



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

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Contents

- **Background** → Weather forecast | Problem statement | Previous work
- **Methodology** → Integration strategies | Elevation-derived features
- **Experimental Setup** → Dataset & pre-processing | Training & validation
- **Results** → Integration strategies | Elevation-derived features | Summary
- **Conclusions**
- **Future work**
- **References**
- **Bonus slides**

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

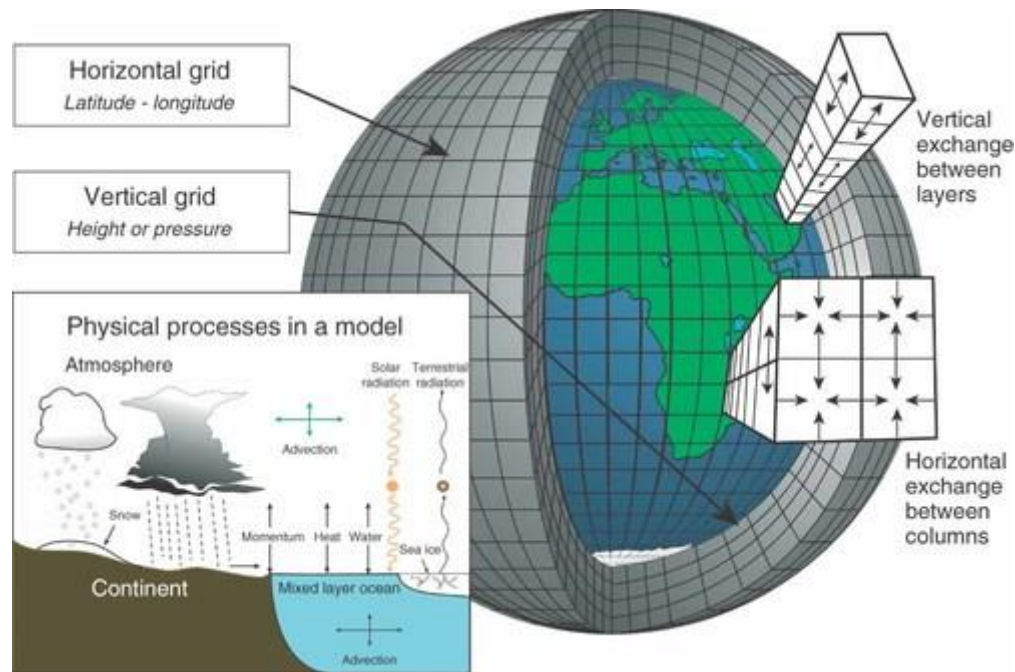


Fig. 1 [1]

Weather forecast trade-offs

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

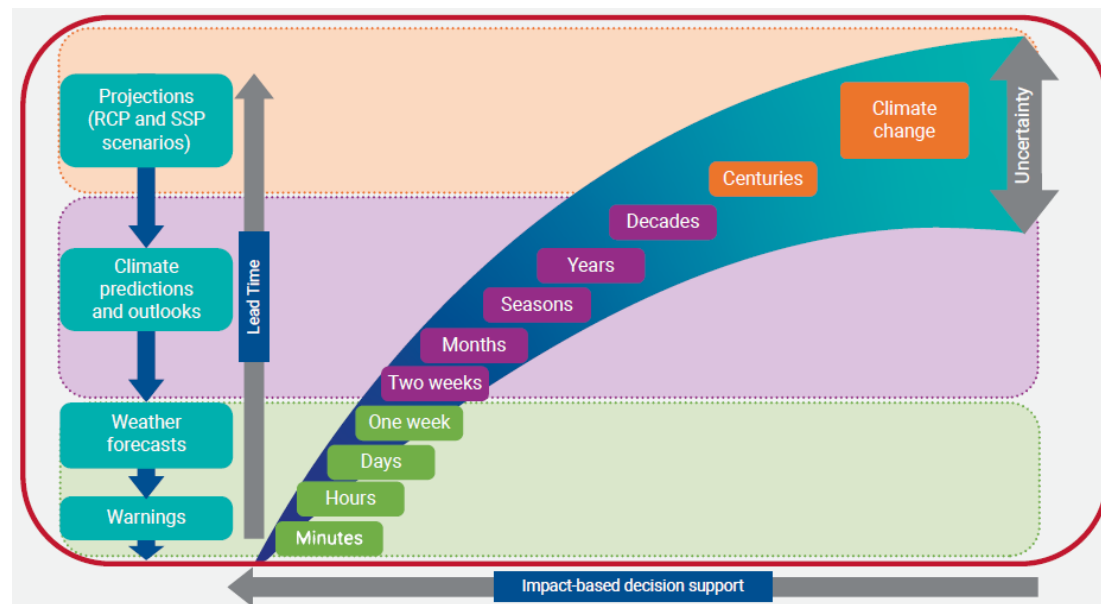


Fig. 2 [2]

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.

