U.S. Geological Survey 3D Elevation Program DEM [8]

Experimental Setup → Training & validation

Validation Metrics:

- Mean Squared Error (MSE)
- Mean Absolute Error (MAE)
- Peak Signal-to-Noise Ratio (PSNR)
- Structural Similarity Index Measure (SSIM)

Loss function:

- MAE (L1 loss) → less sensitive to outliers, reflects average deviation in original units

Optimizer & Learning Rate:

- Adam optimizer
- ReduceLROnPlateau schedule (70 epochs)

Training Details:

- Batch Size: 32
- Training: 250 epochs
- Early Stopping: 100 epochs

Results → Integration strategies

	No DEM	Early Fusion	Late Fusion	Early&Late Fusion
MAE ↓	0.00167	0.00153	0.00156	0.00141
MSE ↓	0.000012	0.000010	0.000010	0.000008
PSNR ↑	49.3268	49.9457	49.9583	50.8118
SSIM ↑	0.9947	0.9955	0.9953	0.9962
Land Mean MAE ↓	0.00266	0.00241	0.00249	0.00223
Land Mean MAE in °C ↓	0.17062	0.15454	0.15987	0.14298
Land Max MAE in °C ↓	1.32484	1.44314	1.15182	1.01760
Training time per epoch ↓	56s	57s	76s	76s
Inference time per sample ↓	4.22ms	3.04ms	3.37ms	3.35ms
Trainable params ↓	93,089	93,377	107,105	107,393

The **Early & Late Fusion** exhibits the **smallest variability in MAE**

Combination of Early & Late Fusion elevation data integration gave the best results

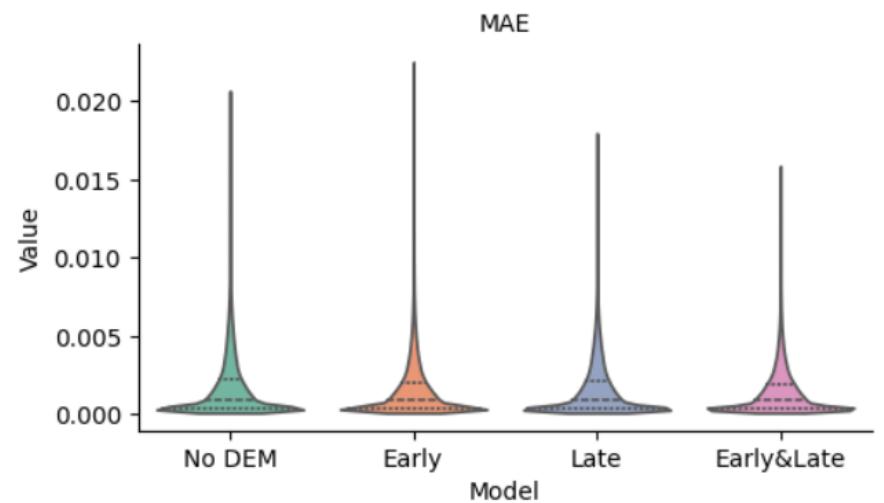


Fig. 9

Results → Elevation-derived features

	Aspect	Slope	Elevation & Aspect	Elevation & Slope
MAE ↓	0.00141	0.00142	0.00142	0.00140
MSE ↓	0.000008	0.000009	0.000008	0.000008
PSNR ↑	50.7447	50.7145	50.7910	50.8345
SSIM ↑	0.9962	0.9961	0.9962	0.9962
Land Mean MAE ↓	0.00223	0.00225	0.00224	0.00222
Land Mean MAE in °C ↓	0.14352	0.14457	0.14364	0.14242
Land Max MAE in °C ↓	1.04202	1.09875	0.86288	1.03497
Training time per epoch ↓	76s	77s	76s	81s
Inference time per sample ↓	3.44ms	3.41ms	3.38ms	3.41ms
Trainable params ↓	107,393	107,393	107,969	107,969

Differences between approaches are minimal across metrics.

The Elevation & Slope combination yields slight but consistent improvements over using elevation alone and is recommended as the most effective approach.

