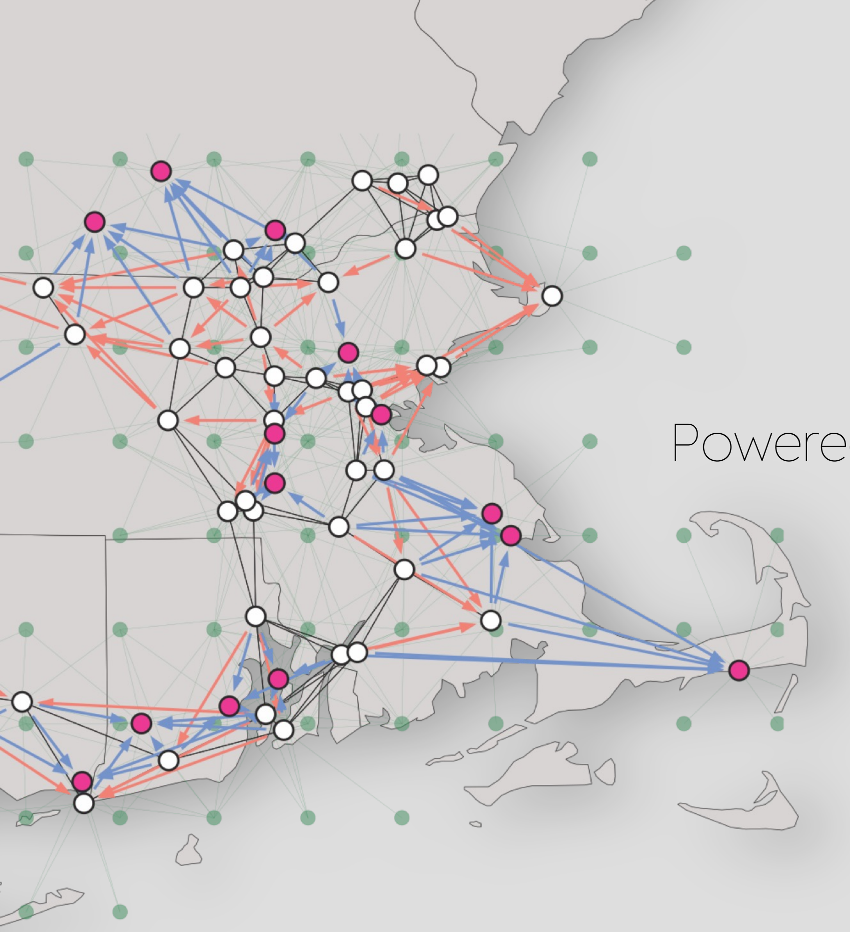


Hyper-Local Weather

Powered by Global Weather & Earth Observations

MIT

Jonathan Giezendanner, Qidong Yang, Chris Hill, Sherrie Wang

IBM

Johannes Jakubik, Daniel S. Civitarese, Campbell Watson

Shell

Eric Schmitt, Anirban Chandra, Jeremy Vila, Detlef Hohl

Living Planet Symposium 2025

Global models don’t always match local reality

Wind

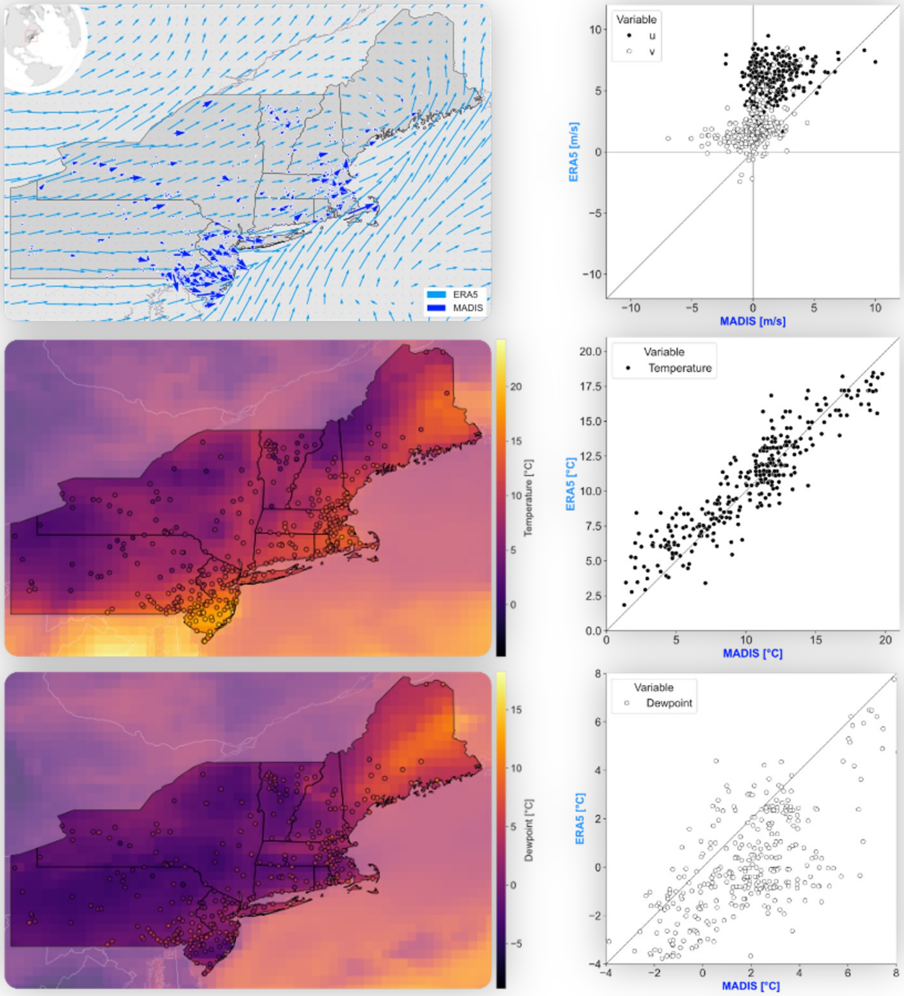
- Local heterogeneity, turbulences ignored by global weather products (ERA 5)
- Obstacles such as buildings and forests are smoothed out