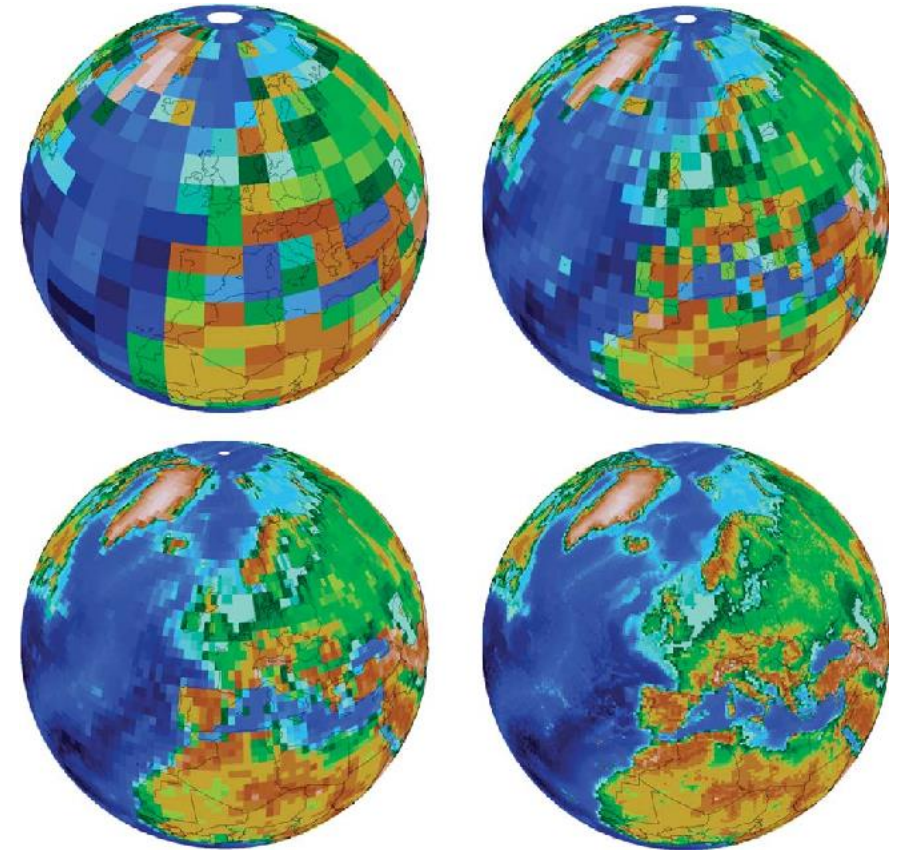


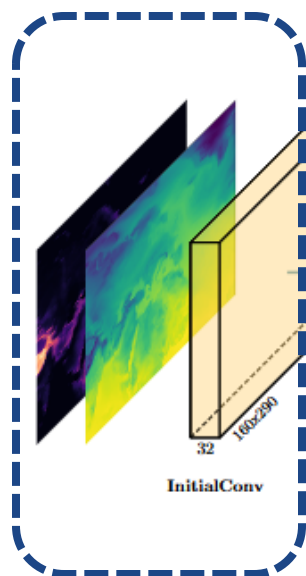
Fig. 3 [3]

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

Early Fusion



Late Fusion

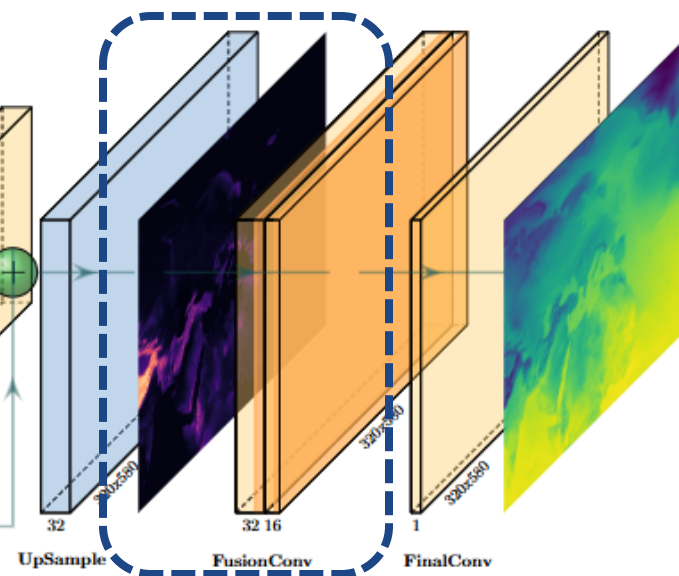


Fig. 4

Methodology → Elevation-derived features

Elevation

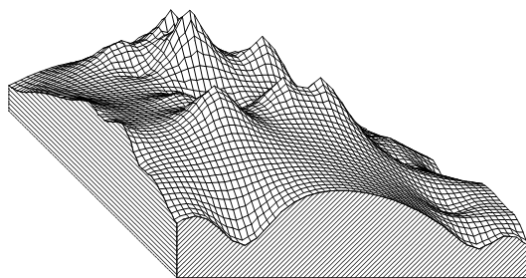


Fig. 5 [5]

Slope

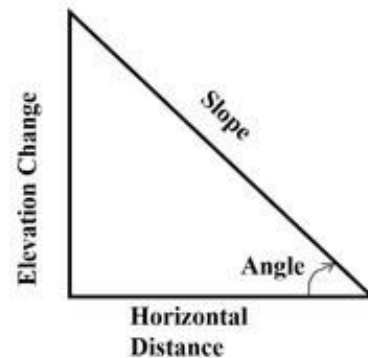


Fig. 6 [6]

Aspect

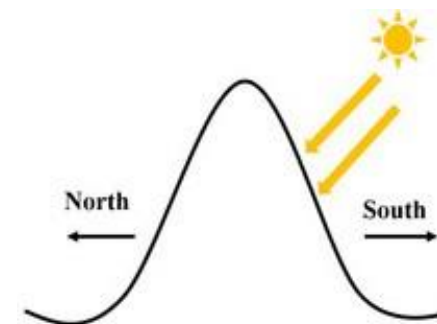


Fig. 7 [6]

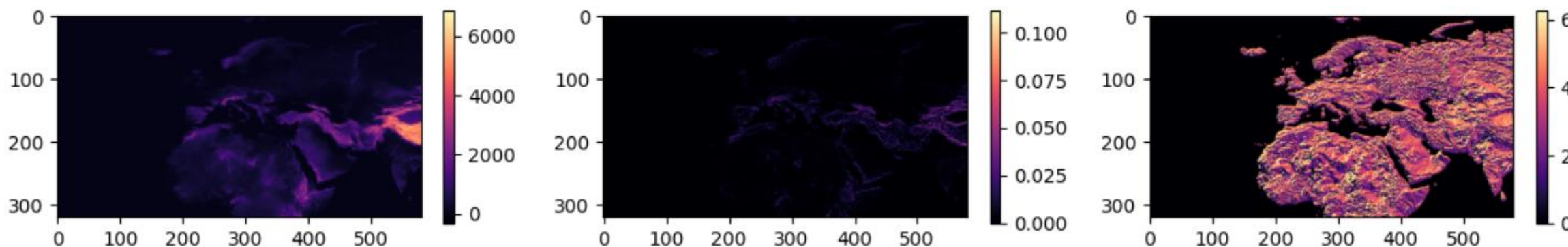
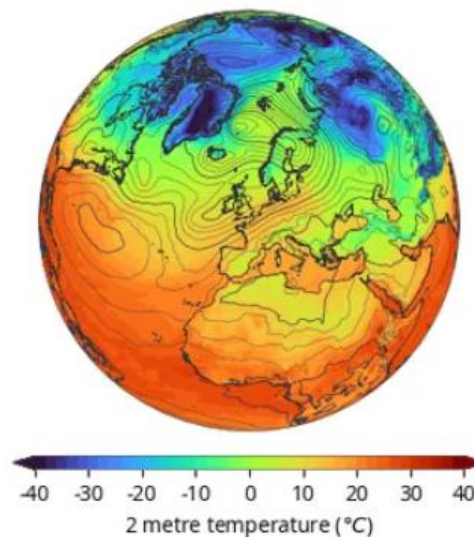


Fig. 8

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

1. **Upscaling:** Bicubic interpolation to match target resolution (from $0.25^\circ \times 0.25^\circ$ to $0.5^\circ \times 0.5^\circ$)
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