Results → Summary

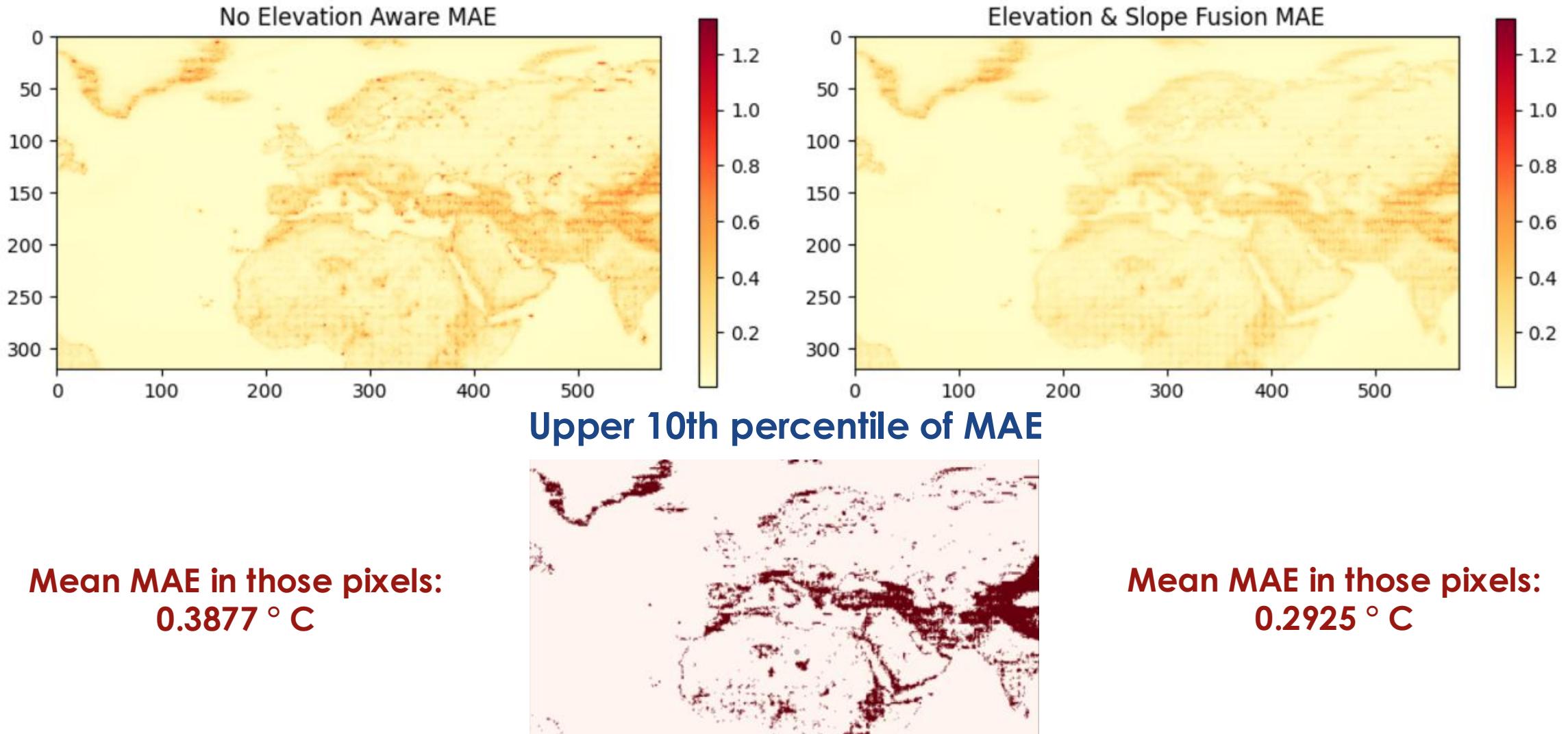


Fig. 10

Conclusions

- Developed an **input model-agnostic method** for **downscaling T2m**, capable of **doubling spatial resolution** (from **0.5°×0.5°** to **0.25°×0.25°** grids).
- Achieved a **low average error** of approximately **0.14 °C per cell**.
- Delivered a **16% reduction in MAE** across all regions through **integration of geospatial information**.
- Improved performance in complex terrains, with **~0.1 °C lower error** in the most challenging areas.

Future work

1. Extension to Other Climate Variables

- Precipitation
- Wind
- Multi-variable modeling (simultaneous downscaling of multiple variables)
- Use of data cubes for efficient multi-dimensional processing

2. Finer-scale downscaling using higher-resolution reanalysis datasets

- ERA5-Land (9km)
- CERRA-Land (5.5km)

3. Predictor Exploration at Each Downscaling Level

For example:

- 100 km → 50 km: Climate zones
- 50 km → 25 km: Elevation and derived features (aspect, slope)
- <25 km: Land use data

4. Model Architecture & Training Optimizations

- Deeper EDSR models
- Explore GAN-based architectures

5. Use of temporal models

- ConvLSTMs

References

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2. UNDRR and WMO (2023), Technical guidance on application of climate information for comprehensive risk management, United Nations Office for Disaster Risk Reduction and World Meteorological Organization.
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8. U.S. Geological Survey, The 3d elevation program (3dep). (2023) <https://www.usgs.gov/core-science-systems/ngp/3dep>

Thank you!

Questions?

Bonus slides

Bonus slides → Metrics

Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

Mean Absolute Error (MAE)

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

Peak Signal-to-Noise Ratio (PSNR)

$$\text{PSNR} = 10 \cdot \log_{10} \left(\frac{L^2}{\text{MSE}} \right)$$

Structural Similarity Index Measure (SSIM)

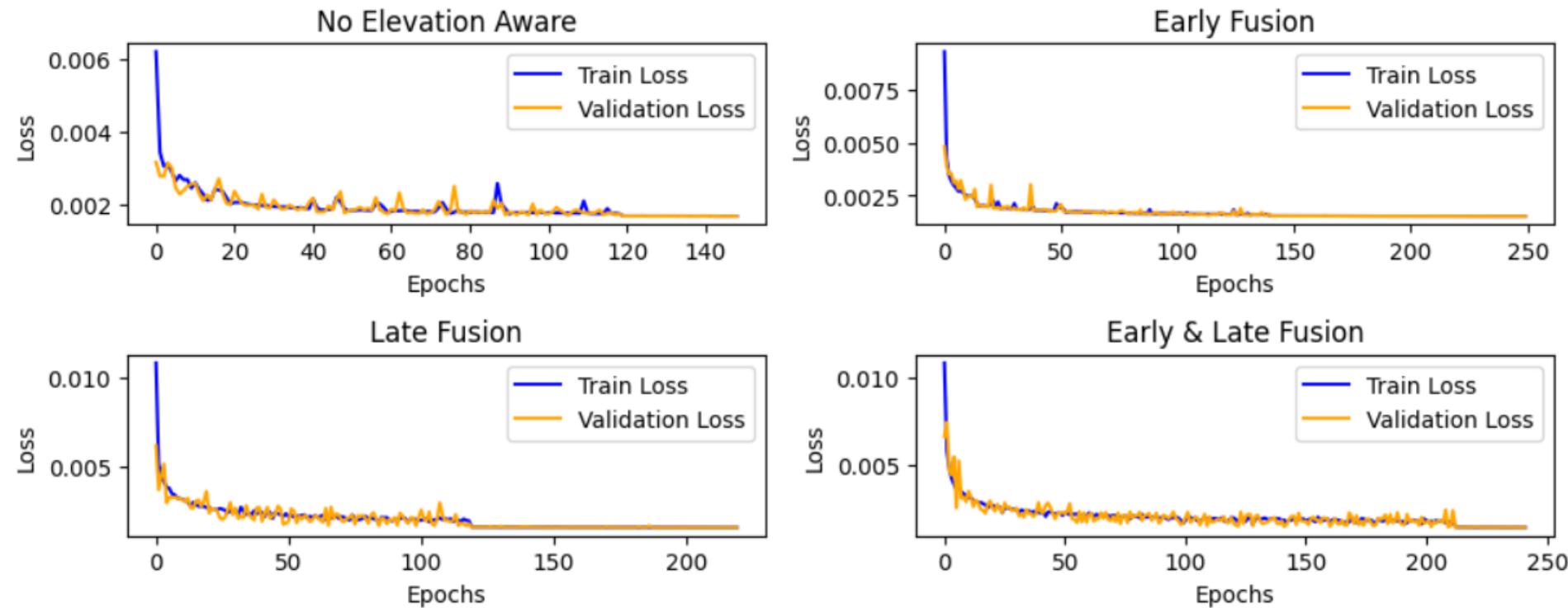
$$\text{SSIM}(x, y) = [l(x, y)]^\alpha \cdot [c(x, y)]^\beta \cdot [s(x, y)]^\gamma$$

