Combining Satellite Images and Local Weather Station Data for Accurate Hyper-Local Weather at Arbitrary Locations

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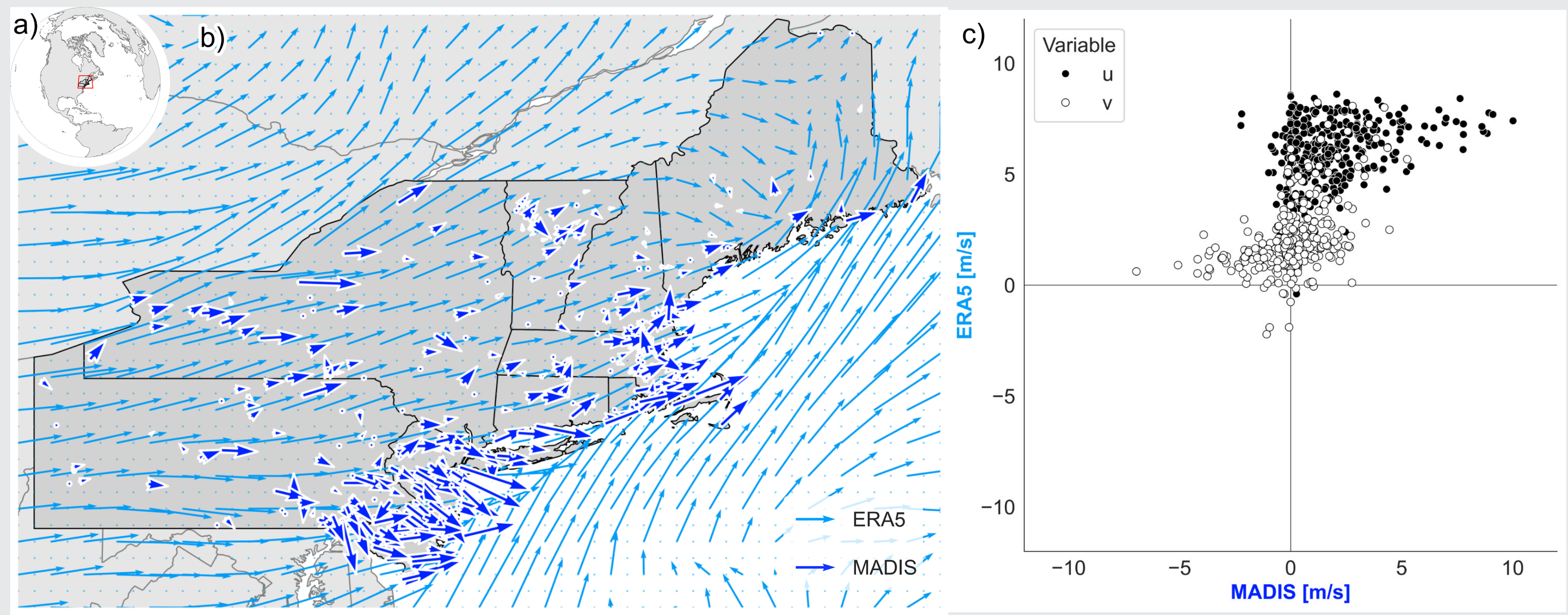
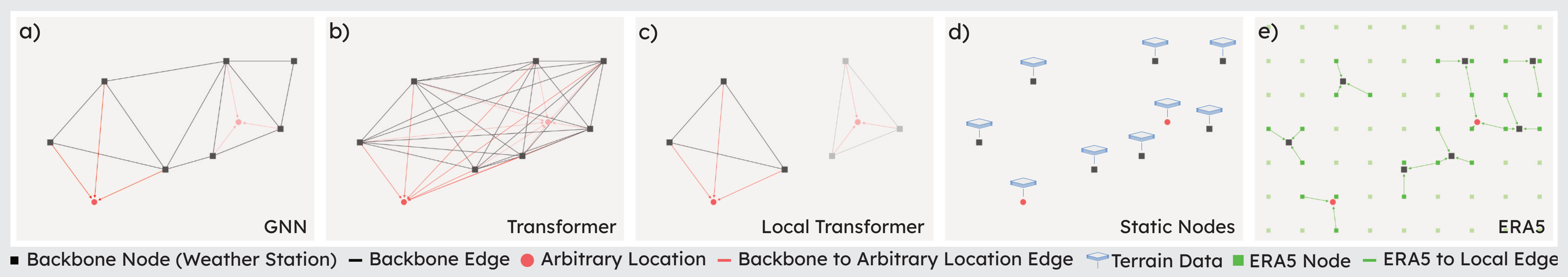
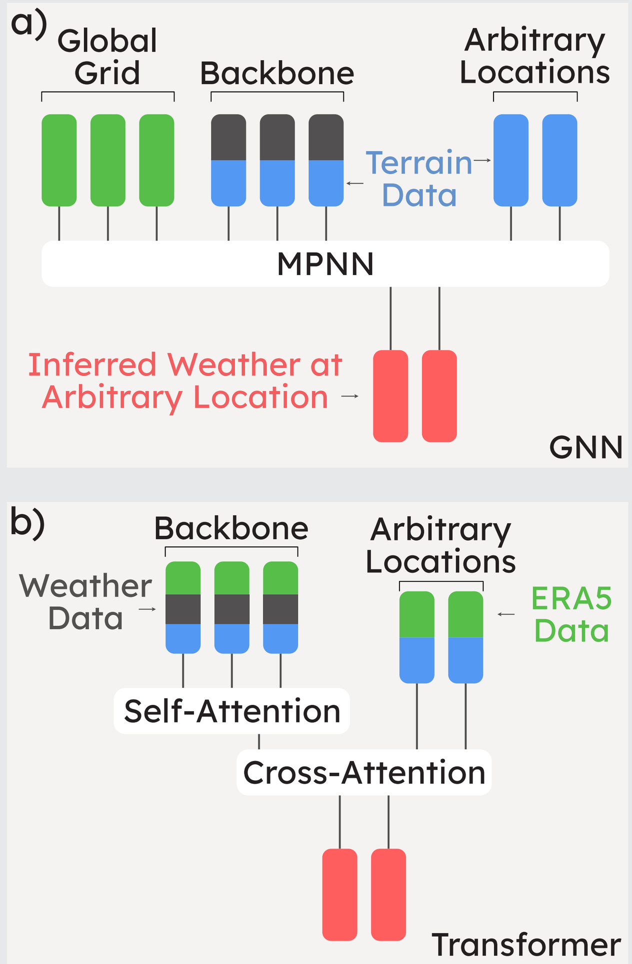
- Hyperlocal weather forecasting addresses the limitations of traditional weather models by providing precise and timely information tailored to specific locations.
- Applications include agriculture, where farmers can make informed decisions, and urban planning, where granular weather data improves infrastructure resilience.
- The proposed approach integrates ground-based weather observations, satellite imagery, and numerical weather prediction data to downscale coarse-resolution weather data to high-resolution locations using advanced methods like GNN and Transformer models.