	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

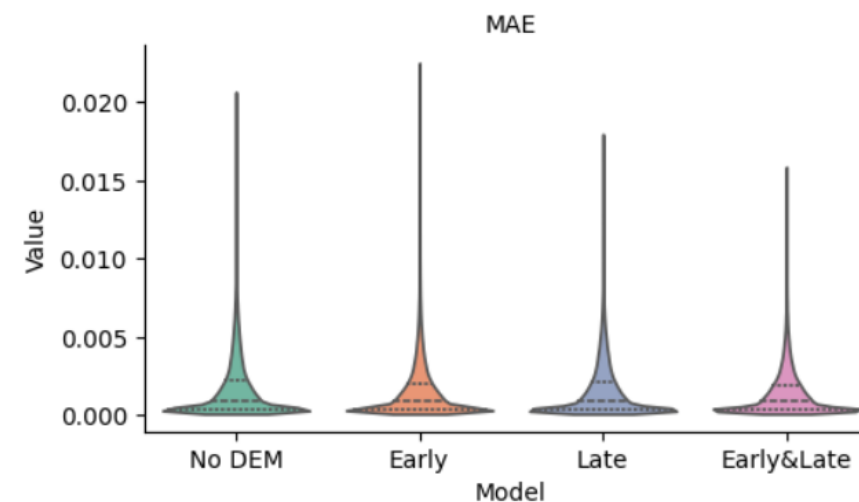


Fig. 9

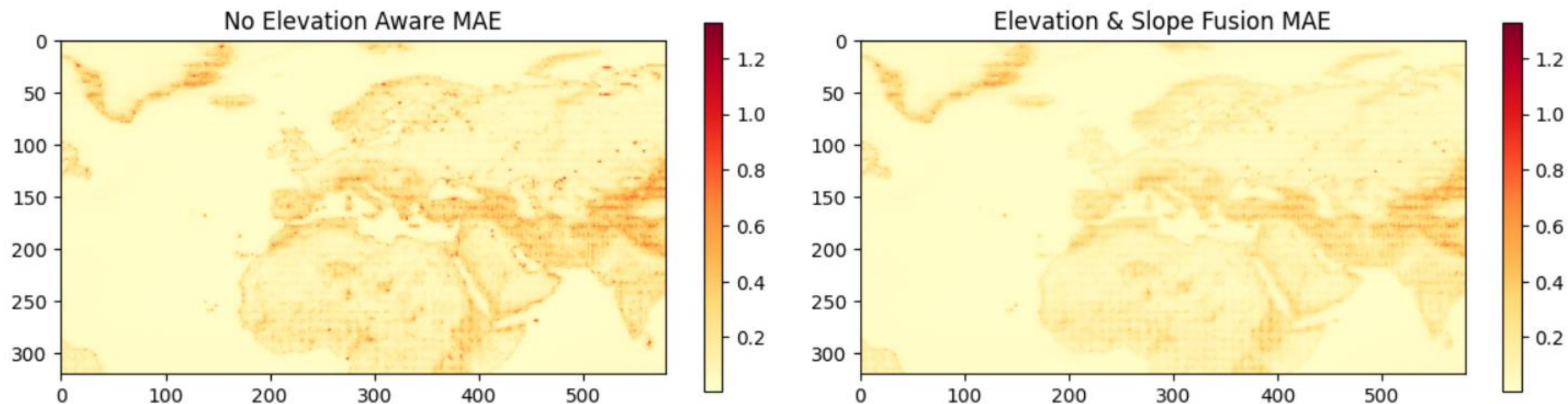
Results → Elevation-derived features

	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.

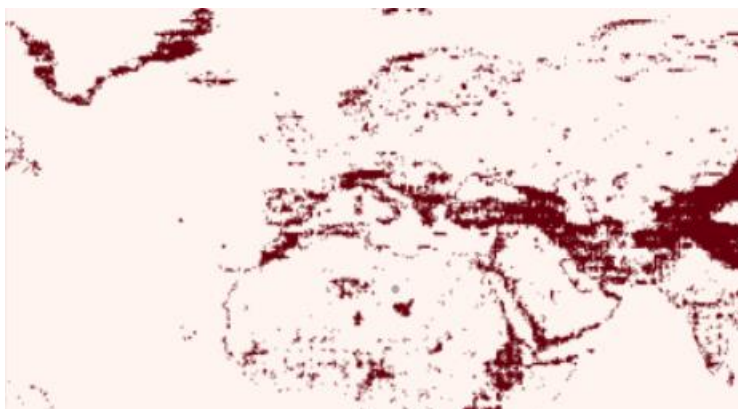
The **Elevation & Slope** combination yields slight but consistent improvements over using elevation alone and **is recommended as the most effective approach**.

Results → Summary



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 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

1. Edwards, P. N. (2010). History of climate modeling. WIREs Climate Change, 2(1), 128–139. <https://doi.org/10.1002/wcc.95>
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.
3. Washington et al.(2008). The computational future for climate and Earth system models: on the path to petaflop and beyond. <https://doi.org/10.1098/rsta.2008.0219>
4. Karozis, S., Klampanos, I. A., Sfetsos, A., & Vlachogiannis, D. (2023). A deep learning approach for spatial error correction of numerical seasonal weather prediction simulation data. Big Earth Data, 7(2), 231–250. <https://doi.org/10.1080/20964471.2023.2172820>
5. Digital Elevation Model (DEM). Geoportal.gov.pl. <https://www.geoportal.gov.pl/en/data/digital-elevation-model-dem/>
6. Bhakare, S., et al. (2024). Intercomparison of Machine Learning Models for Spatial Downscaling of Daily Mean Temperature in Complex Terrain. Atmosphere, 15(9), 1085. <https://doi.org/10.3390/atmos15091085>
7. C3S. (2018). ERA5 hourly data on single levels from 1940 to present [Dataset]. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). <https://doi.org/10.24381/CDS.ADBB2D47>
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)