Land MAE

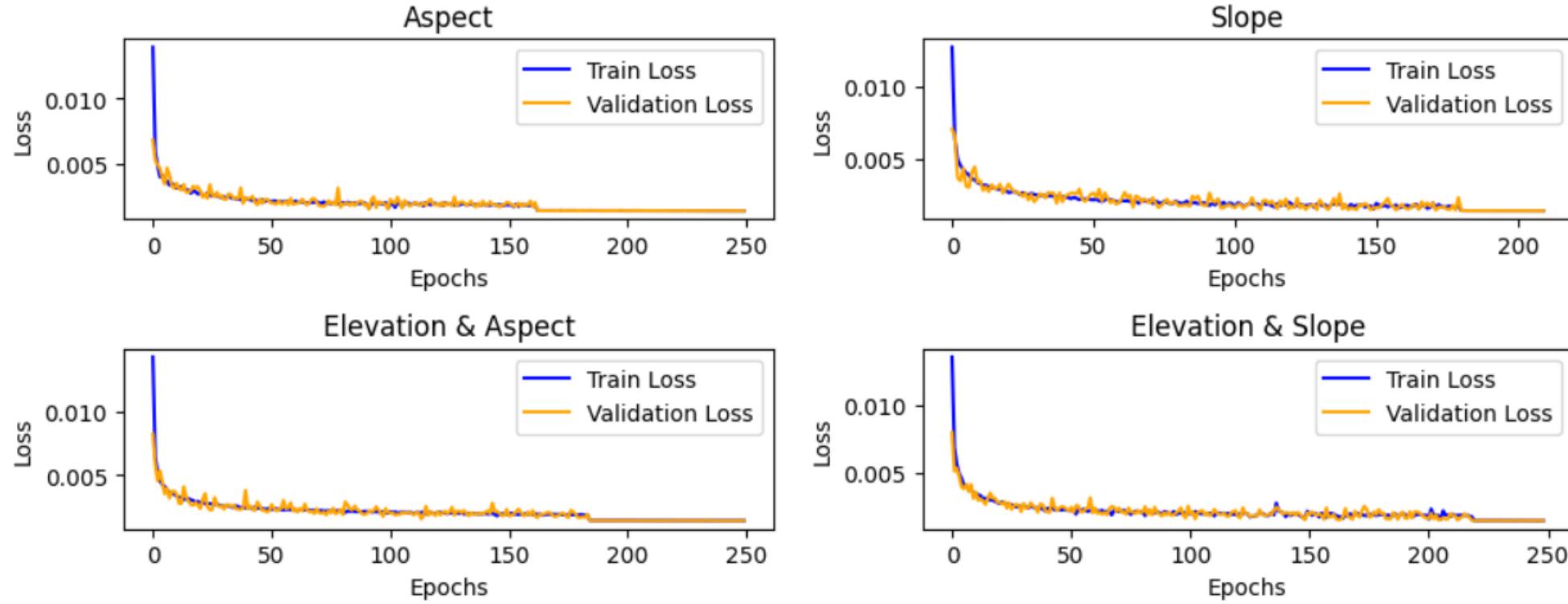


Land MAE in °C

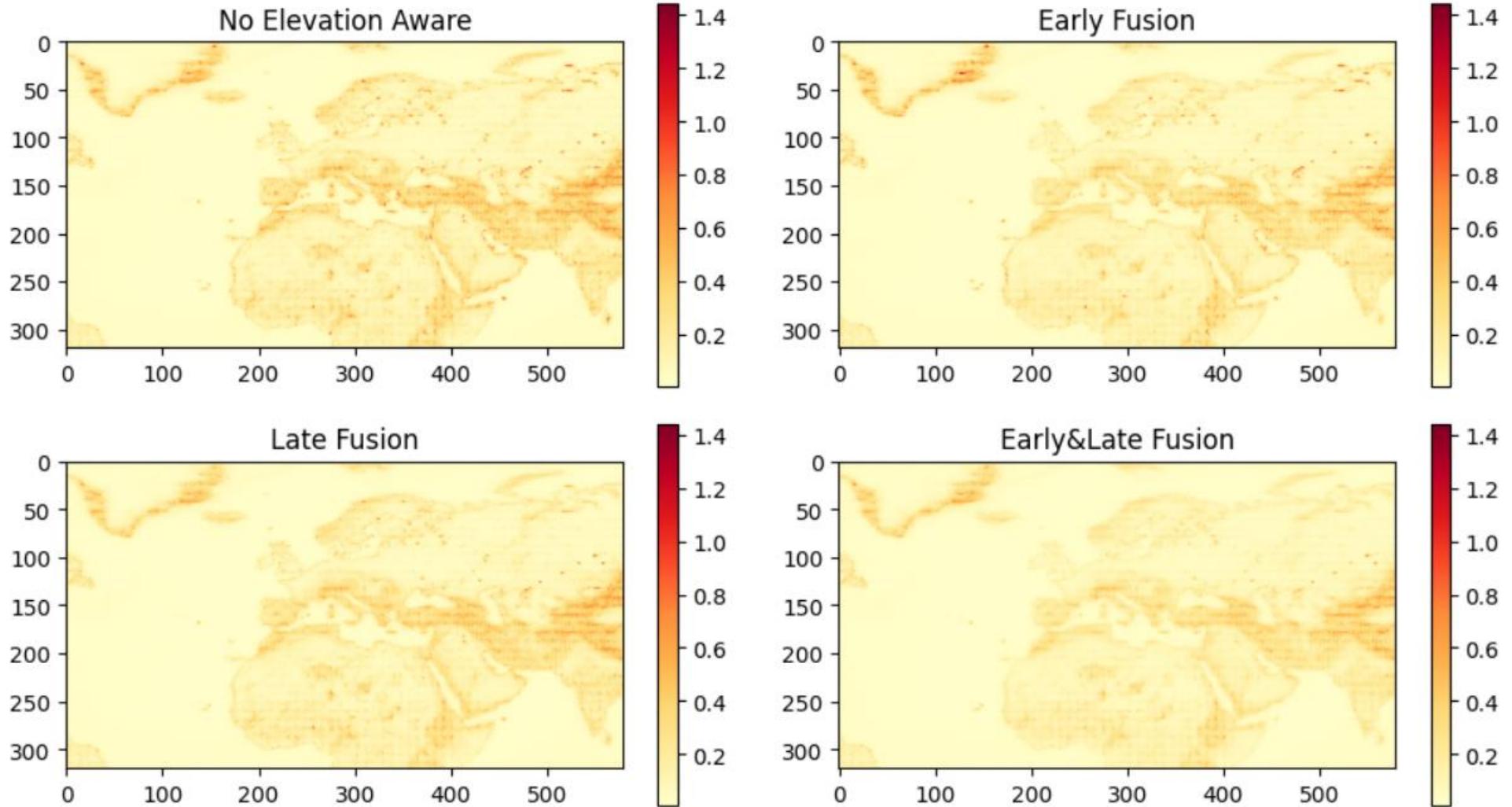
Bonus slides → Integration