Temperature

- Global model is pretty good, but very smooth compared to local observations

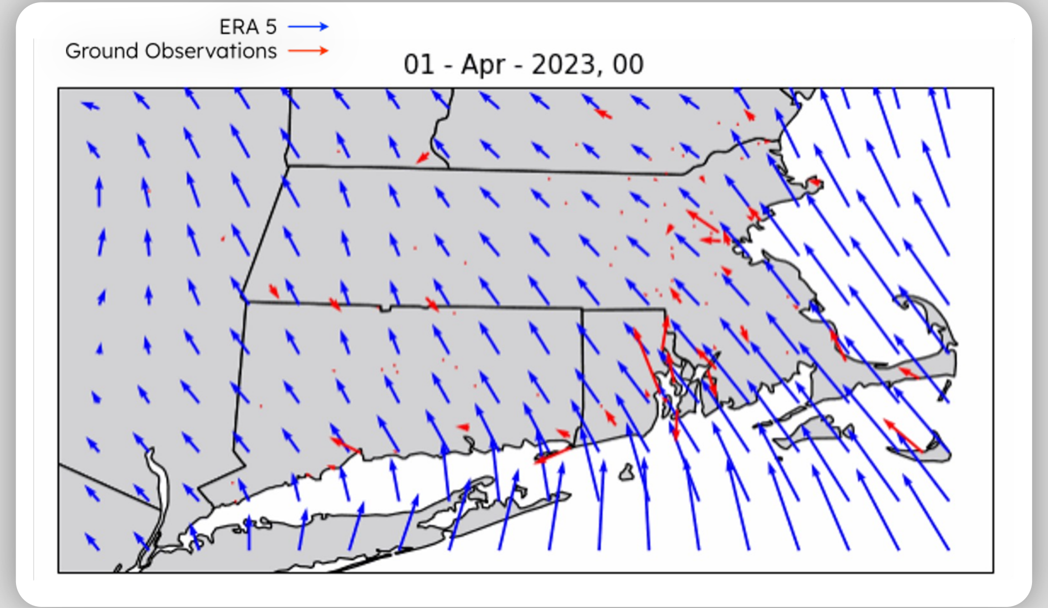
Dewpoint

- Not as good as temperature; not as bad as wind
- Global model again smoother than local observations