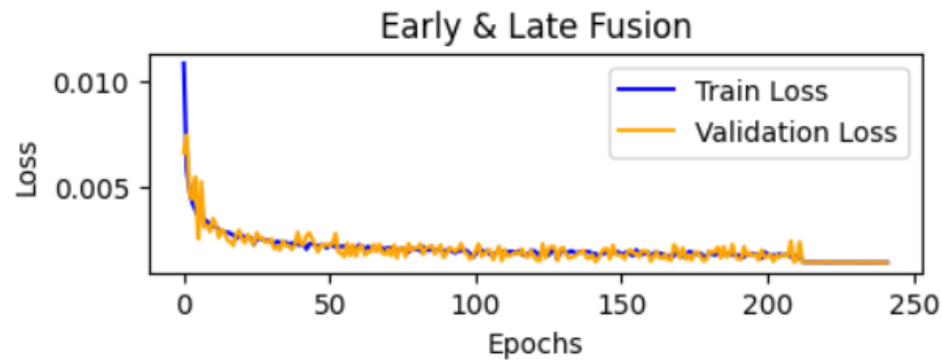
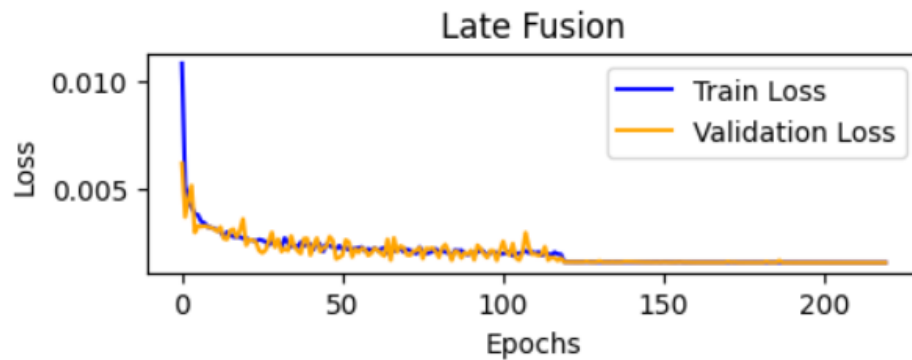
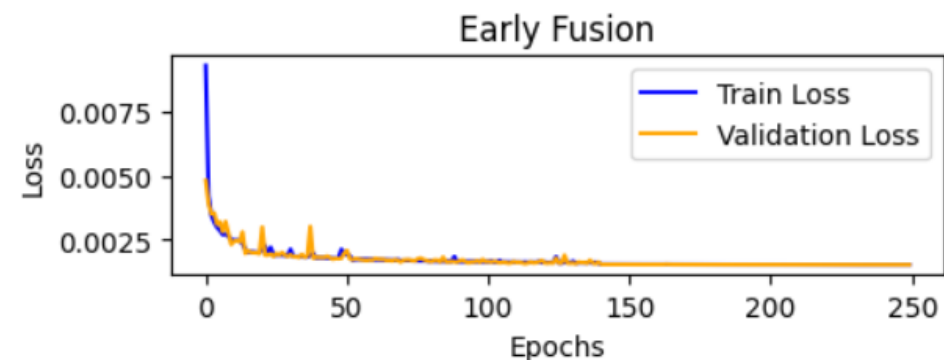
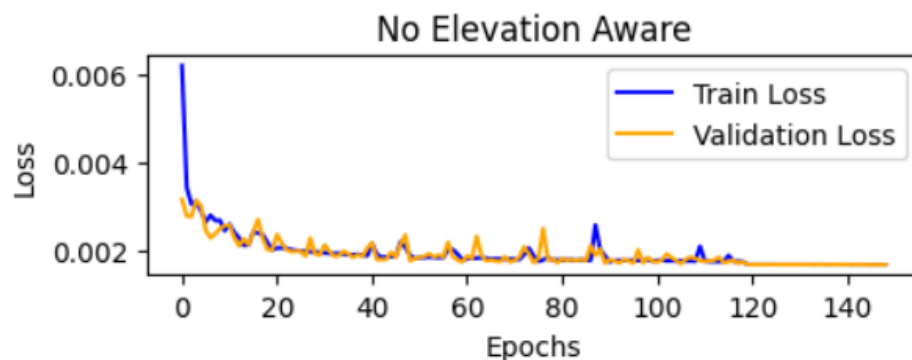
$$\text{SSIM}(x, y) = [l(x, y)]^\alpha \cdot [c(x, y)]^\beta \cdot [s(x, y)]^\gamma$$

Land MAE

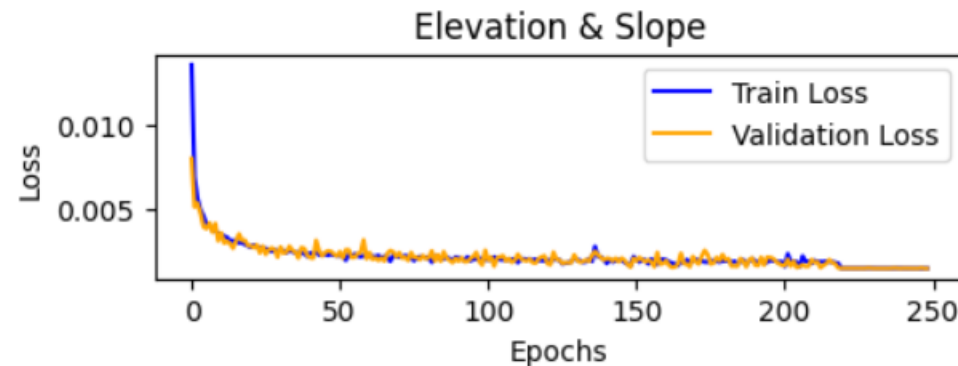
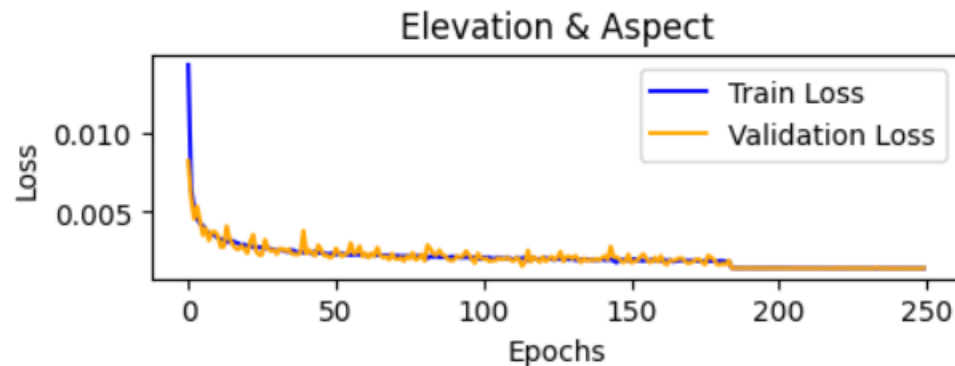
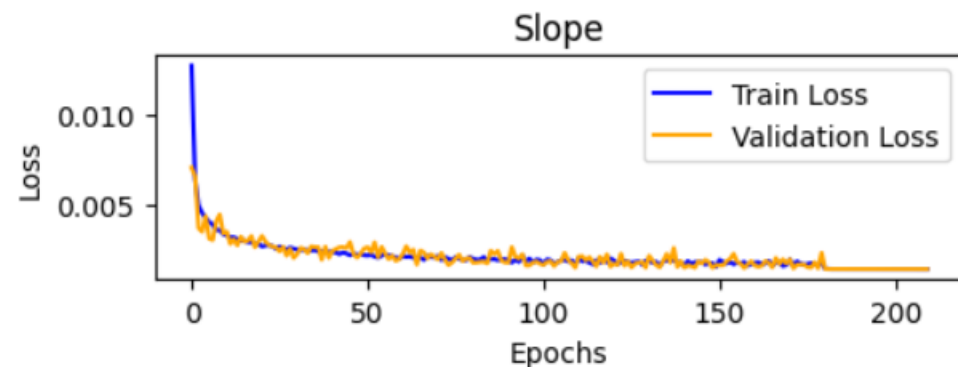
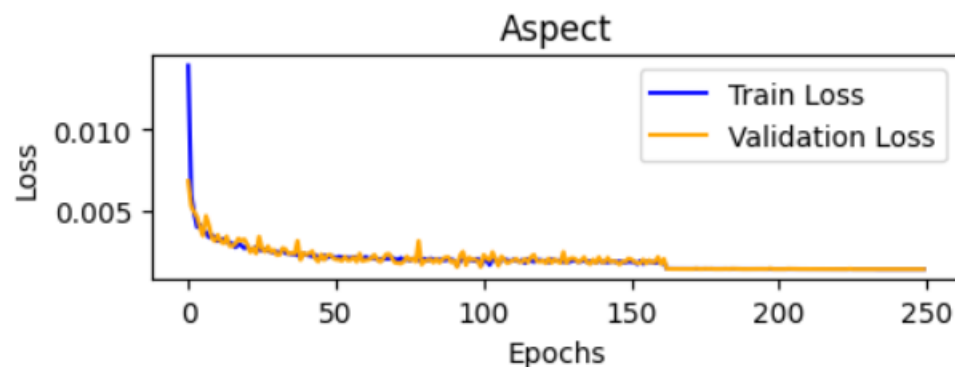