strategies training history



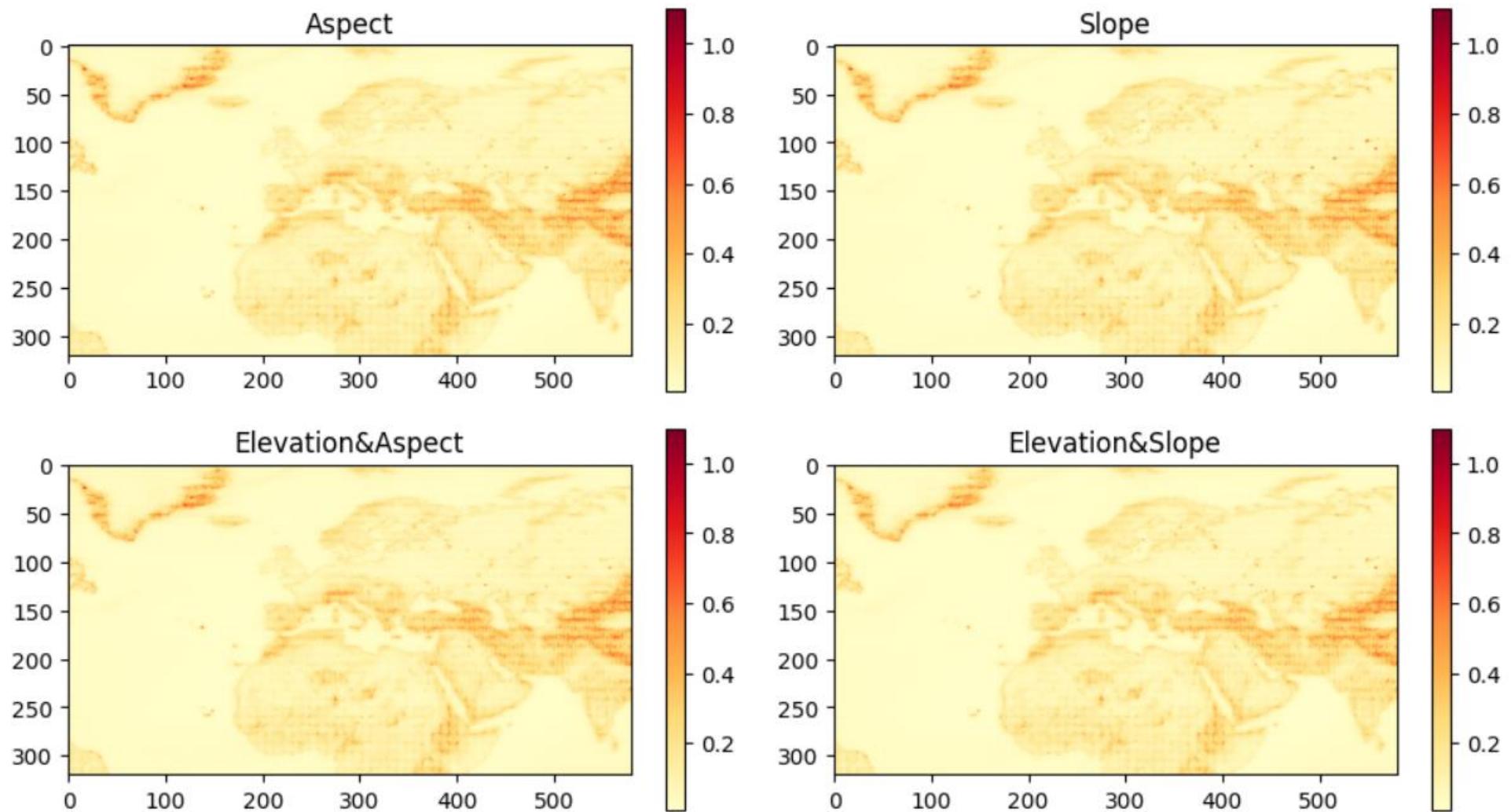
Bonus slides → Elevation-derived features training history