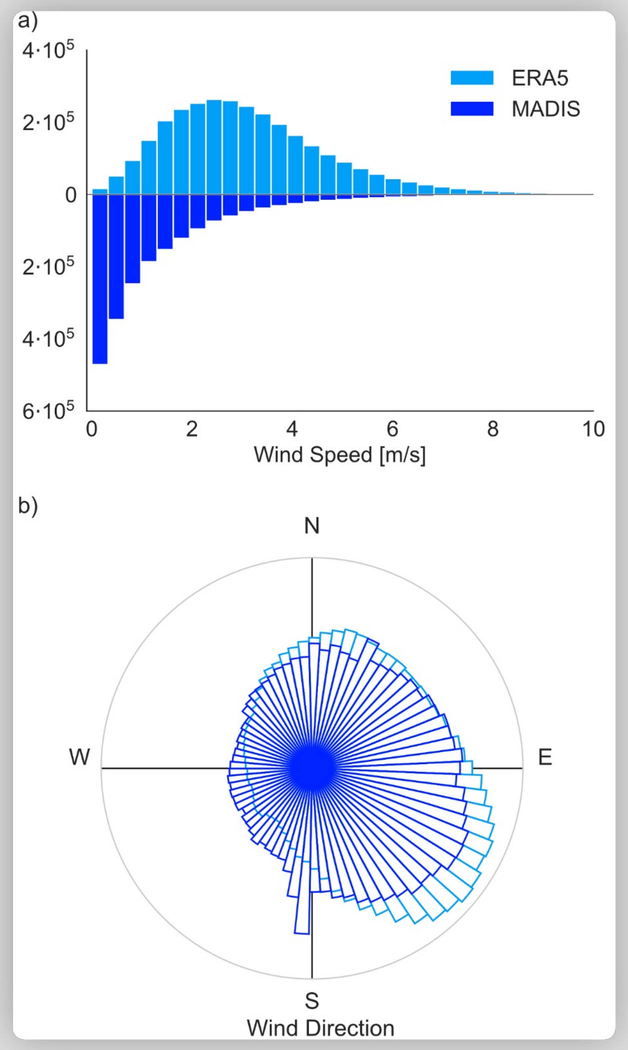


Global Model vs Local Weather Stations

Particularly apparent for Wind

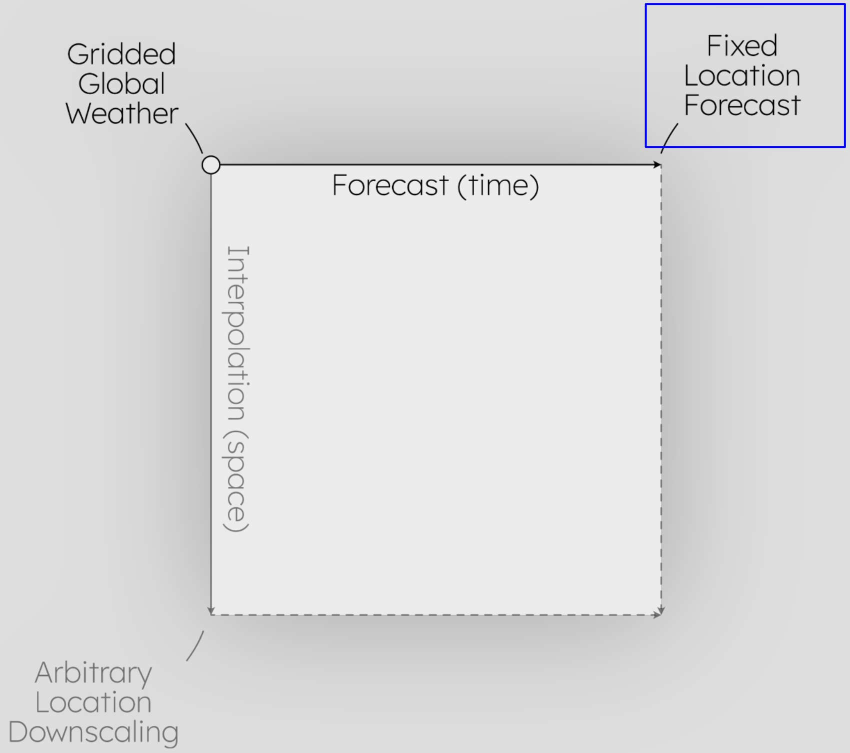


Animated figure of ERA 5 (blue) vs ground observations (red)



Local Weather:

Fixed Location Forecast



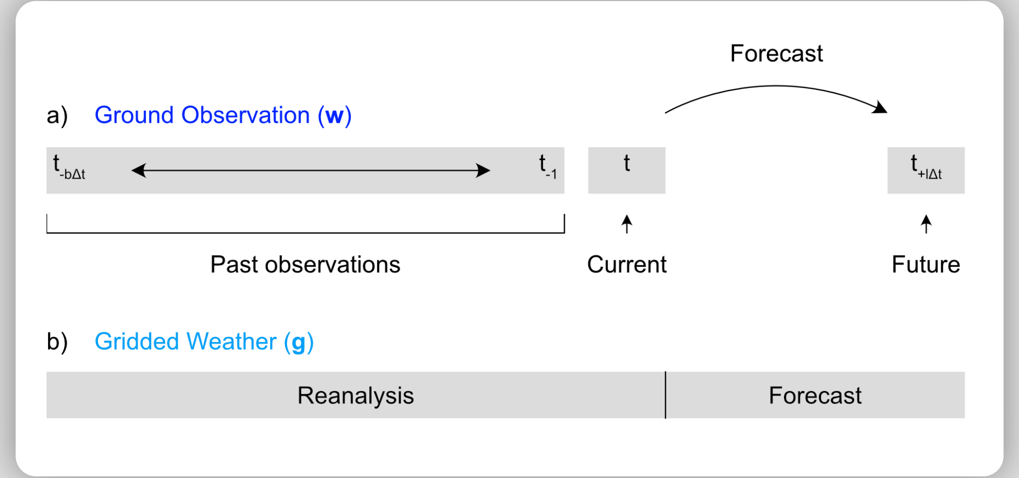
Yang, et al. (submitted)

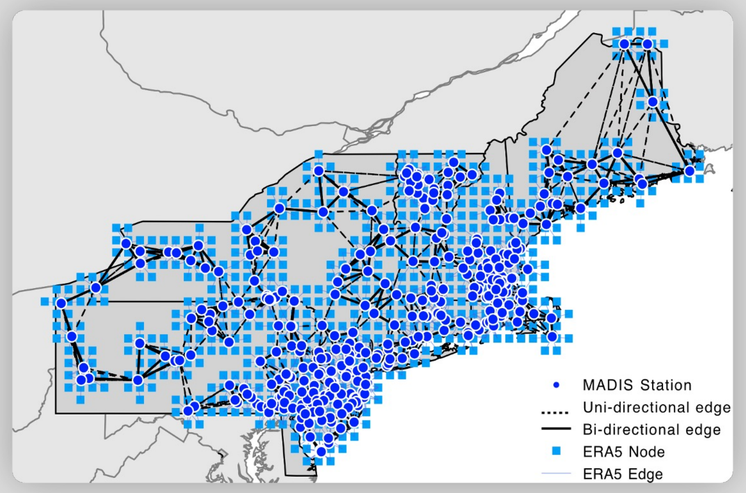
Local Off-Grid Weather Forecasting with Multi-Modal Earth Observation Data

