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

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Contents

Background → Weather Forecast

Numerical Weather Prediction (NWP) Models

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

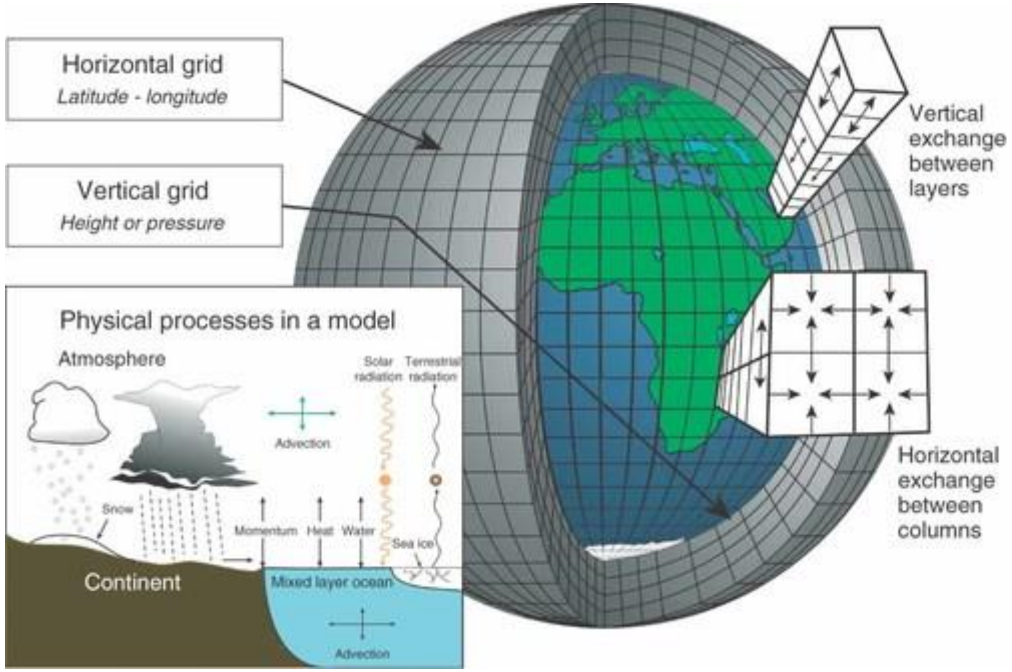


Fig. 1 [1]

Weather forecast trade-offs

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

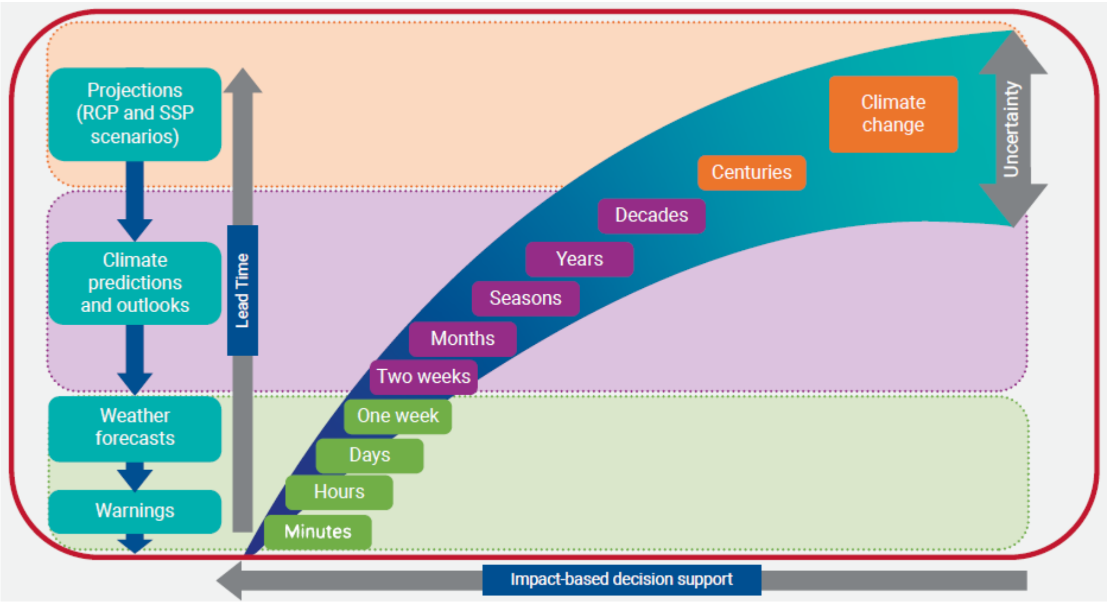


Fig. 2 [2]

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

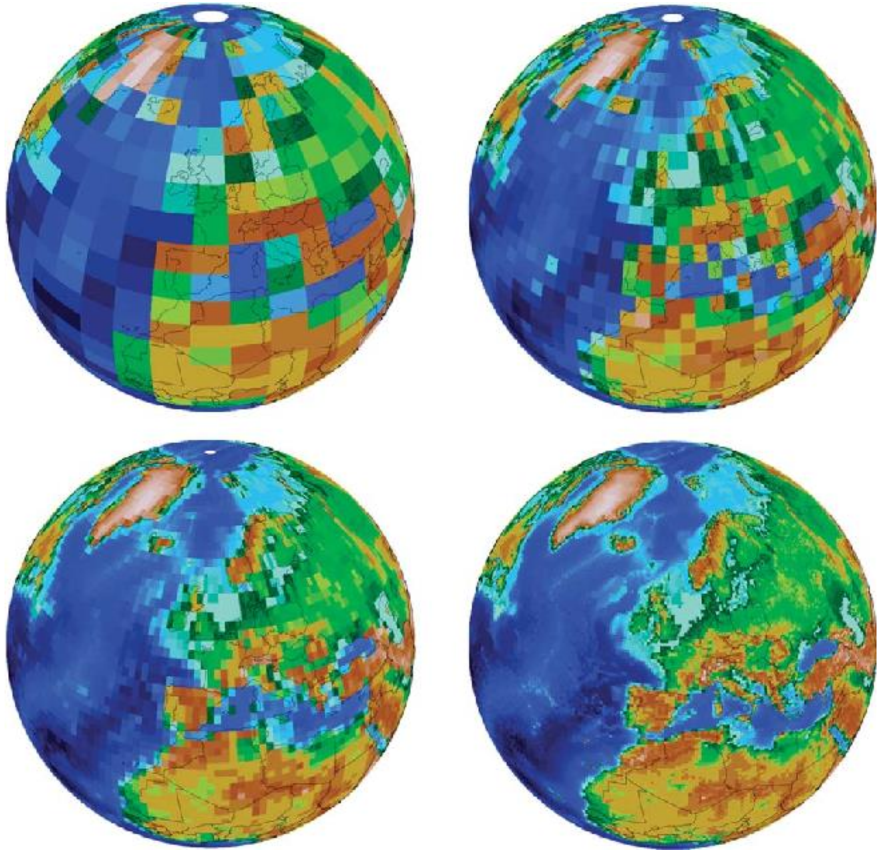


Fig. 3 [3]

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 Project Nevermore: Development of models and tools for simulating and assessing the impacts and risks of climate change**

Methodology → Integration strategies

Enhanced Deep Super-Resolution Network (EDSR)