Bonus slides → Integration strategies MAE comparison



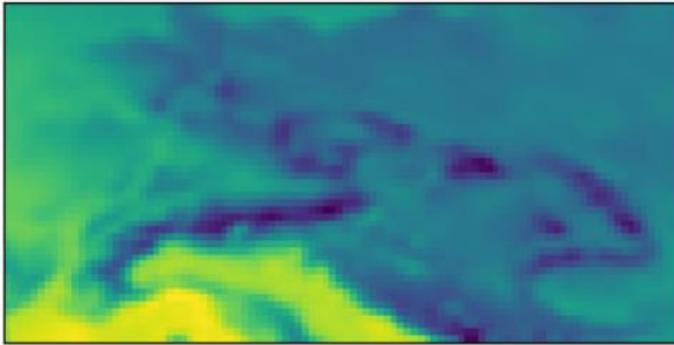
Bonus slides → Elevation-derived features MAE comparison



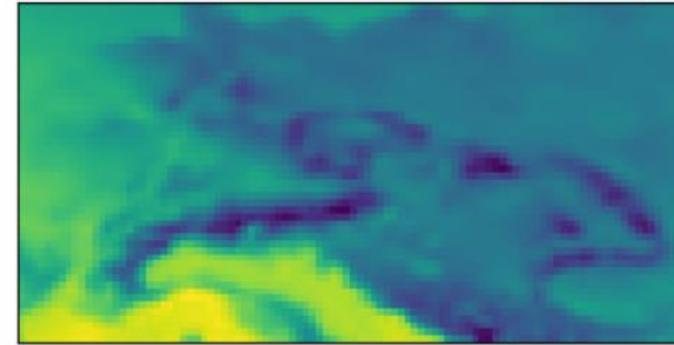
Bonus slides → Outputs “Central Europe” (1)

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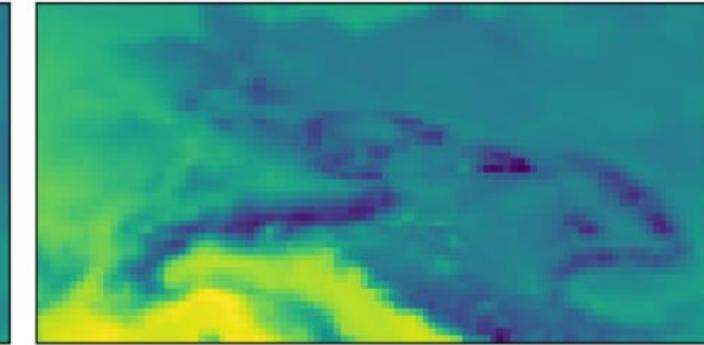
No DEM



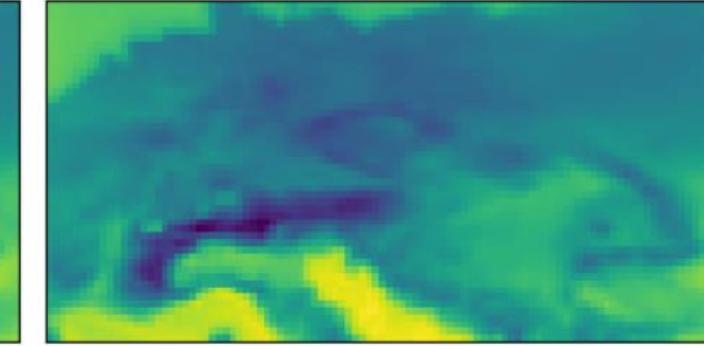
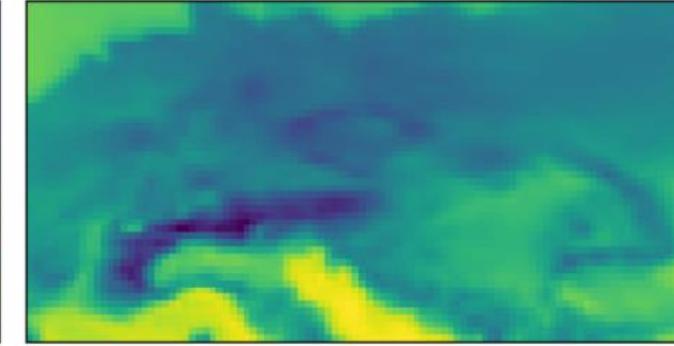
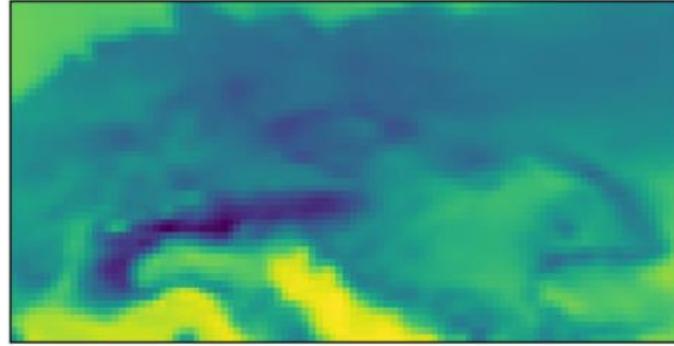
Elevation & Slope