Our approach: Use ML to correct global gridded models

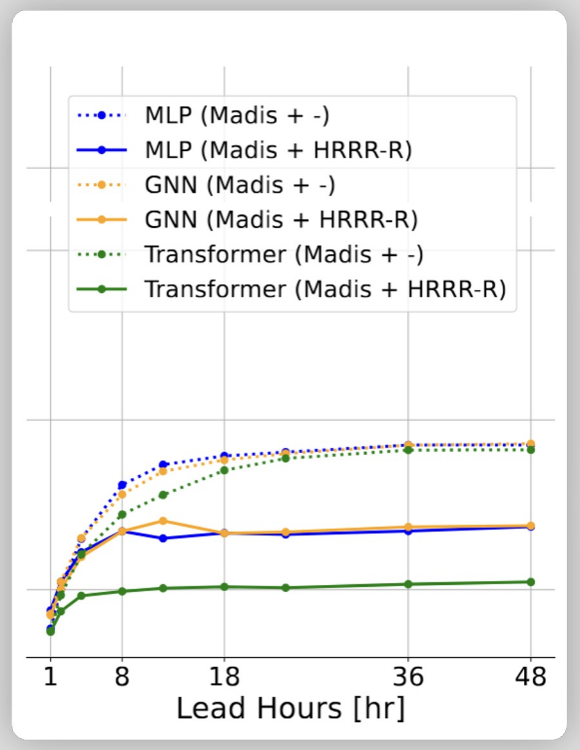
Integrate **numerical forecast** to inform about high level dynamics

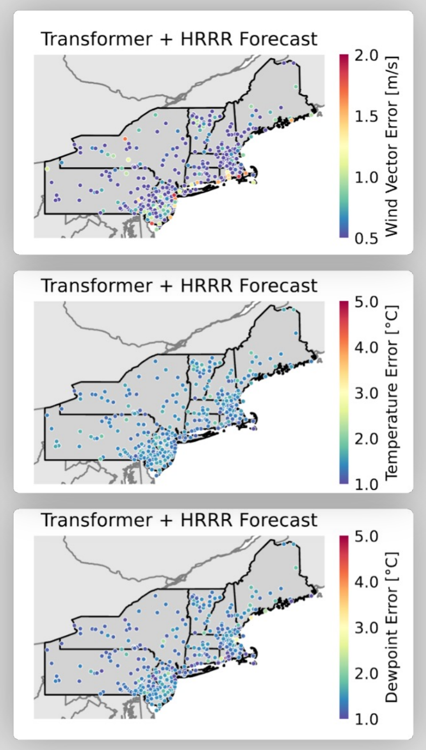
Each **station** becomes a **token**, combined with nearest gridded forecast

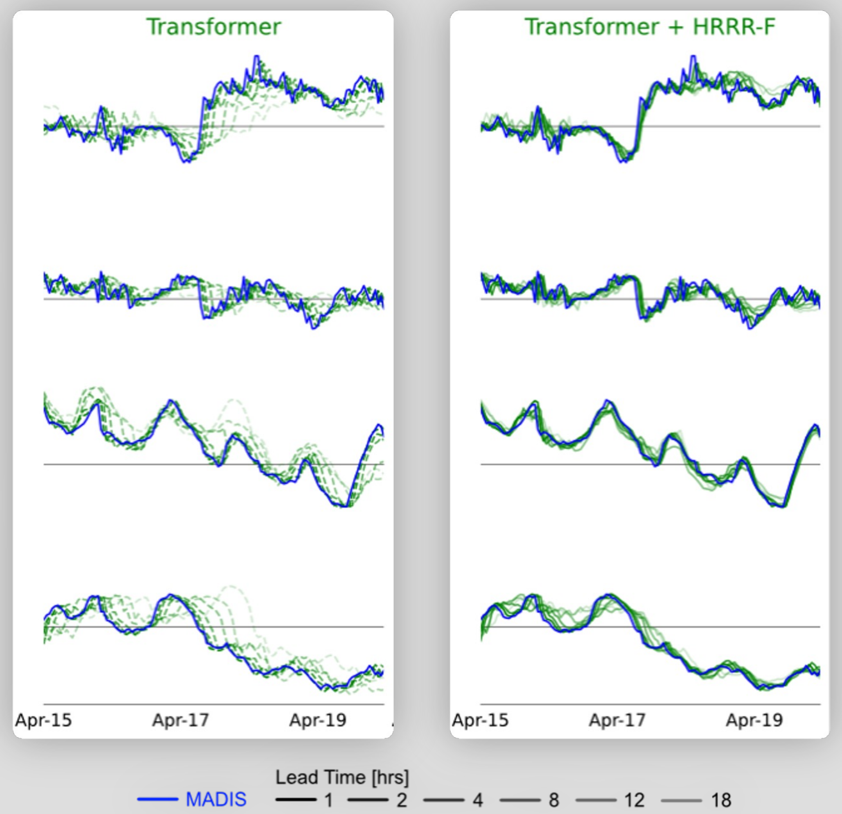




Transformer provides most accurate Global model forecast correction towards local reality