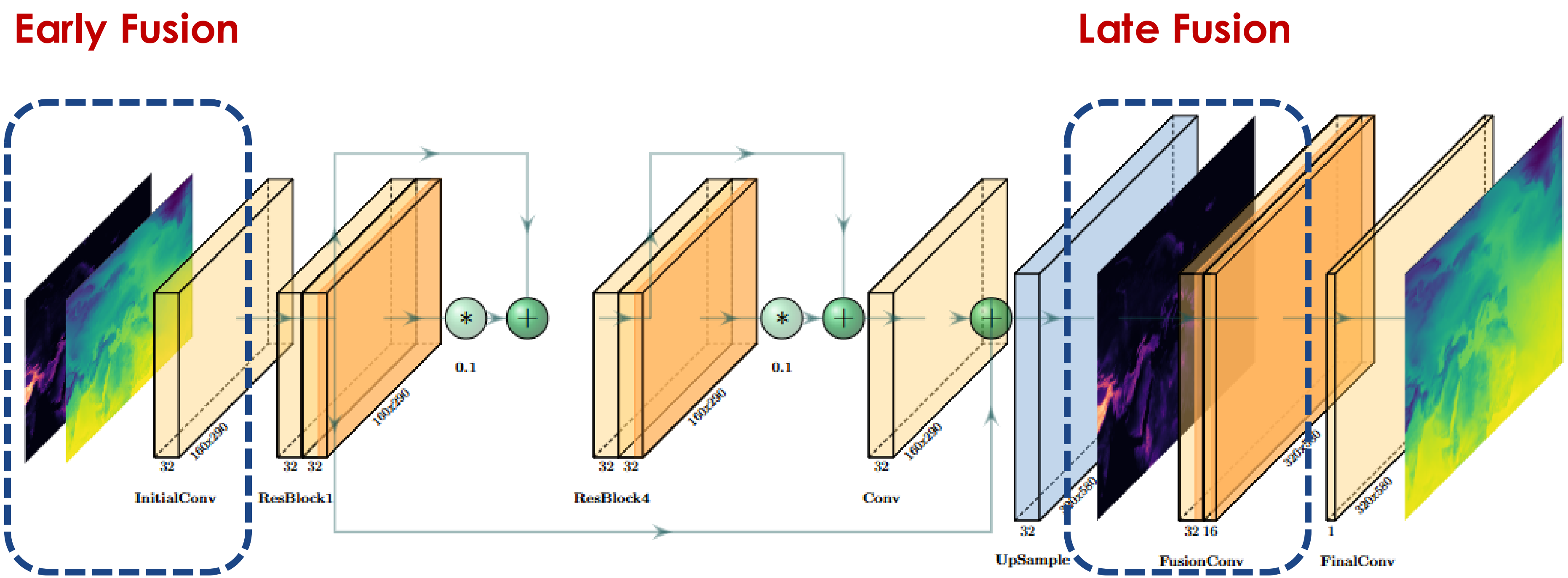


Fig. 4

Methodology → Elevation-derived features

Elevation

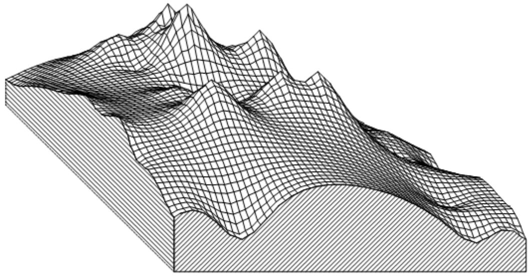


Fig. 5 [5]

Slope

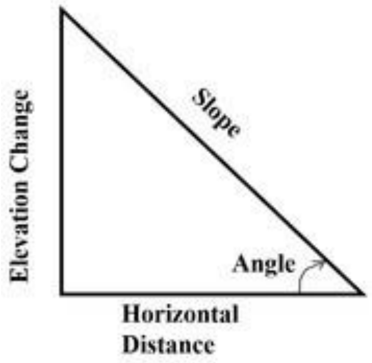


Fig. 6 [6]

Aspect

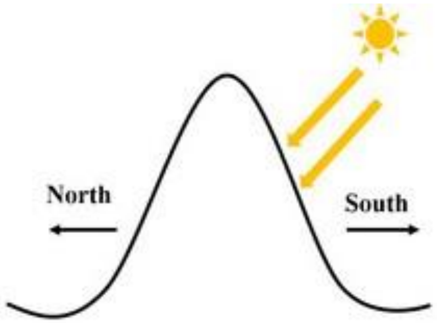
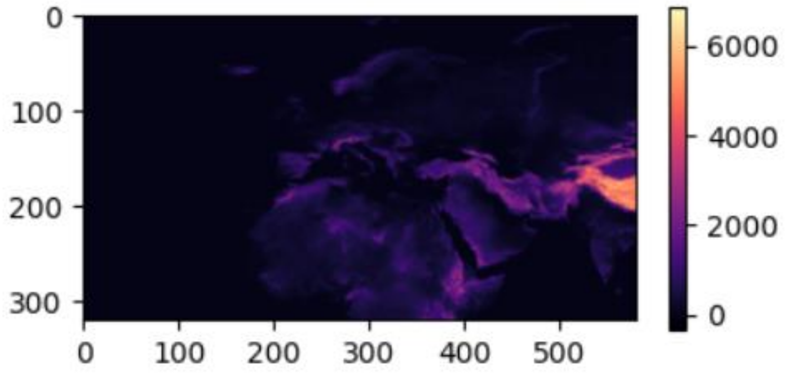
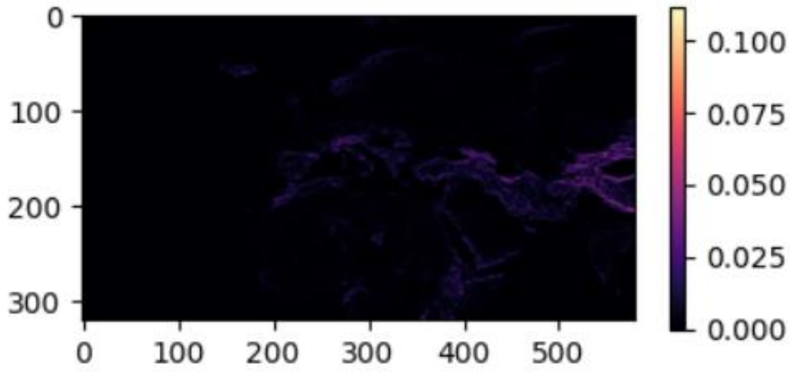


Fig. 7 [6]





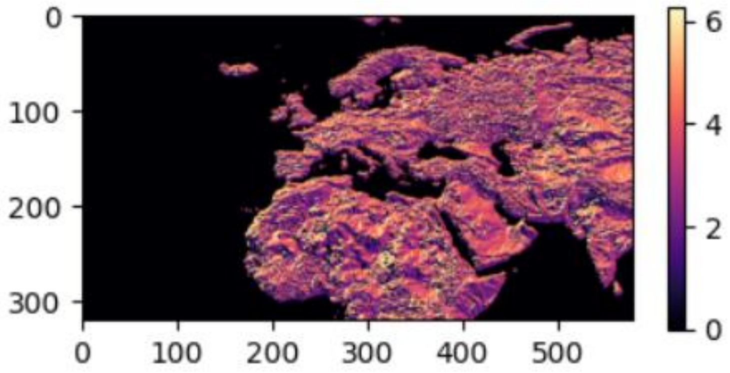
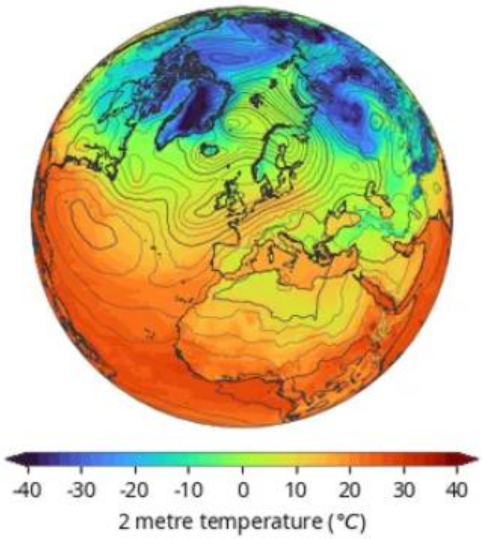


Fig. 8

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° x 0.25° (atmosphere), 0.5° x 0.5° (ocean waves)
Temporal coverage	1940 to present
Temporal resolution	Hourly
File format	GRIB
Update frequency	Daily



Pre-Processing Steps

1. **Upscaling:** Bicubic interpolation to match target resolution (from 0.25 ° x 0.25 ° to 0.5 ° x 0.5 °)
2. **Normalization:** Z-score standardization
3. **Shuffling:** Randomize data order to remove temporal bias
4. **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