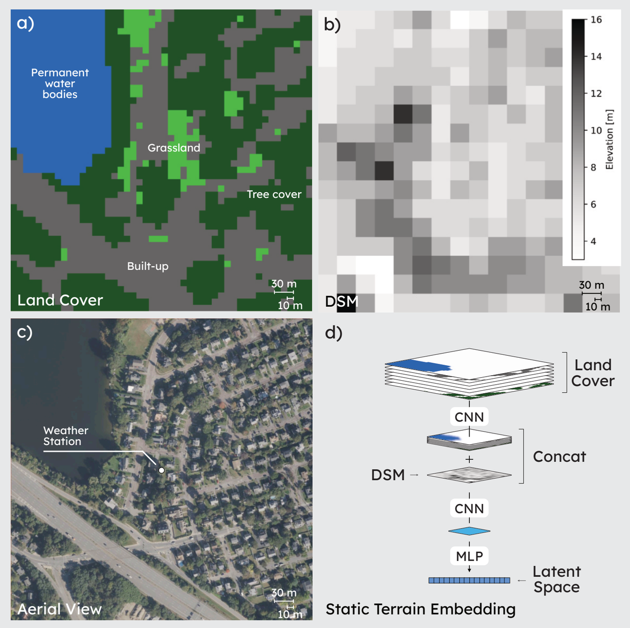


Deep Learning Framework for Hyperlocal Weather Inference

- Integration of Multiple Data Sources: The framework combines data from ground weather stations, Earth Observation-derived static terrain data, and a fixed-grid global reanalysis weather model (ERA5).
- Model Types: Two types of models are investigated for integrating spatial information: Graph Neural Networks (GNN) and Transformers.
- Data Utilization: Ground weather stations provide anchor points, static terrain data enhances local understanding, and ERA5 data captures large-scale weather patterns.