Original High-Resolution



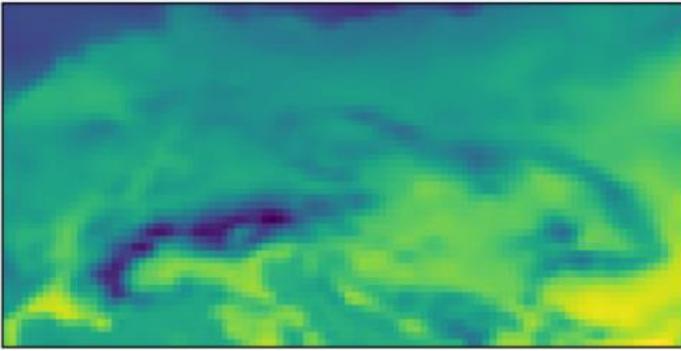
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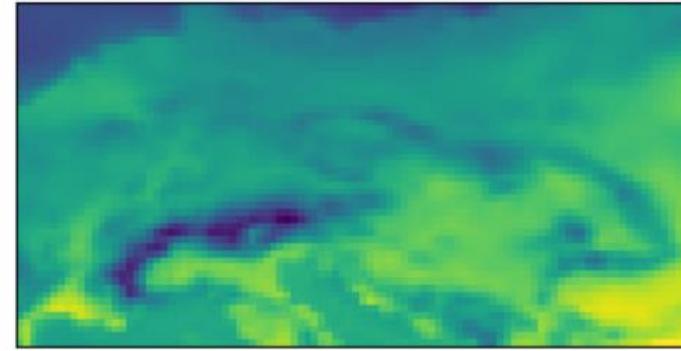
Bonus slides → Outputs “Central Europe” (2)

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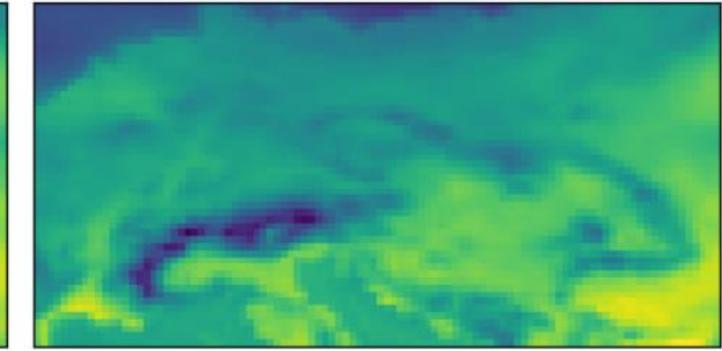
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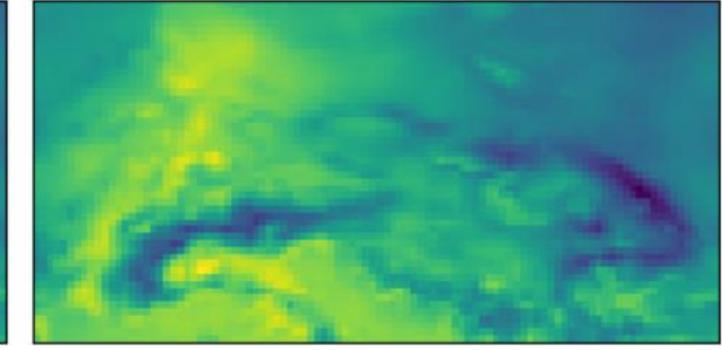
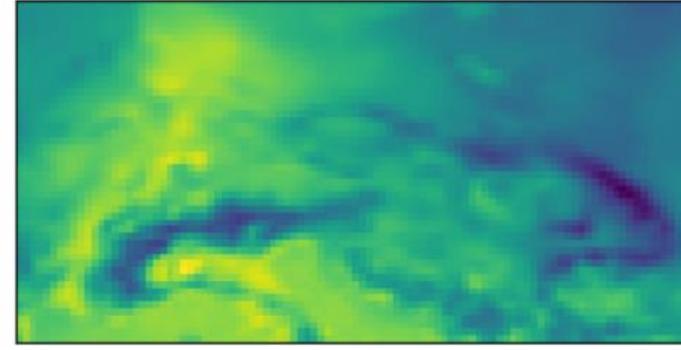
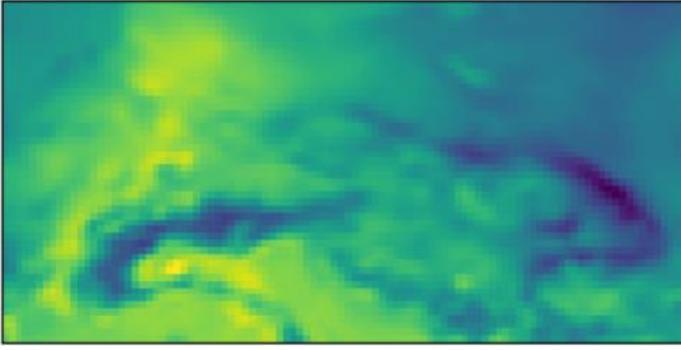
Elevation & Slope