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

	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**

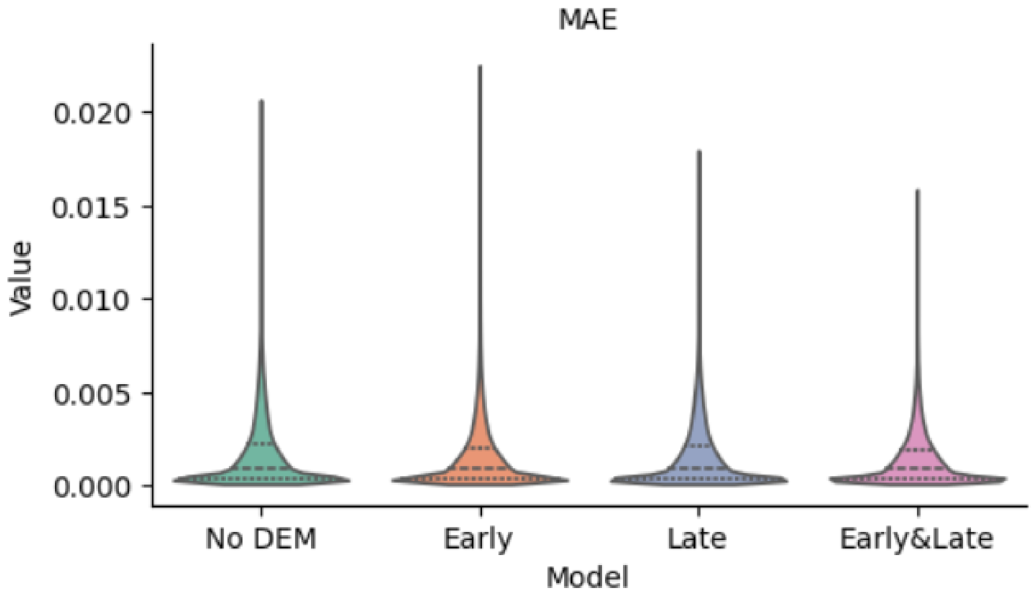
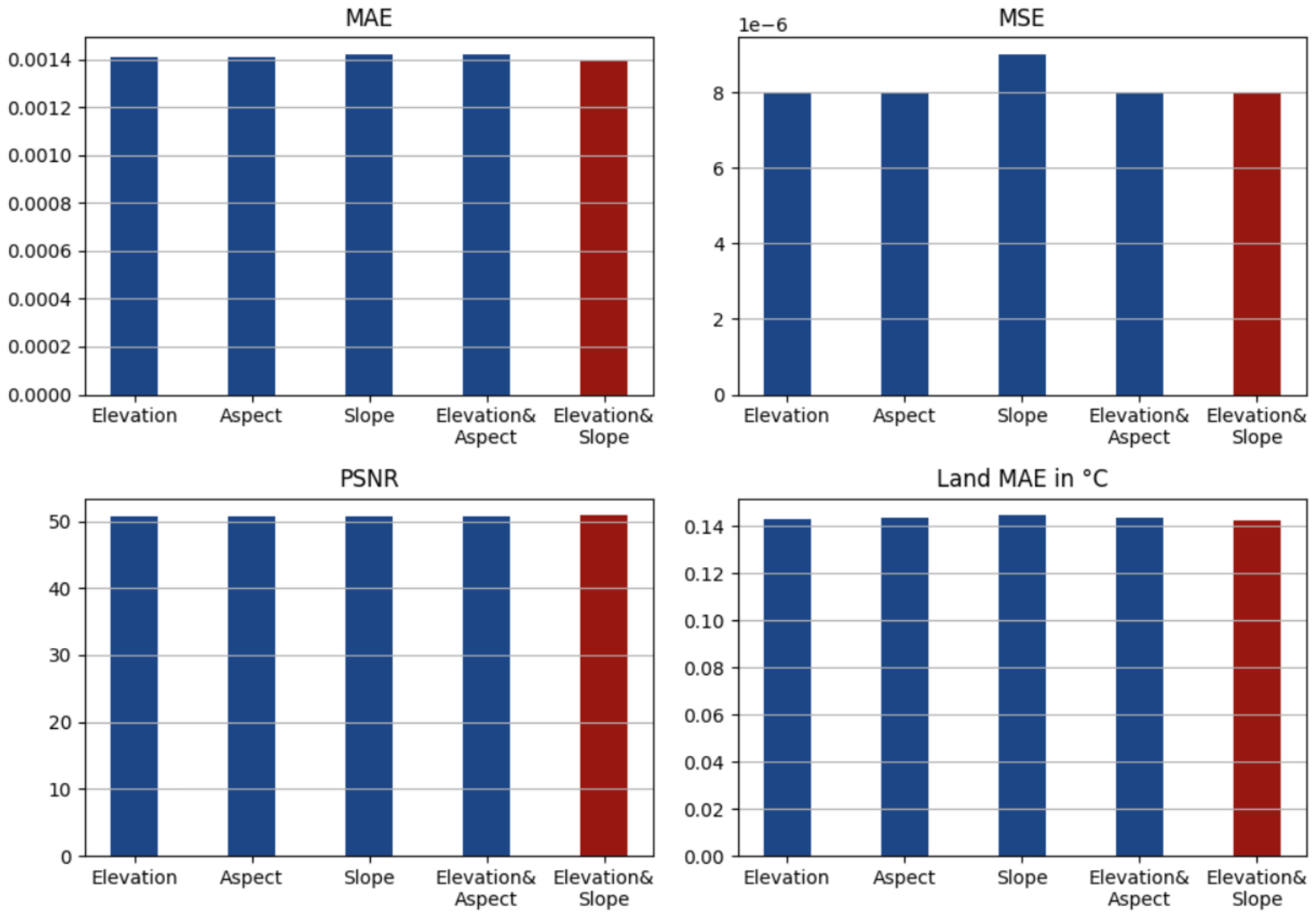