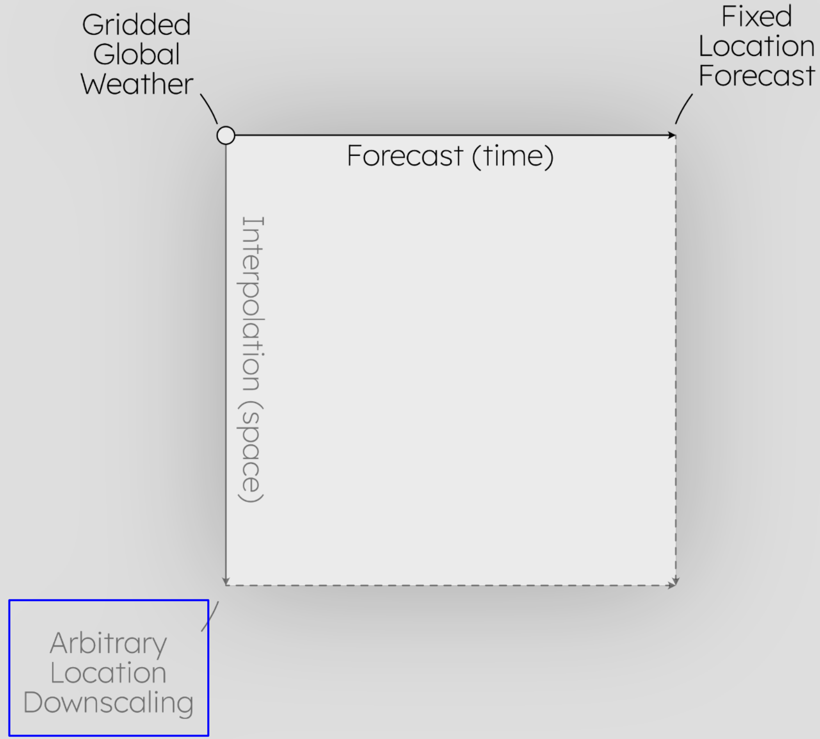




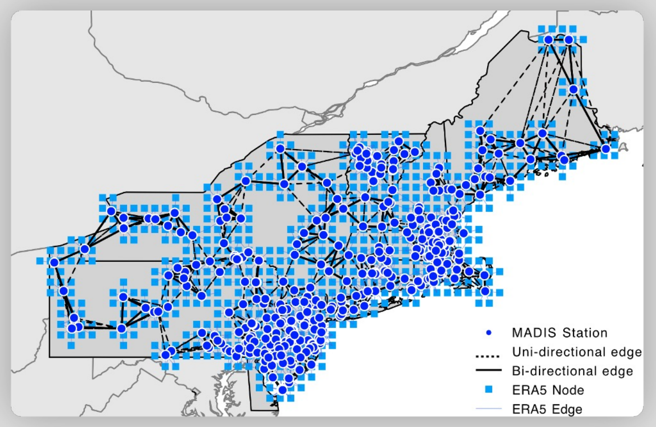


Local Weather:

Downscaling to Arbitrary Locations

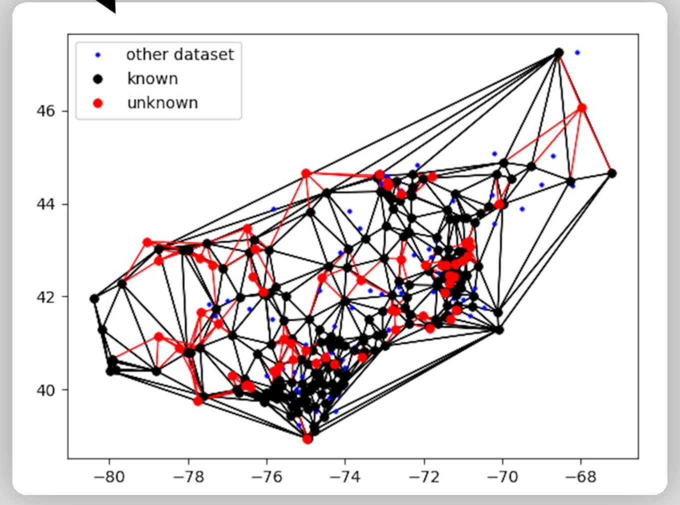


Can we move beyond fixed weather station locations?



Base:

- Network of weather stations
- Global NWP (or AI model) nodes

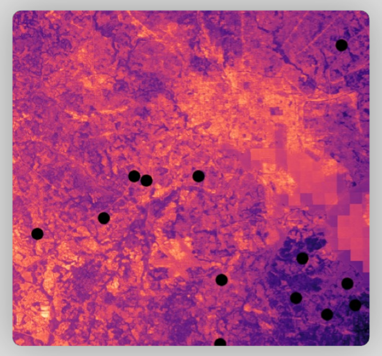


Idea

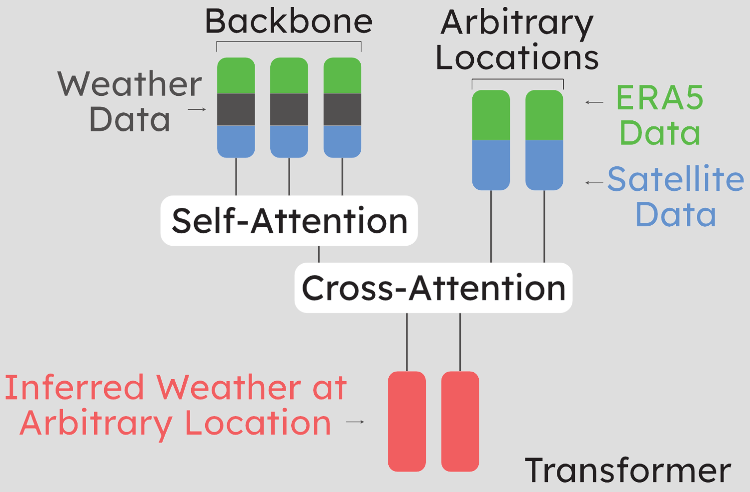
Create model to infer weather at hold-out weather stations from other modalities:

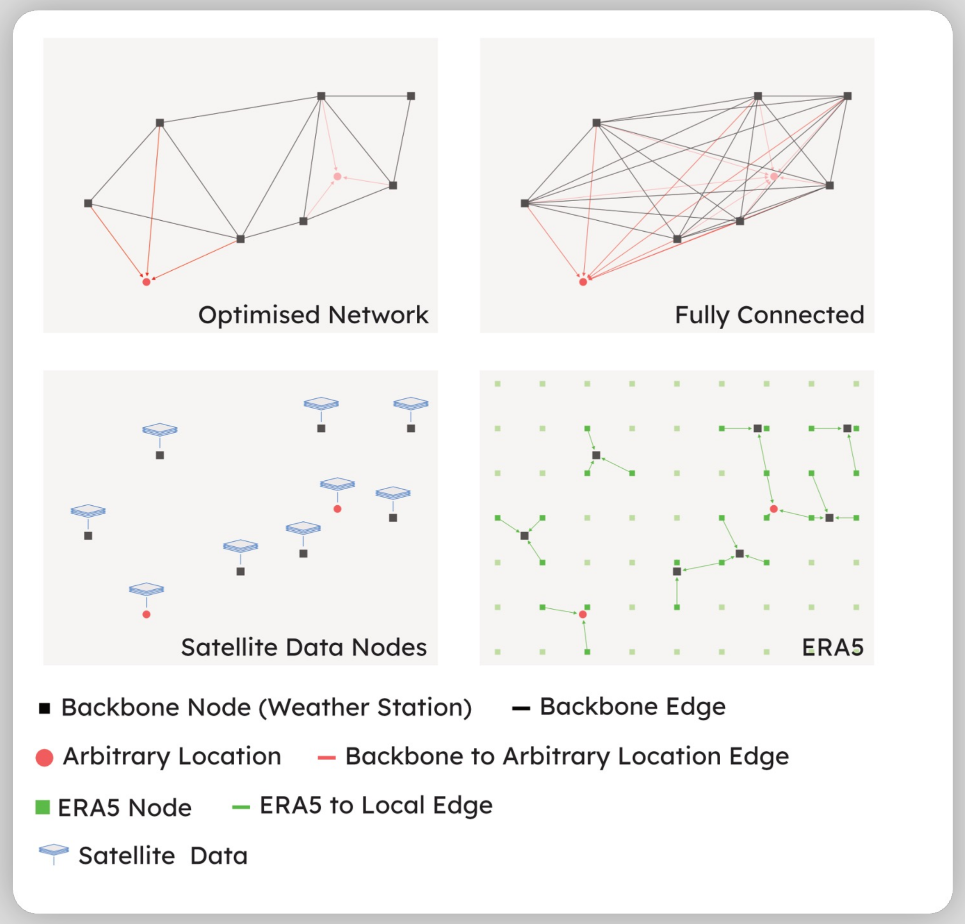
- Surrounding stations
- Global weather
- Terrain information
- Satellite images