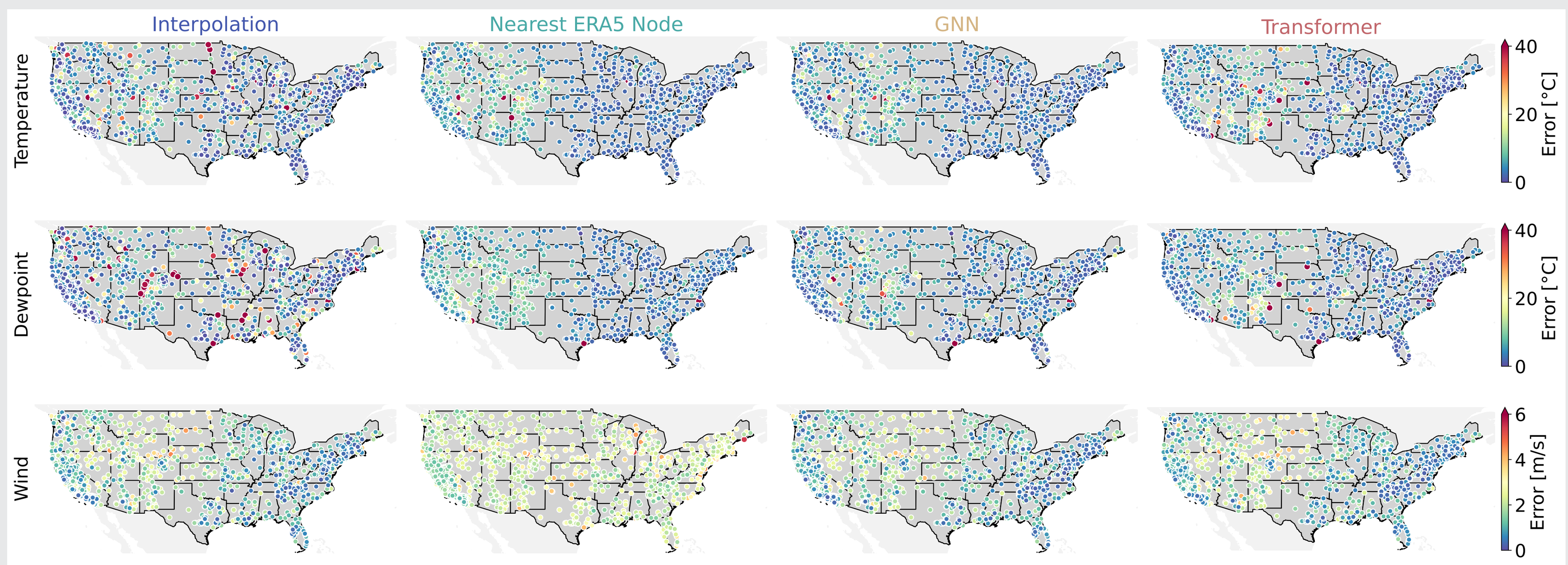


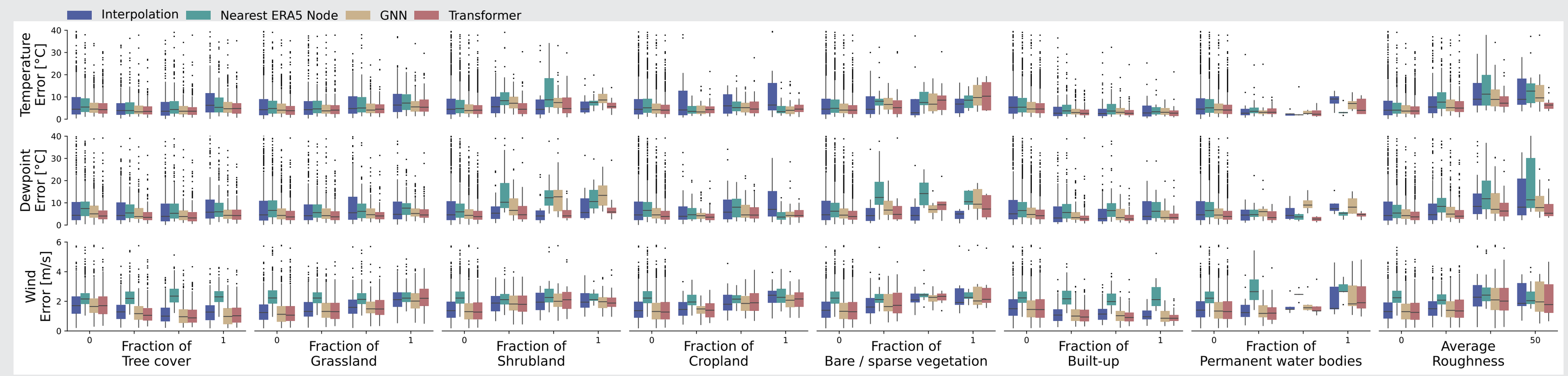
Models

- **Graph Neural Network (GNN)**: Constructs a network in three parts (main network of weather stations, ERA5 nodes, and arbitrary locations) using Message Passing Neural Networks (MPNN) to propagate and aggregate information through nodes and edges.
- **Transformer**: Utilizes a Vision Transformer (ViT) to handle spatial relationships between weather stations, static terrain data, and global weather data, employing self-attention and cross-attention mechanisms with positional encodings.