Fig. 9

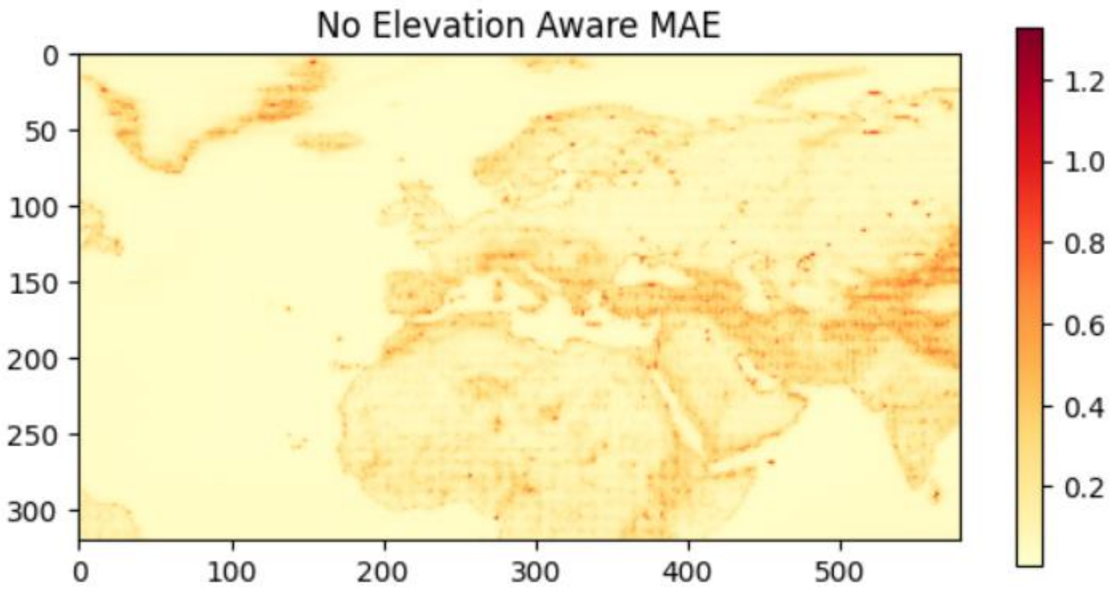
Results → Elevation-derived features

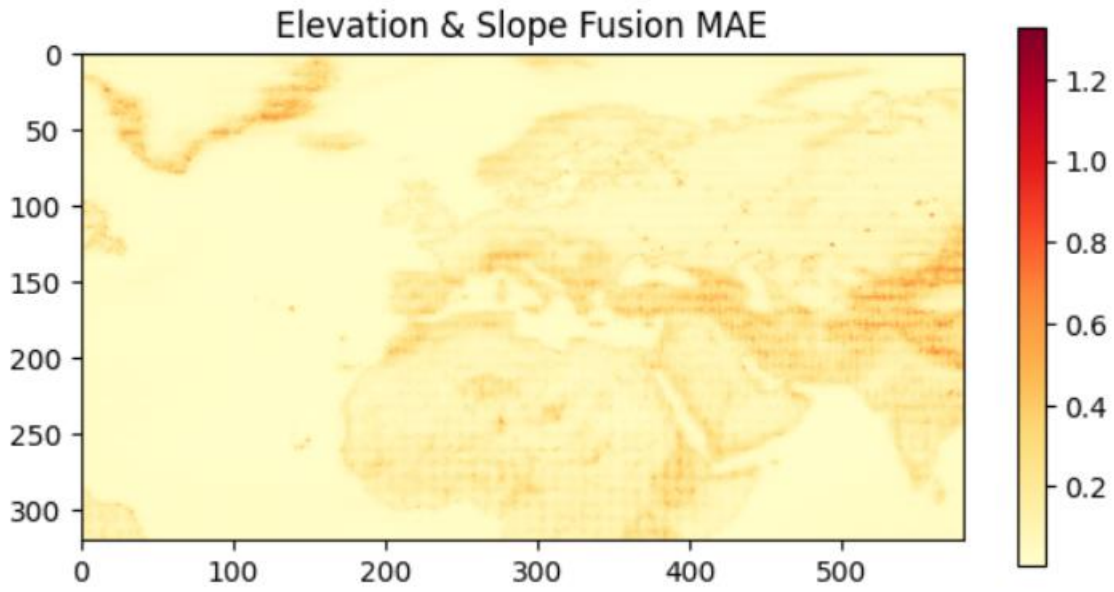


Differences between approaches are minimal across metrics.

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

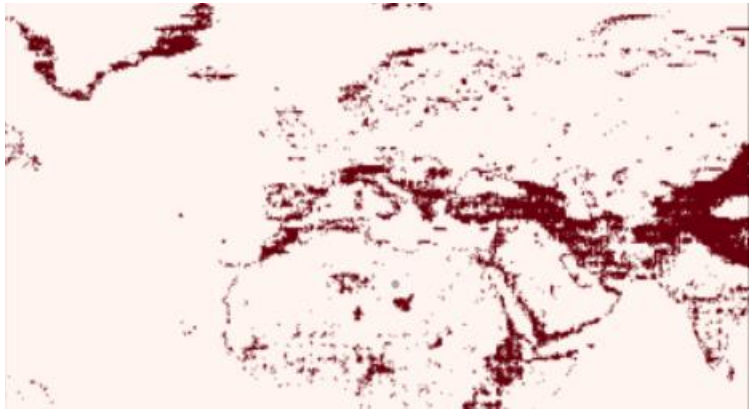
Results → Summary





Upper 10th percentile of MAE

Mean MAE in those pixels: 0.3877 ° C



Mean MAE in those pixels: 0.2925 ° C

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 the entire domain 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

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Thank you!

Questions?

Bonus slides

Bonus slides → Metrics

Mean Squared Error (MSE)

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

Mean Absolute Error (MAE)

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

Peak Signal-to-Noise Ratio (PSNR)

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

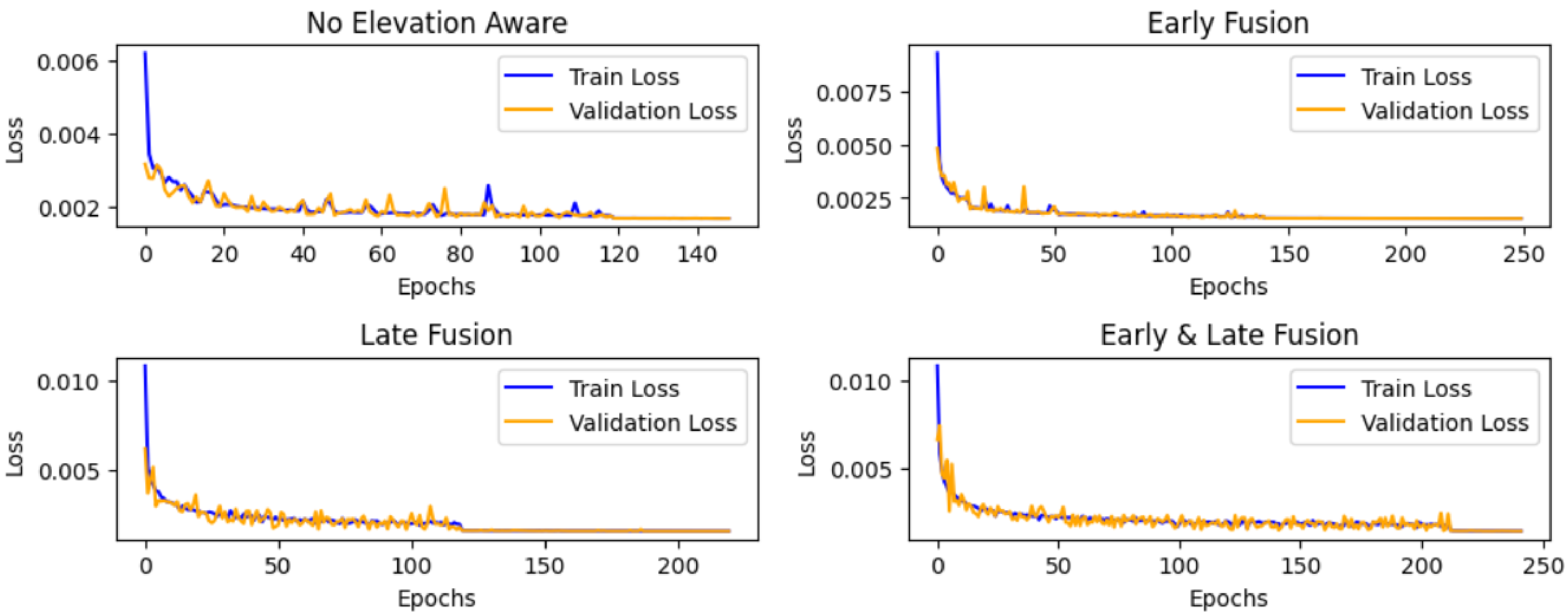
Structural Similarity Index Measure (SSIM)