Infer weather at arbitrary locations

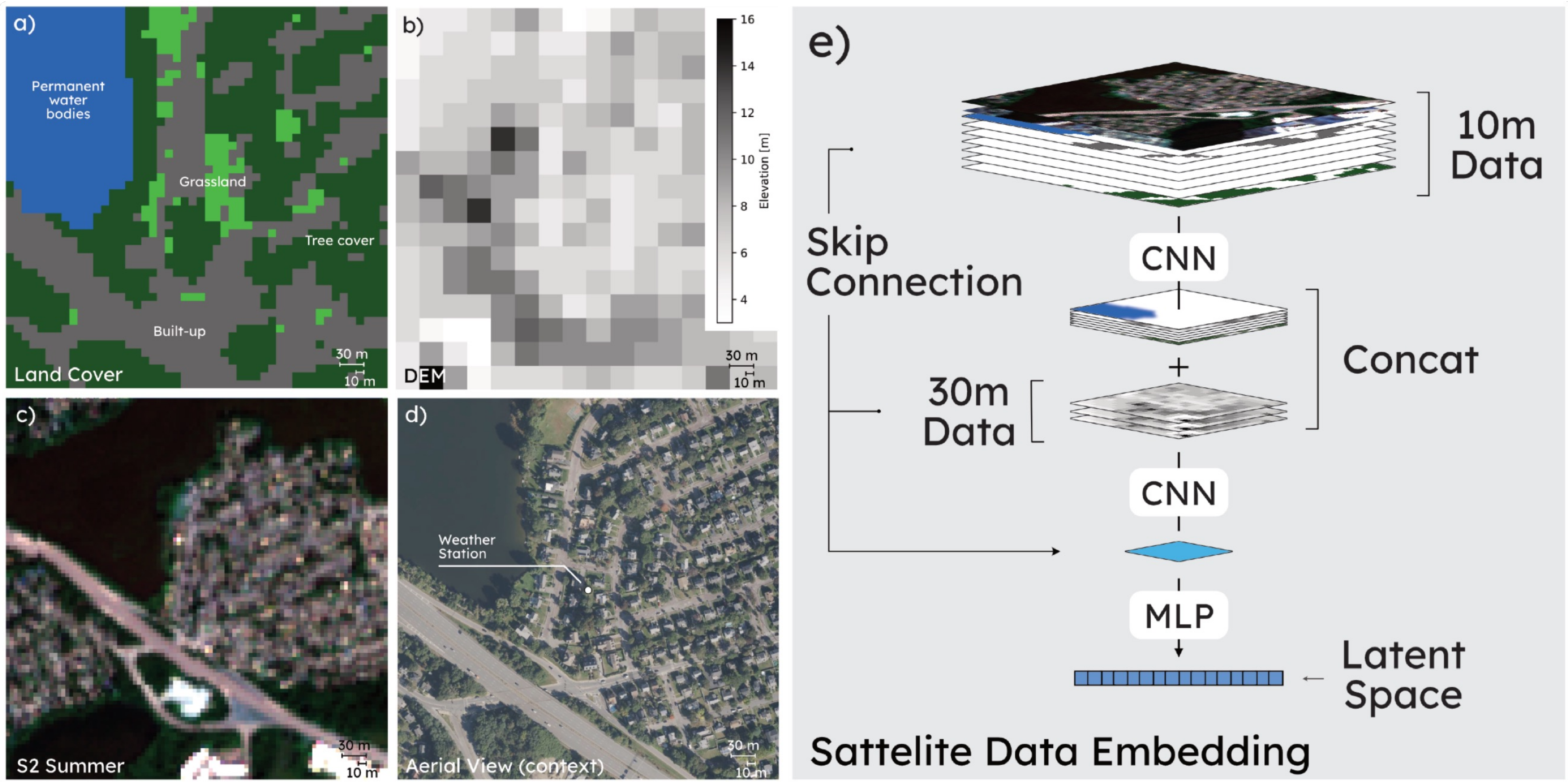


Technical approach - Neural network architectures

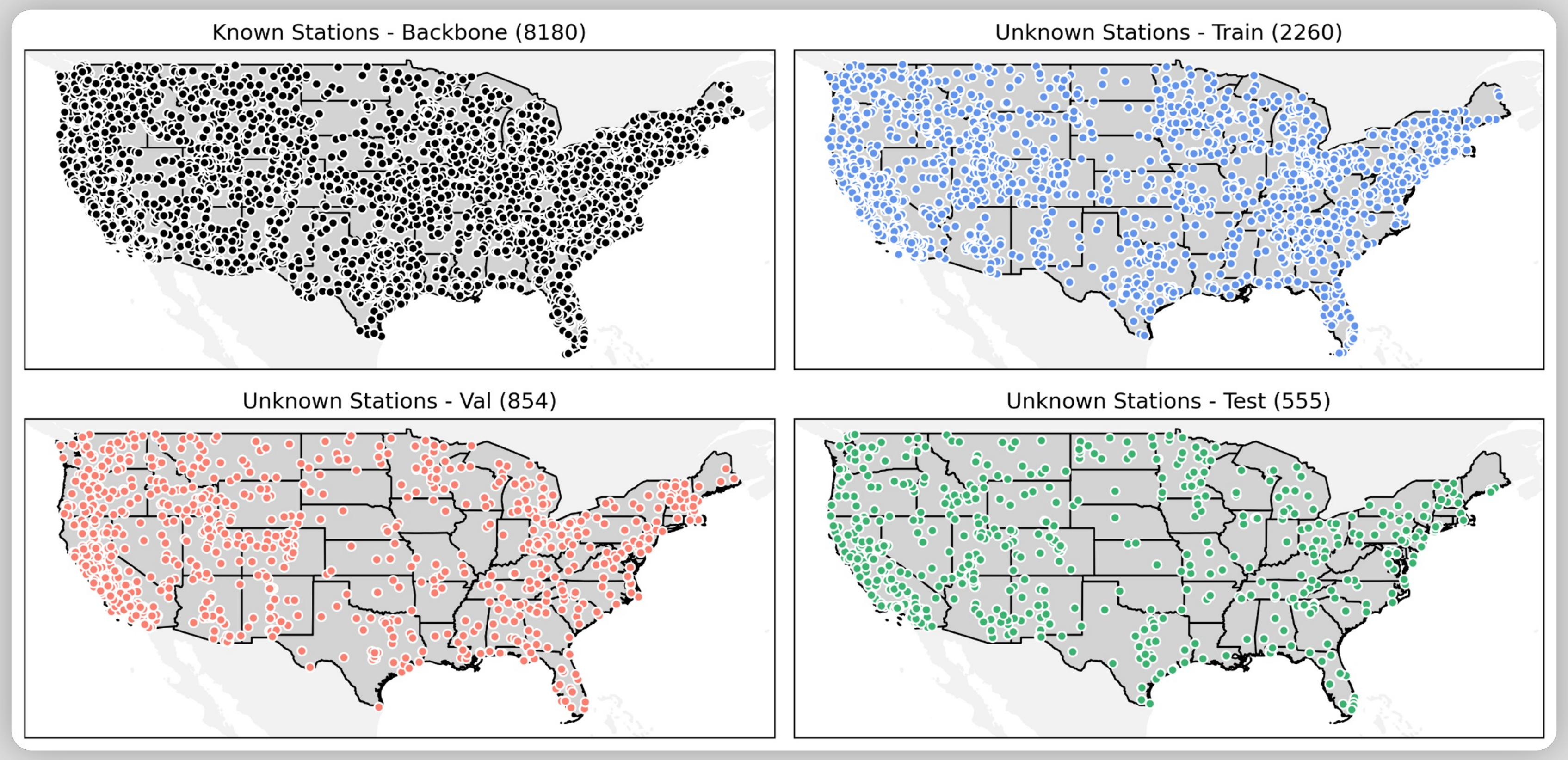




Satellite Data and Node Embedding



Split dataset into Backbone and Target stations



Best performance when adding **satellite** images w/ **context window** and **optimized backbone**

Model	**Wind Vector Error** [m/s]	**Temperature MAE** [°C]	**Dewpoint MAE** [°C]