- **Static Terrain Embedding**: Integrates static terrain information (Land Cover map and Digital Surface Model) using a convolutional approach inspired by CvT to capture local characteristics and improve weather predictions.

Results

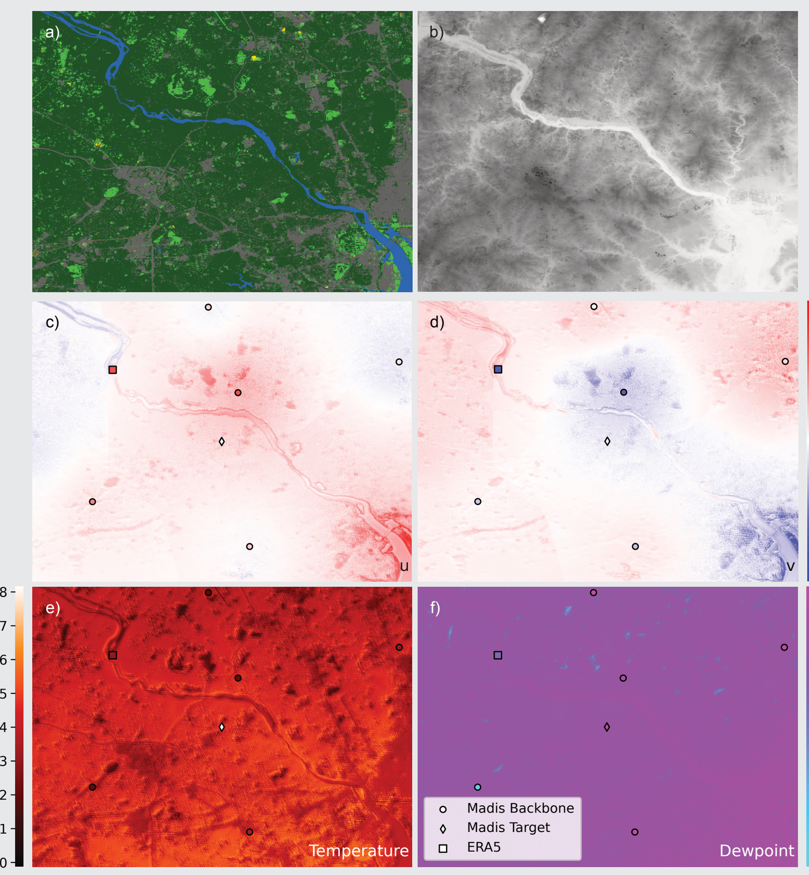
	Interpolation	Nearest ERA5 Node	GNN	Transformer
Temperature [°C]	2.79	2.70	2.33	**2.27**
Dewpoint [°C]	3.07	2.90	2.38	**2.23**
Wind [m/s]	1.54	2.33	**1.46**	1.48