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

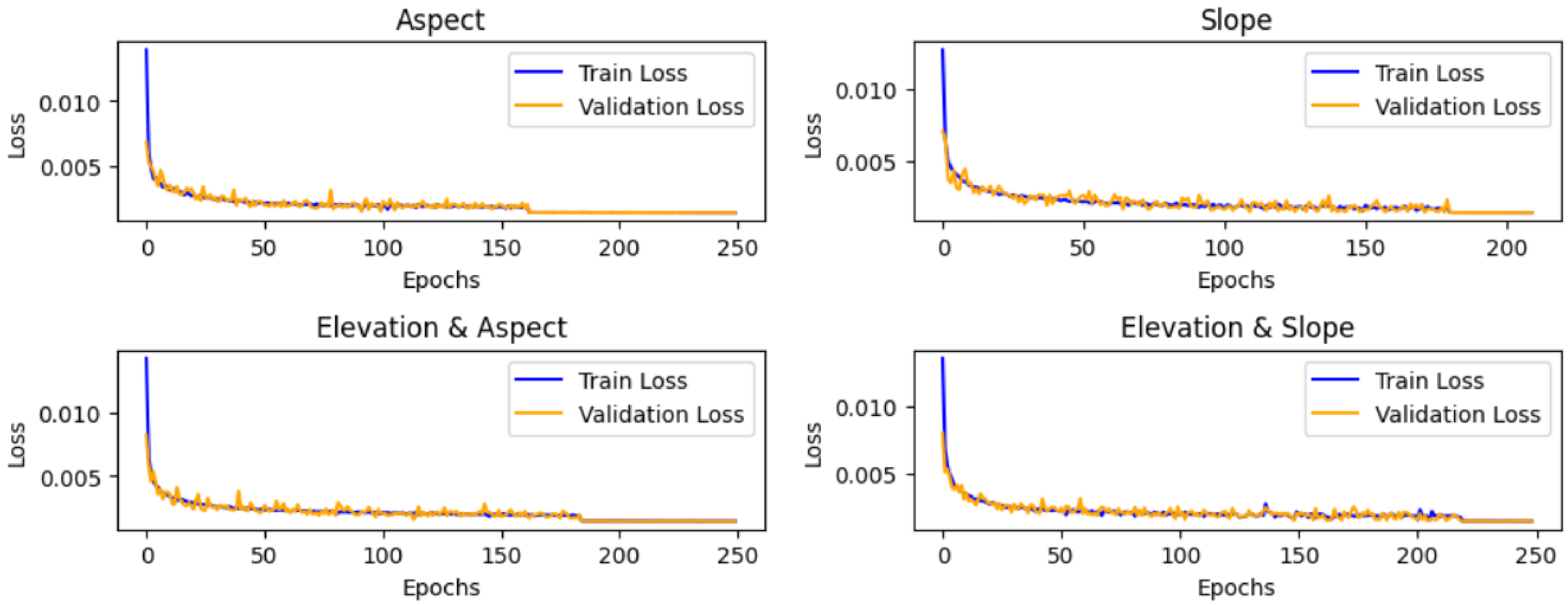
Land MAE

Land MAE in °C

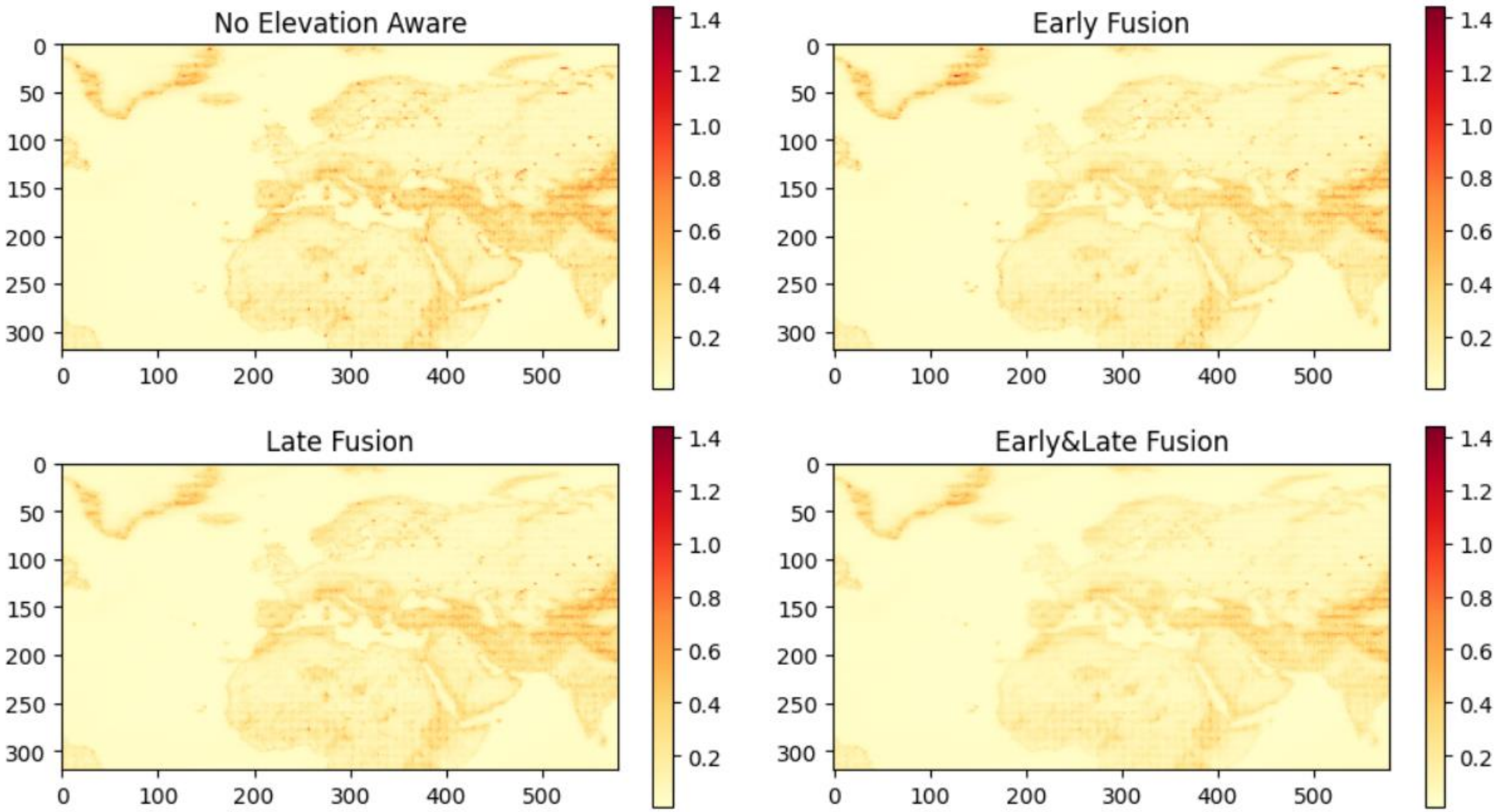
Bonus slides → Integration strategies training history



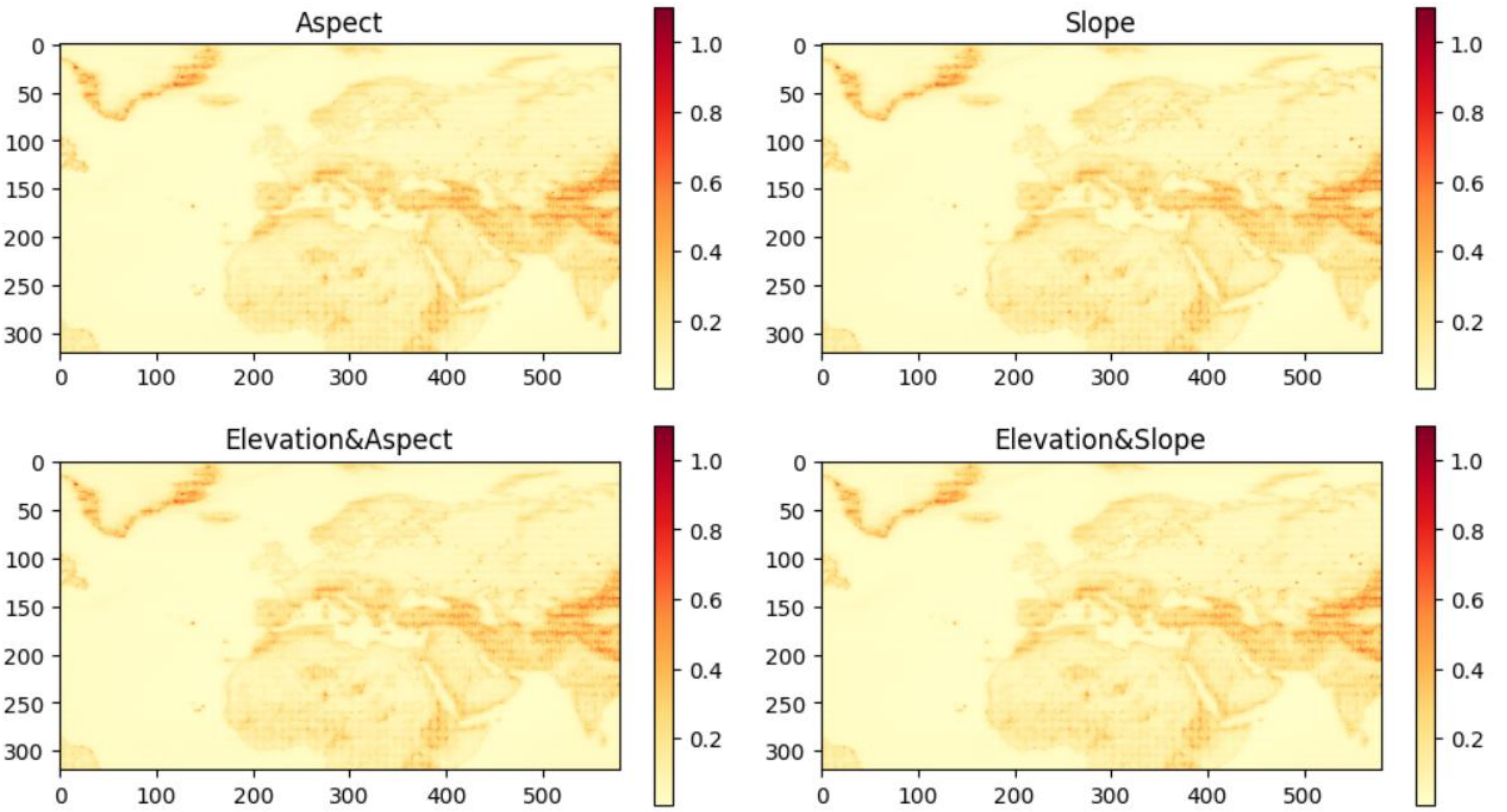
Bonus slides → Elevation-derived features training history