Land MAE in °C

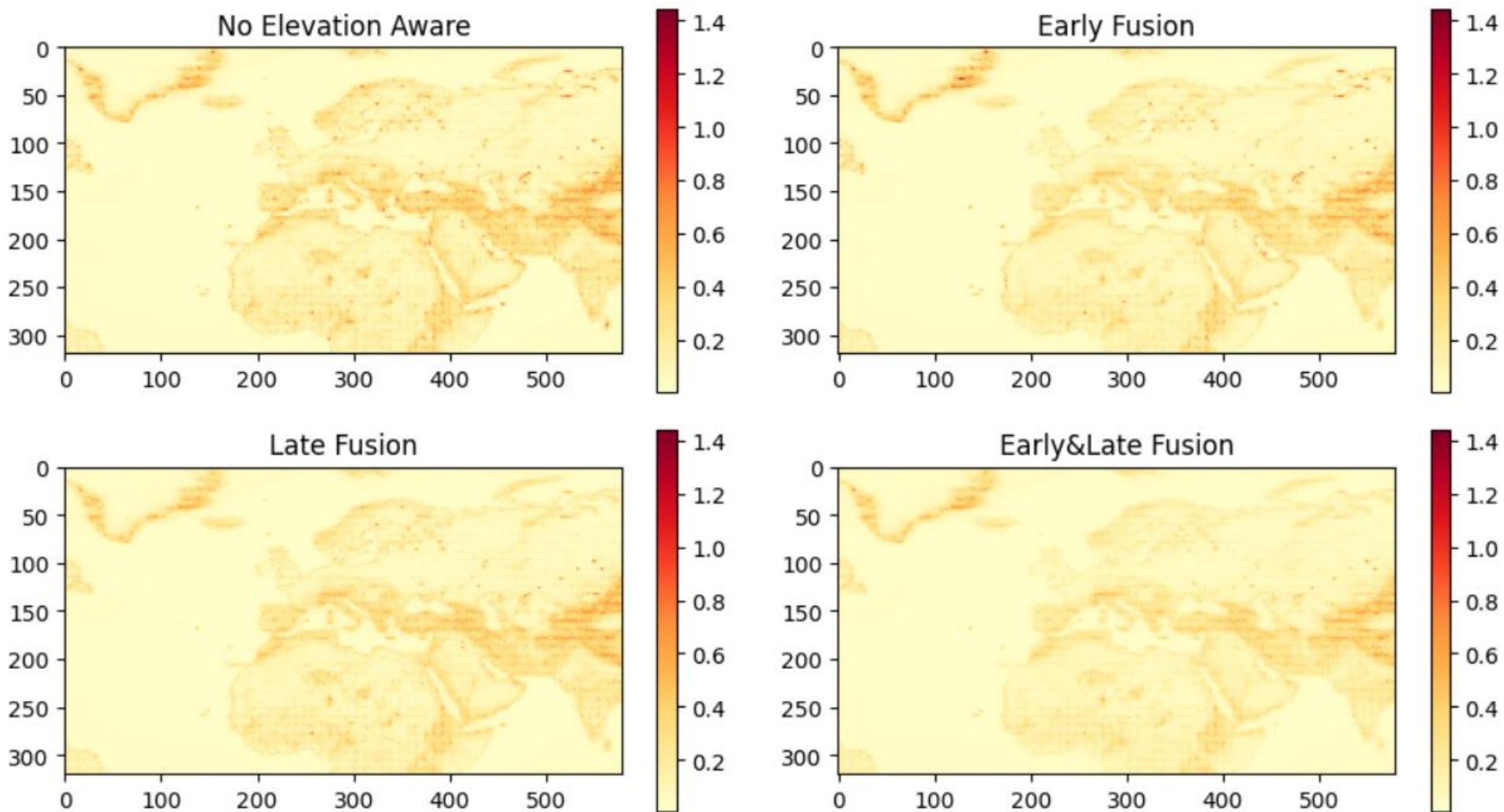
Bonus slides → Integration strategies training history



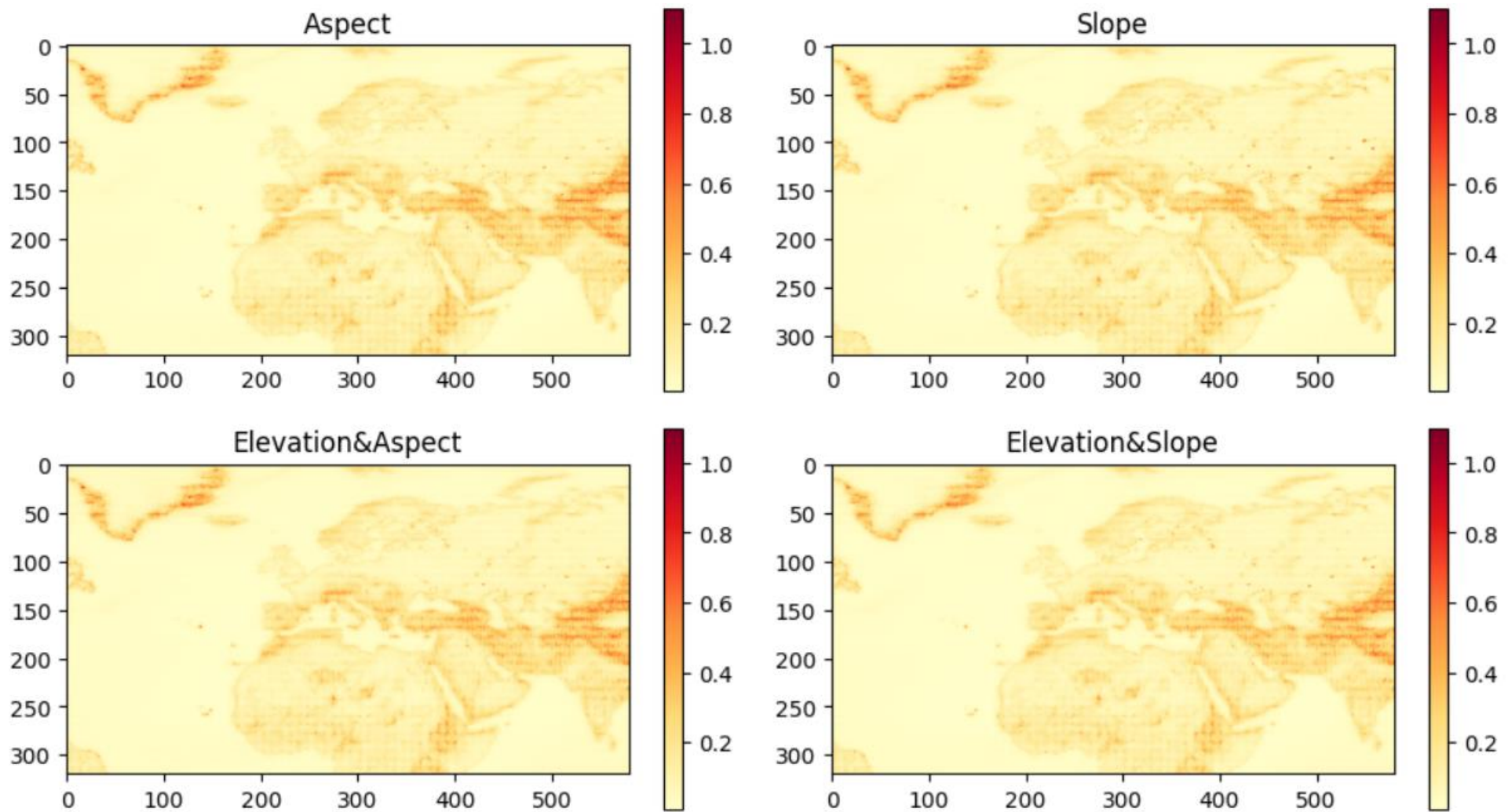
Bonus slides → Elevation-derived features training history