Original High-Resolution

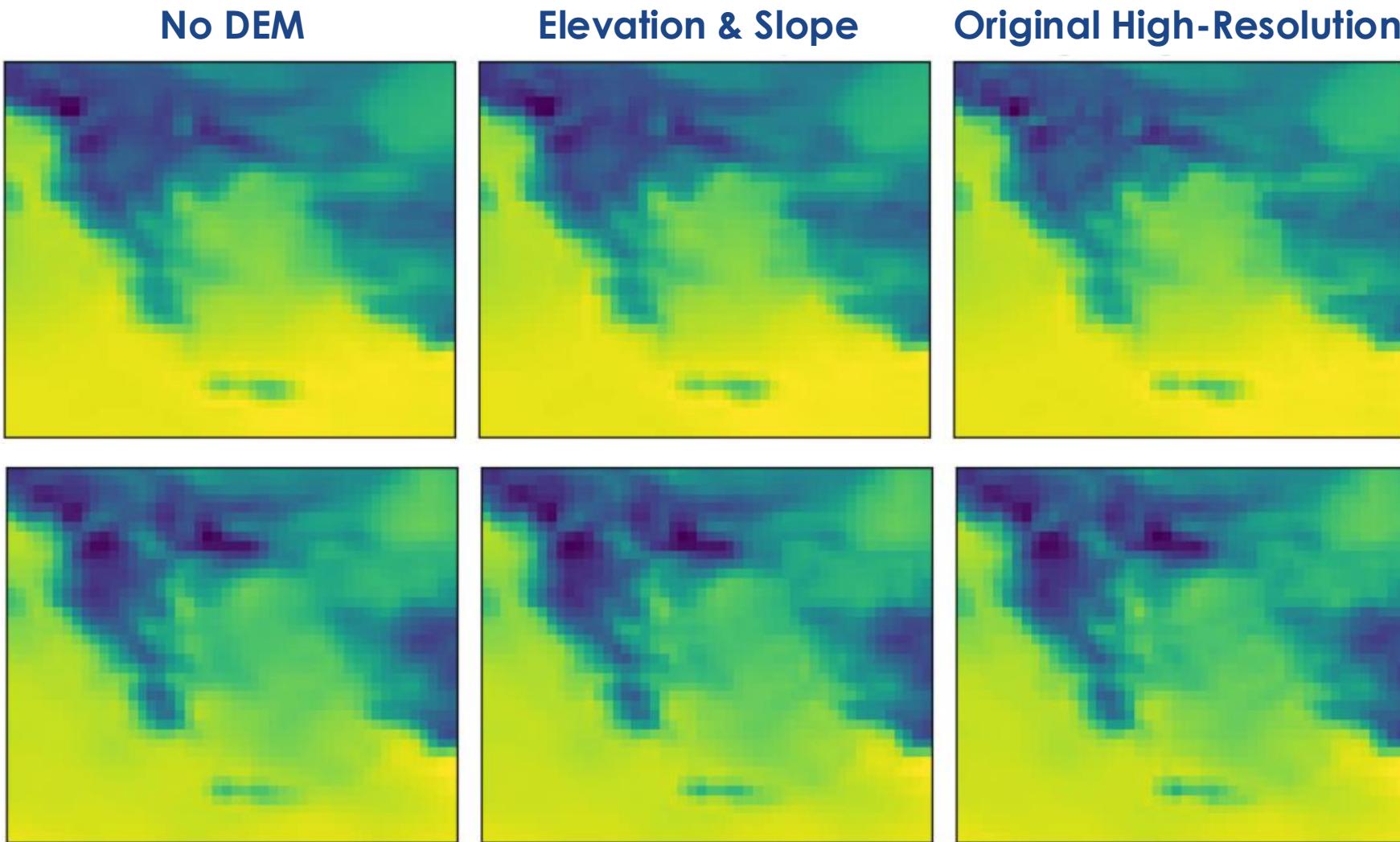


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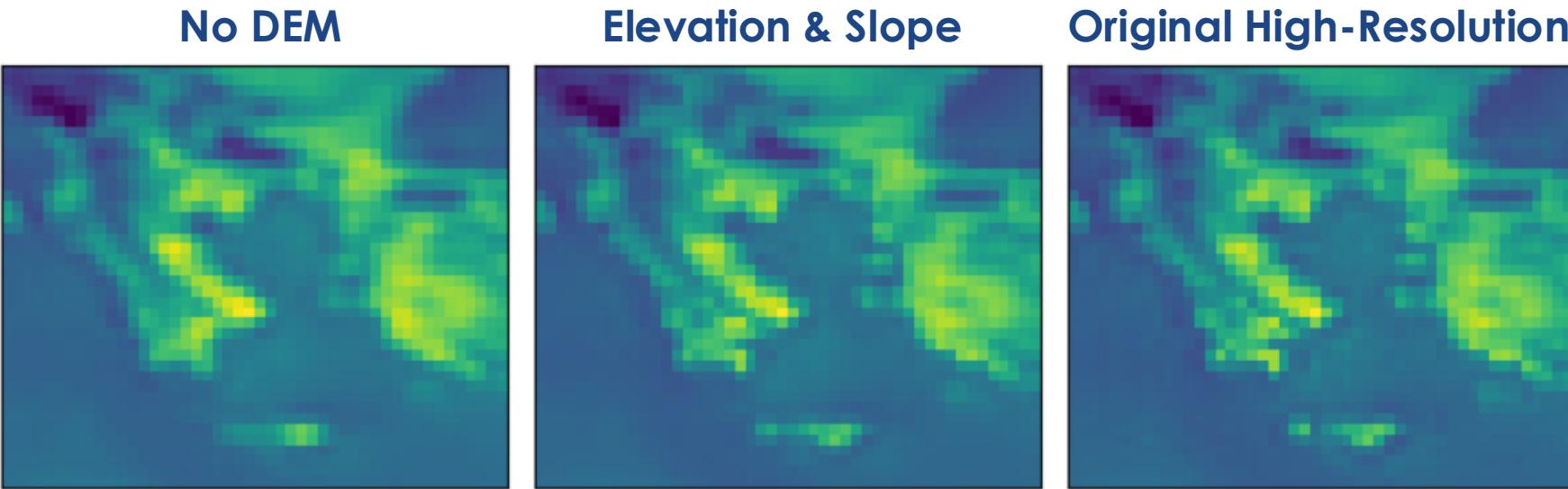
Bonus slides → Outputs “Greece” (1)