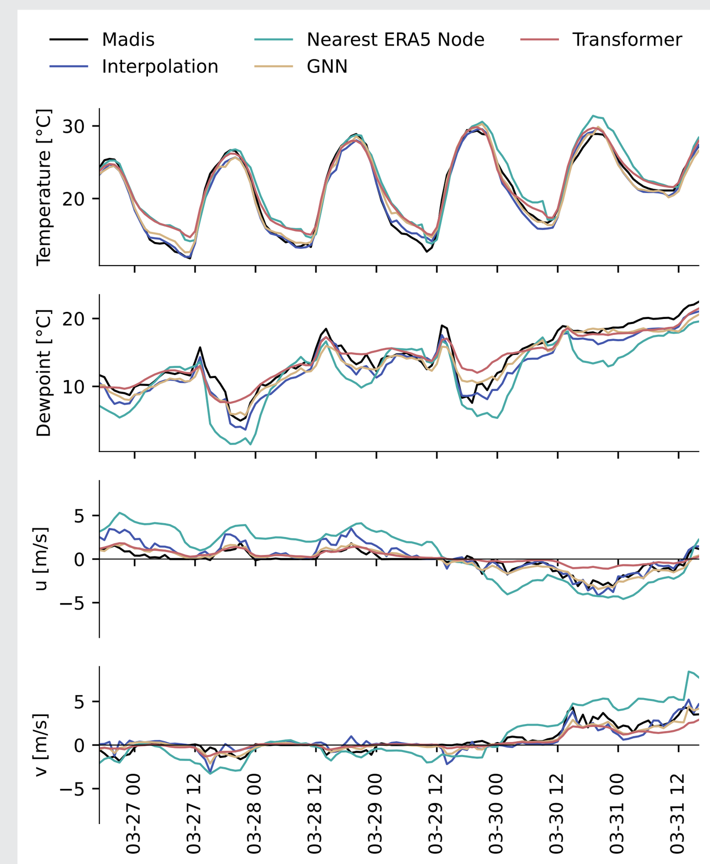




- The Transformer model significantly improves Temperature and Dewpoint predictions compared to nearest station interpolation and Nearest ERA5 Node, while the GNN model shows substantial improvement in Wind prediction. Both models show lower errors across the country, with higher errors in mountainous and isolated regions.
- Error distribution analysis by terrain type indicates that both models improve with higher fractions of Tree Cover, Grassland, Built-up areas, and increased roughness. The GNN struggles with Shrublands, where the Transformer performs better.
- Terrain data improves weather forecasts. GNN and Transformer models outperform interpolation and ERA5 node methods, though they overfit near stations. They perform well in downscaling and capturing weather trends.

Inference





[1]Yang, Giezendanner et al. (2024): Multi-modal graph neural networks for localized off-grid weather forecasting

Acknowledgements

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