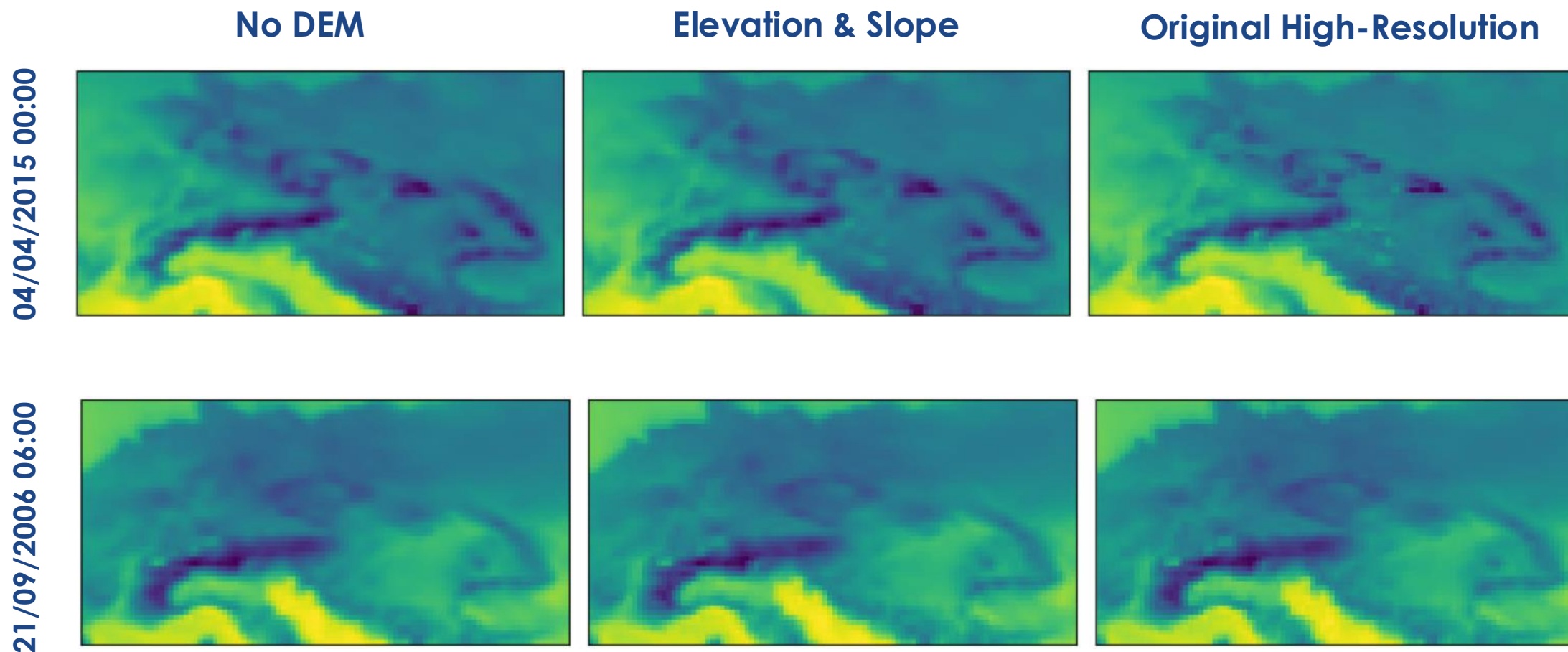
Bonus slides → Integration strategies MAE comparison