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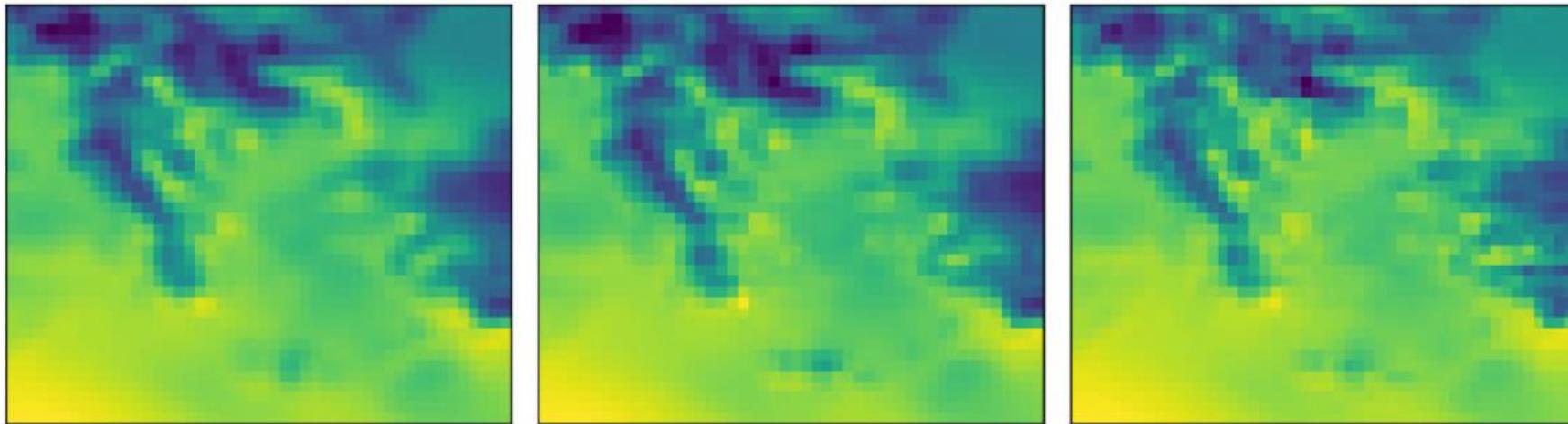


Bonus slides → Outputs “Greece” (2)

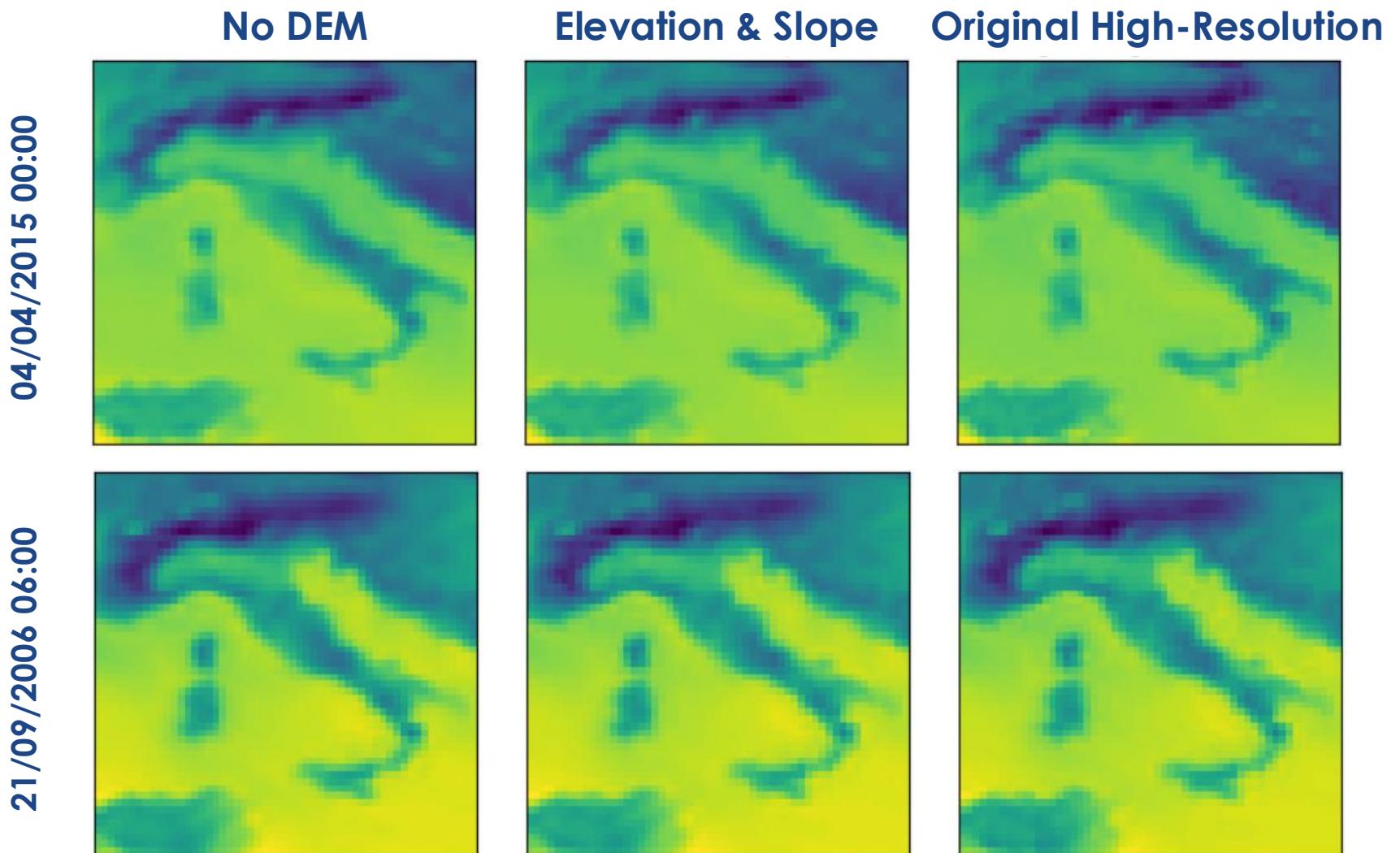
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Bonus slides → Outputs “Italy” (1)



Bonus slides → Outputs “Italy” (2)