Bonus slides → Integration strategies MAE comparison



Bonus slides → Elevation-derived features MAE comparison



Bonus slides → Elevation-derived features metrics table

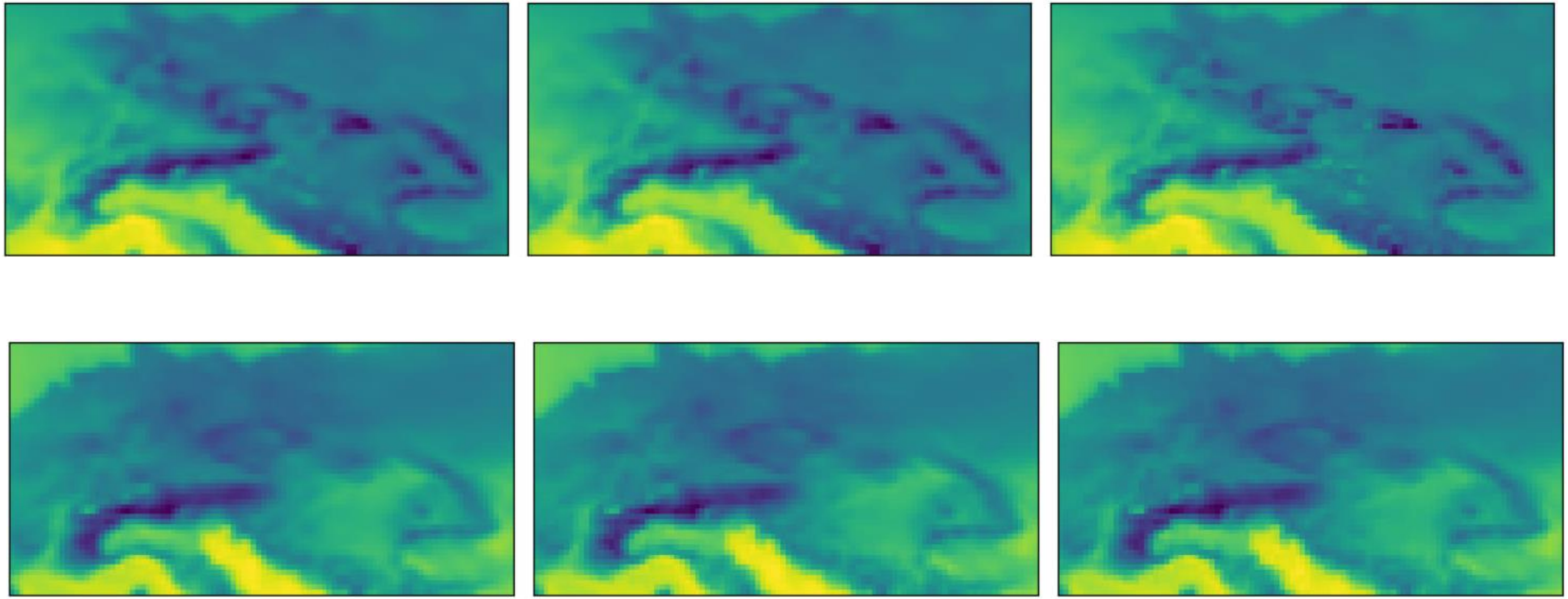
	Aspect	Slope	Elevation &Aspect	Elevation &Slope
MAE ↓	0.00141	0.00142	0.00142	**0.0014**
MSE ↓	**0.000008**	0.000009	**0.000008**	**0.000008**
PSNR ↑	50.7447	50.7145	50.7910	**50.8345**
SSIM ↑	**0.9962**	0.9961	**0.9962**	**0.9962**
Land Mean MAE ↓	0.00223	0.00225	0.00224	**0.00222**
Land Mean MAE in °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

Bonus slides → Outputs “Central Europe” (1)

No DEM | **Elevation & Slope** | **Original High-Resolution**

04/04/2015 00:00

21/09/2006 06:00

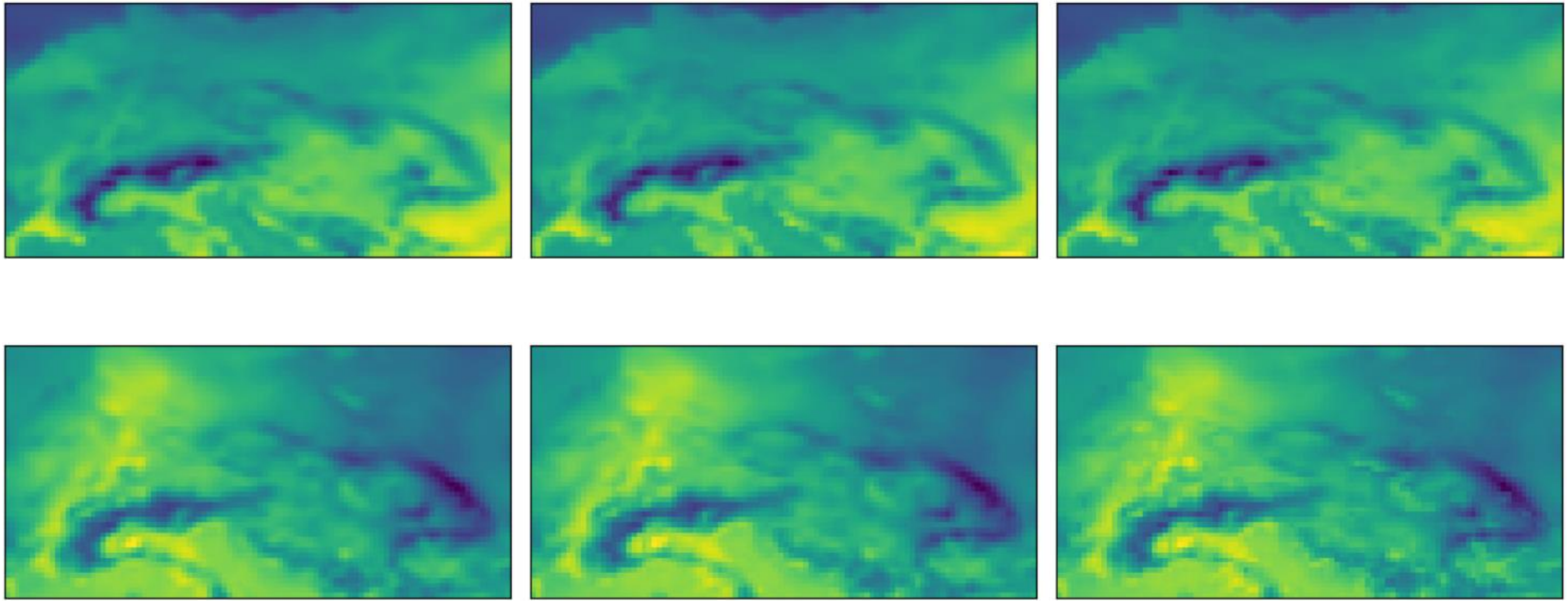


Bonus slides → Outputs “Central Europe” (2)