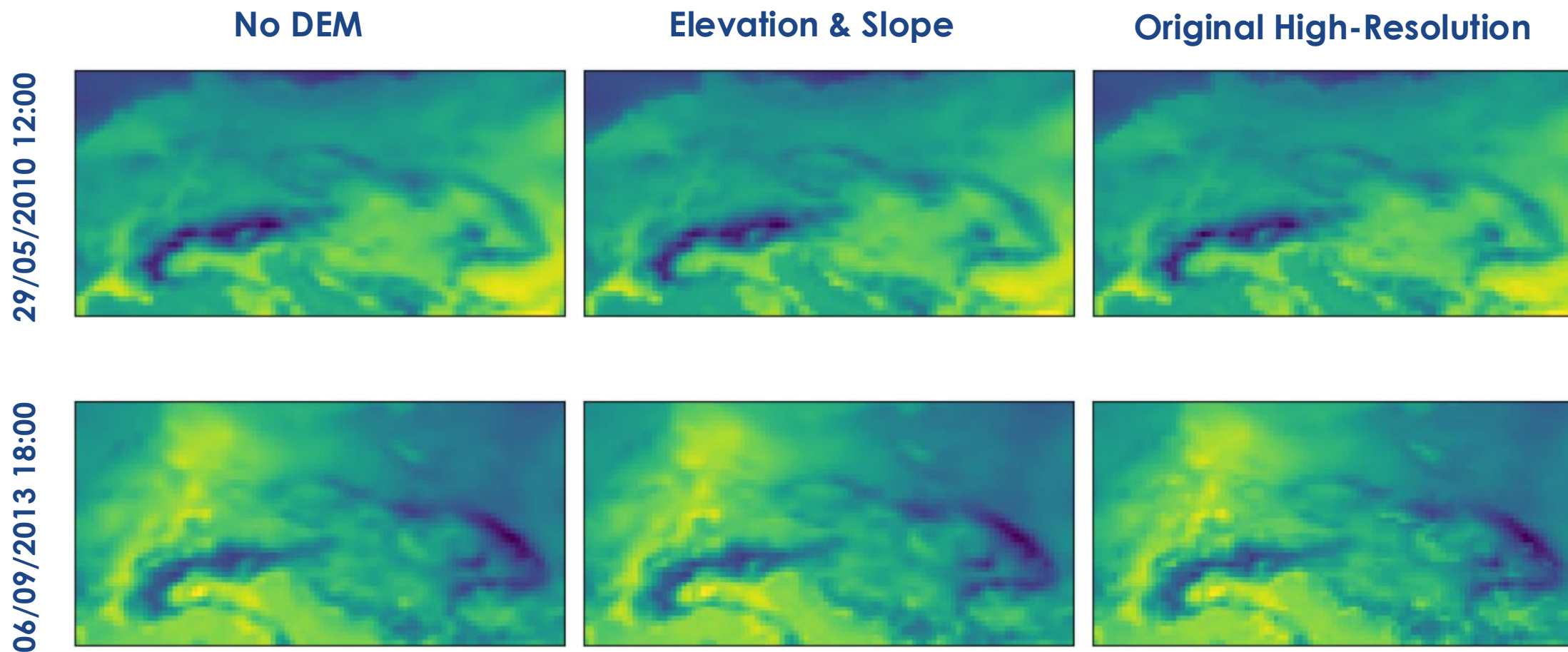
Bonus slides → Elevation-derived features MAE comparison



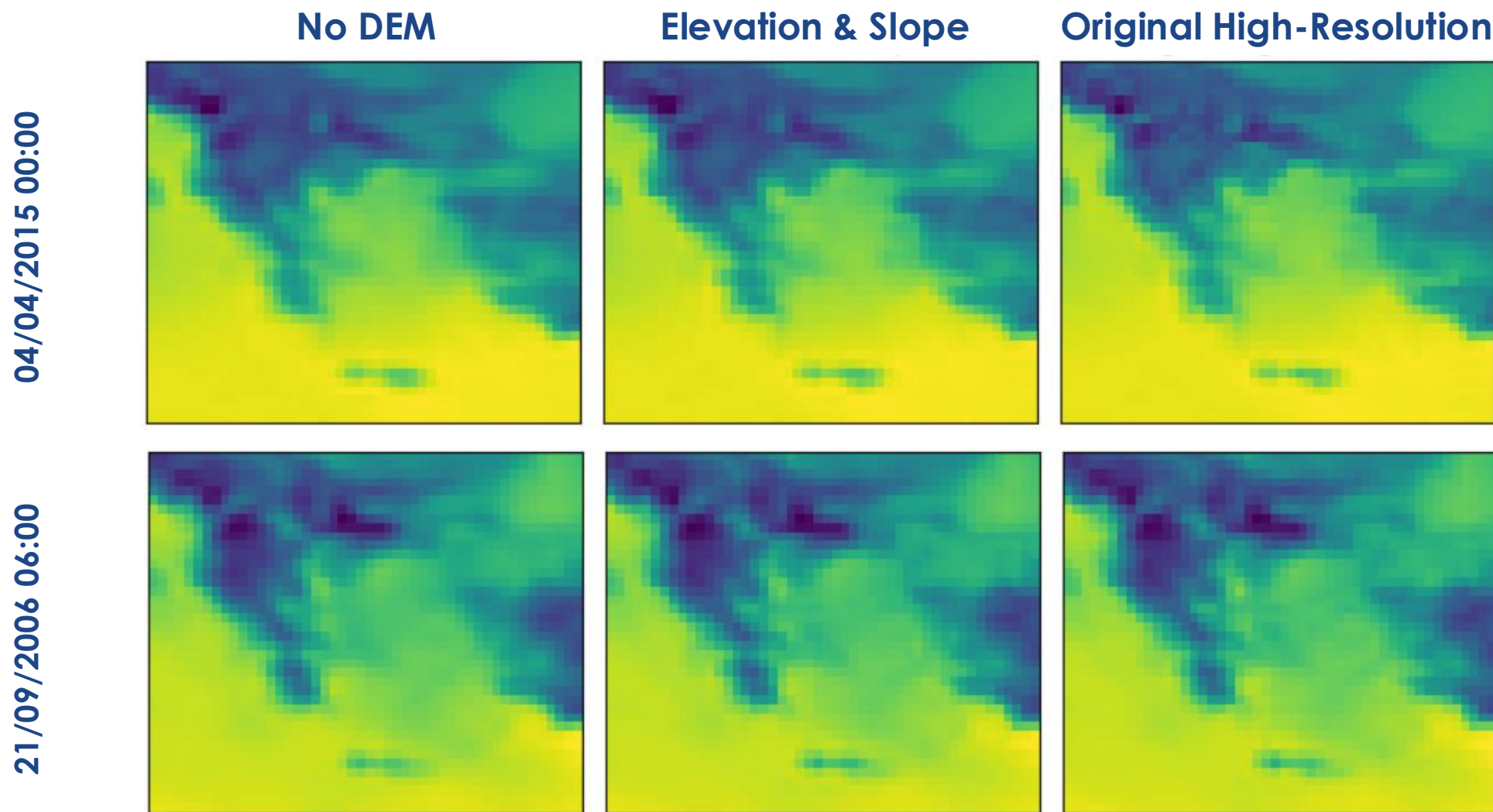
Bonus slides → Outputs “Central Europe” (1)