No DEM | Elevation & Slope | Original High-Resolution

29/05/2010 12:00

06/09/2013 18:00

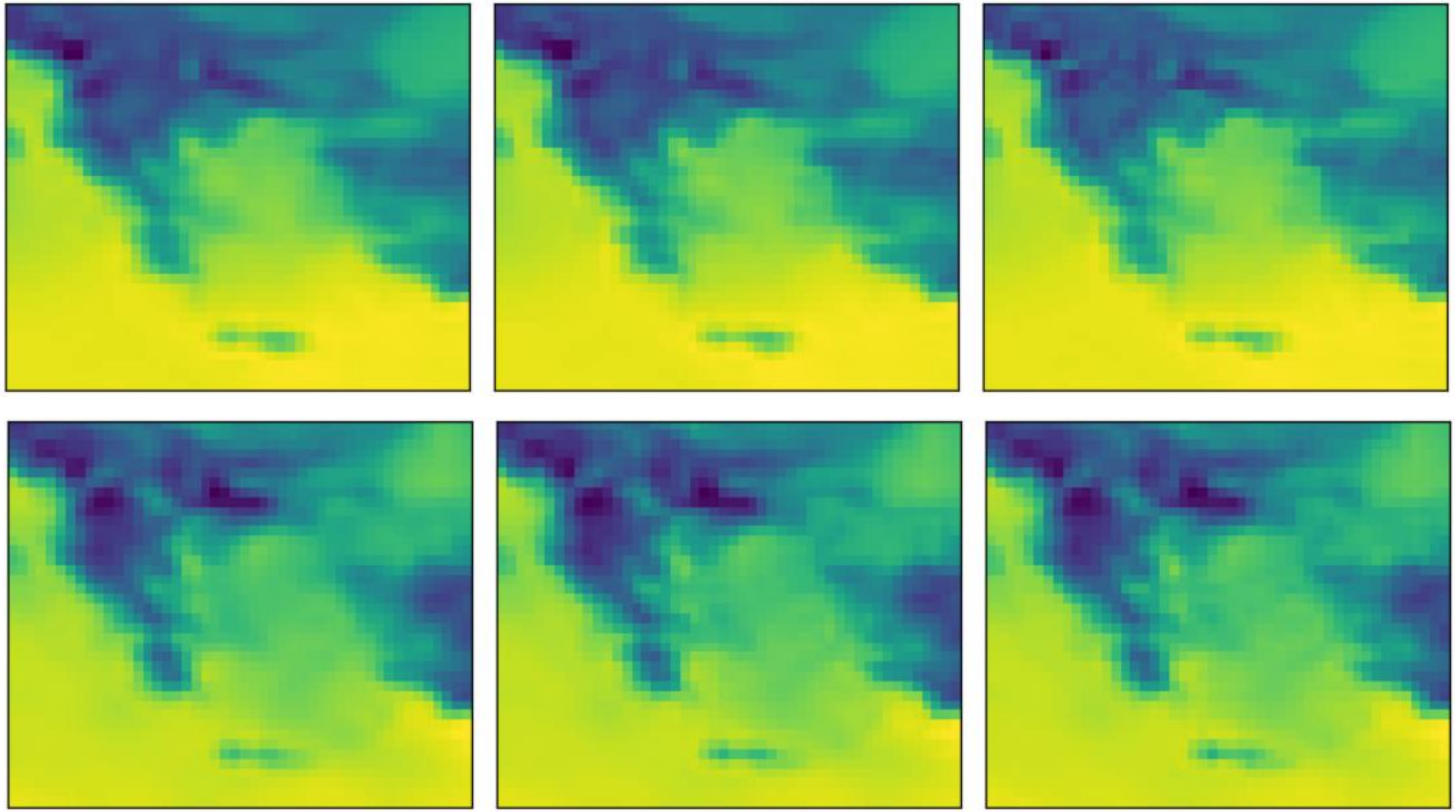


Bonus slides → Outputs “Greece” (1)

No DEM | **Elevation & Slope** | **Original High-Resolution**

04/04/2015 00:00

21/09/2006 06:00



Bonus slides → Outputs “Greece” (2)

No DEM | **Elevation & Slope** | **Original High-Resolution**

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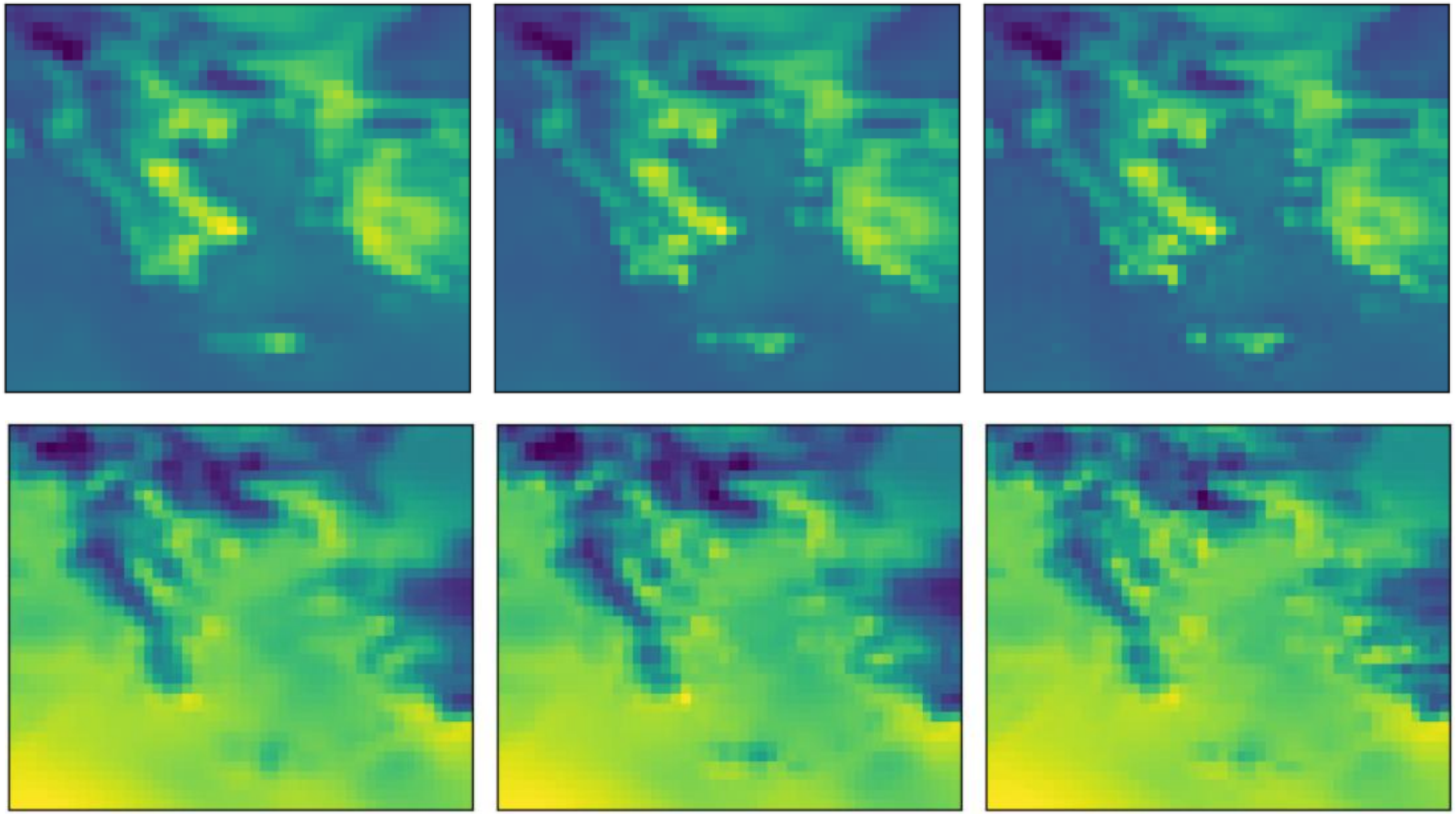
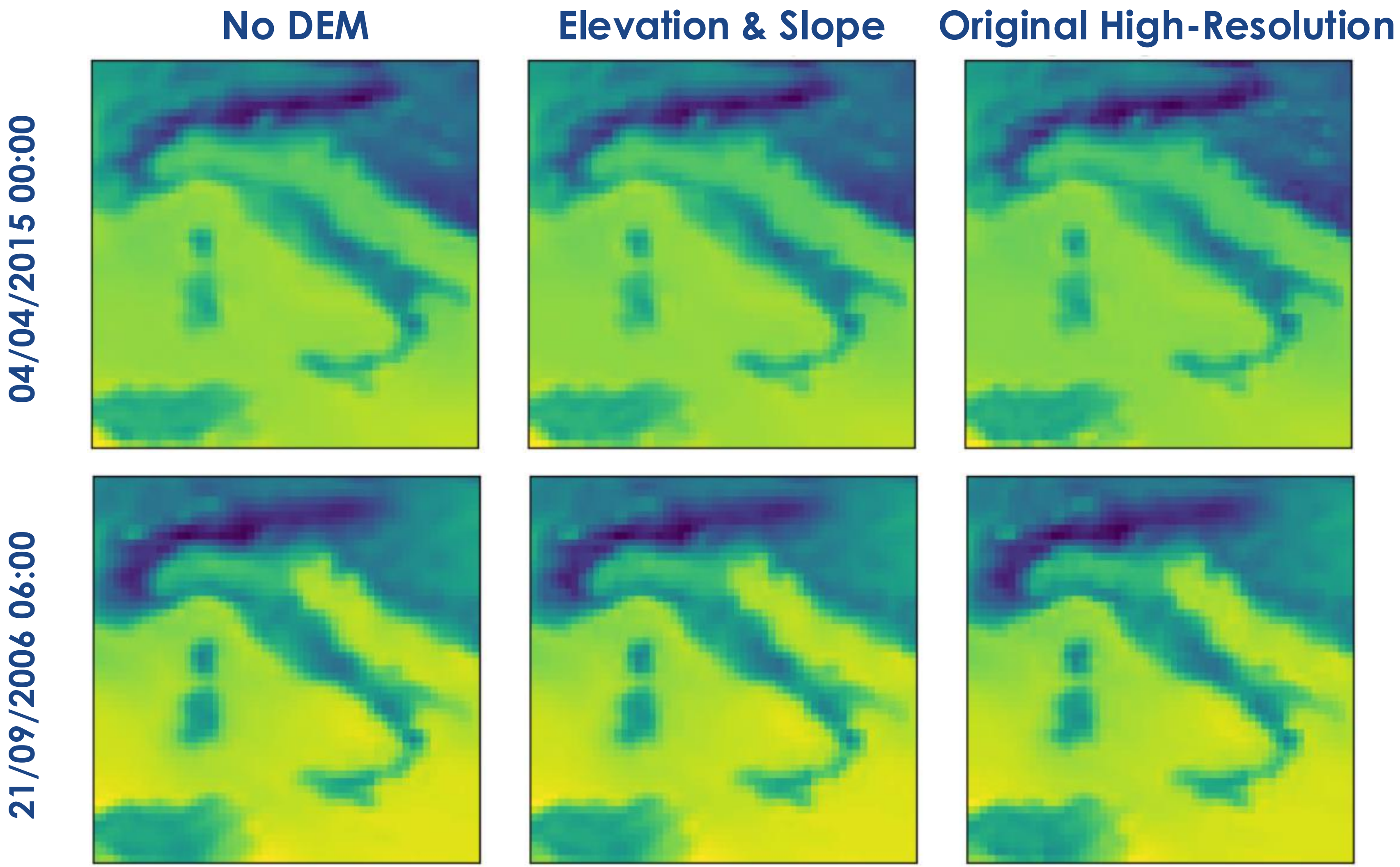
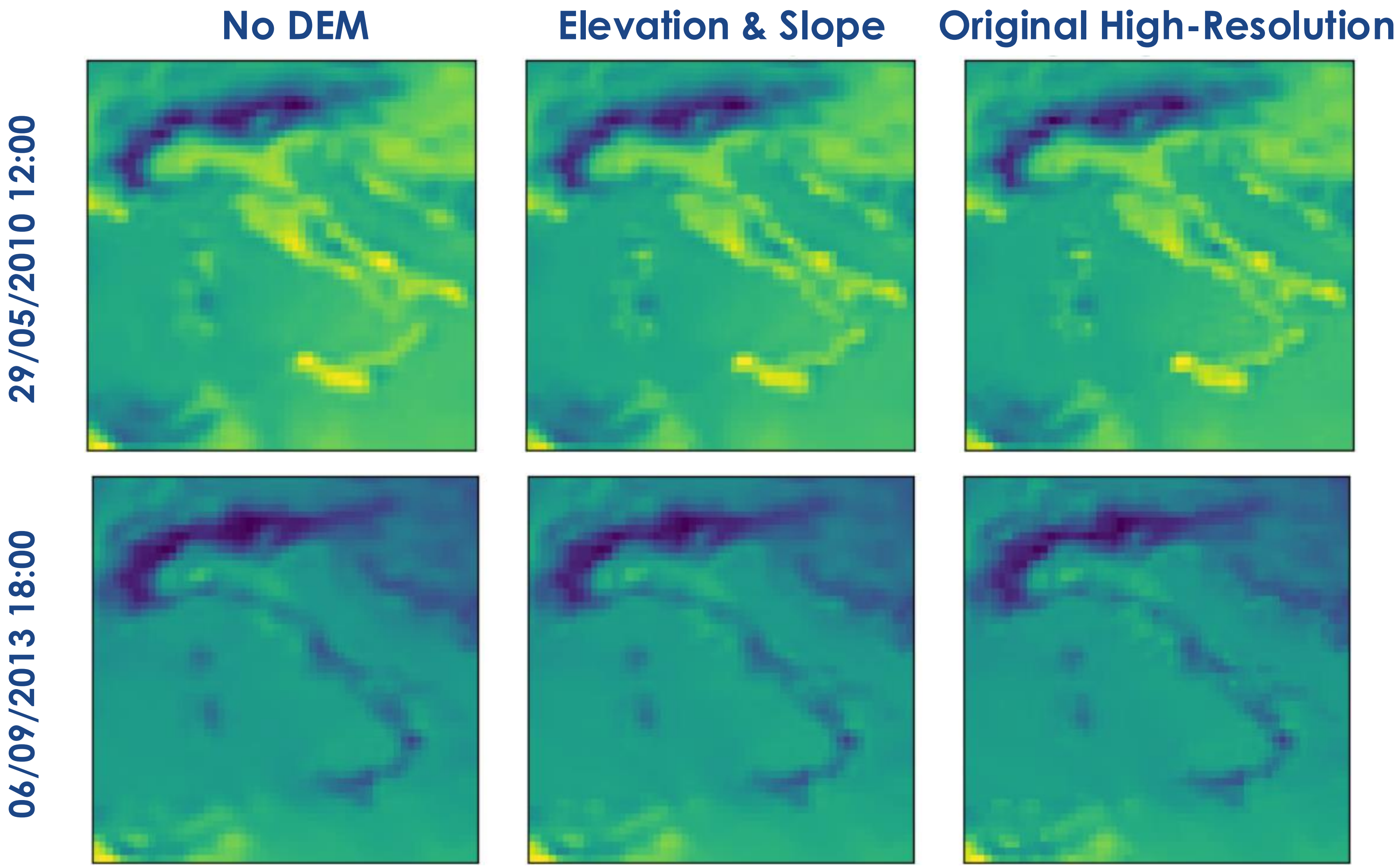


Bonus slides → Outputs “Italy” (1)



Bonus slides → Outputs “Italy” (2)



Bonus slides →Slope and Aspect Equations

$$\text{slope} = \tan^{-1}\left(\sqrt{\left(\frac{\partial z}{\partial x}\right)^2 + \left(\frac{\partial z}{\partial y}\right)^2}\right)$$

$$\text{aspect} = \tan_2^{-1}\left(-\frac{\partial z}{\partial y}, \frac{\partial z}{\partial x}\right)$$

$$\frac{\partial z}{\partial x} \approx \frac{z_{i,j+1} - z_{i,j-1}}{2\,\Delta}$$

$$\frac{\partial z}{\partial y} \approx \frac{z_{i+1,j} - z_{i-1,j}}{2\,\Delta}$$