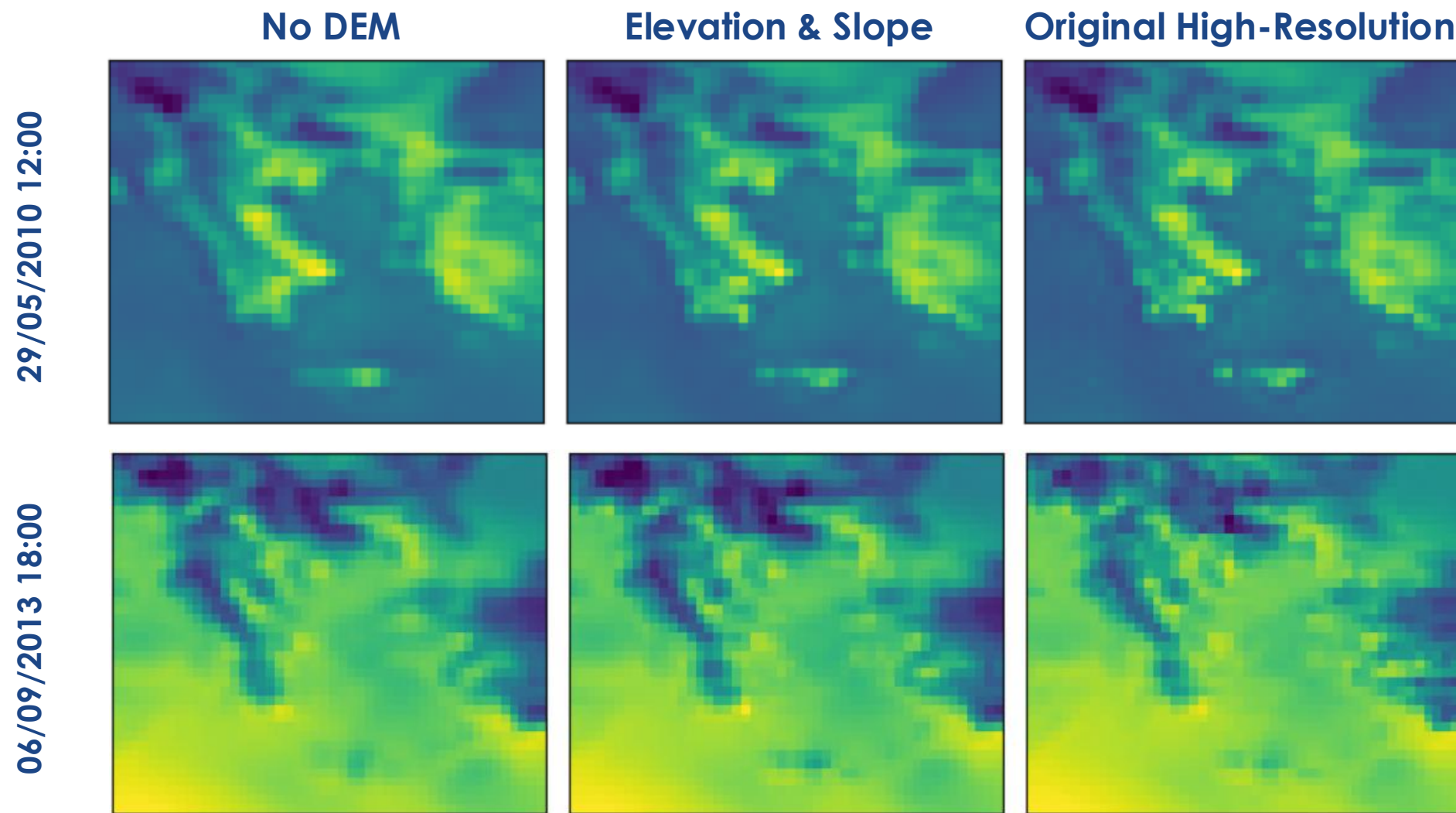
Bonus slides → Outputs “Central Europe” (2)



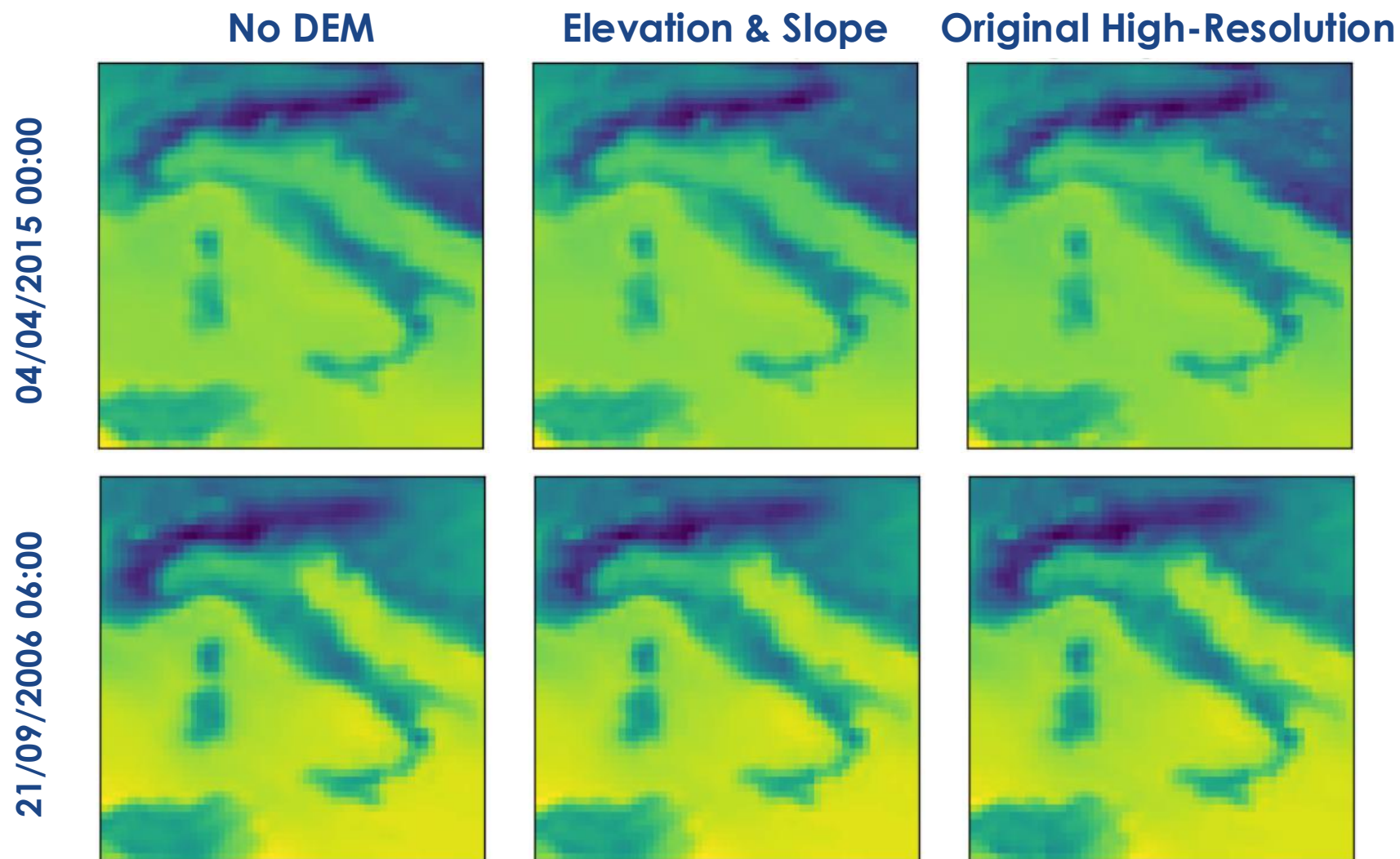
Bonus slides → Outputs “Greece” (1)



Bonus slides → Outputs “Greece” (2)



Bonus slides → Outputs “Italy” (1)



Bonus slides → Outputs “Italy” (2)