Interpolation Madis	2.256	2.134	2.177
Interpolation ERA5	2.352	1.958	2.002
Transformer Terrain (T)	1.705	1.857	1.91
Transformer T + S2 Summer	1.705	1.866	1.926
Transformer T + S2 All Seasons (A)	**1.69**	**1.851**	**1.898**

w/ sat. images

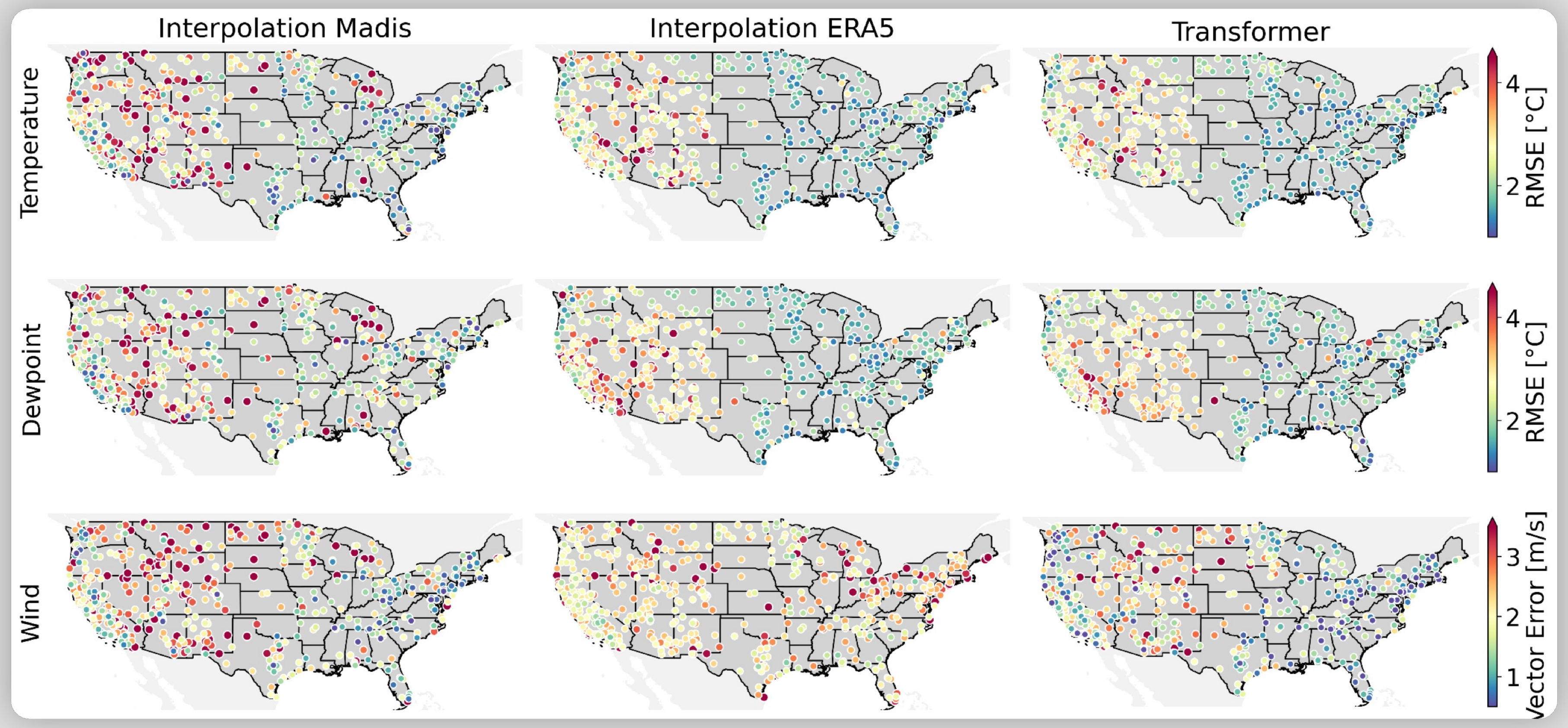
Transformer T + S2 A	**1.69**	**1.851**	**1.898**
Transformer T + S2 A (1 value)	1.732	1.865	1.899

w/ context window

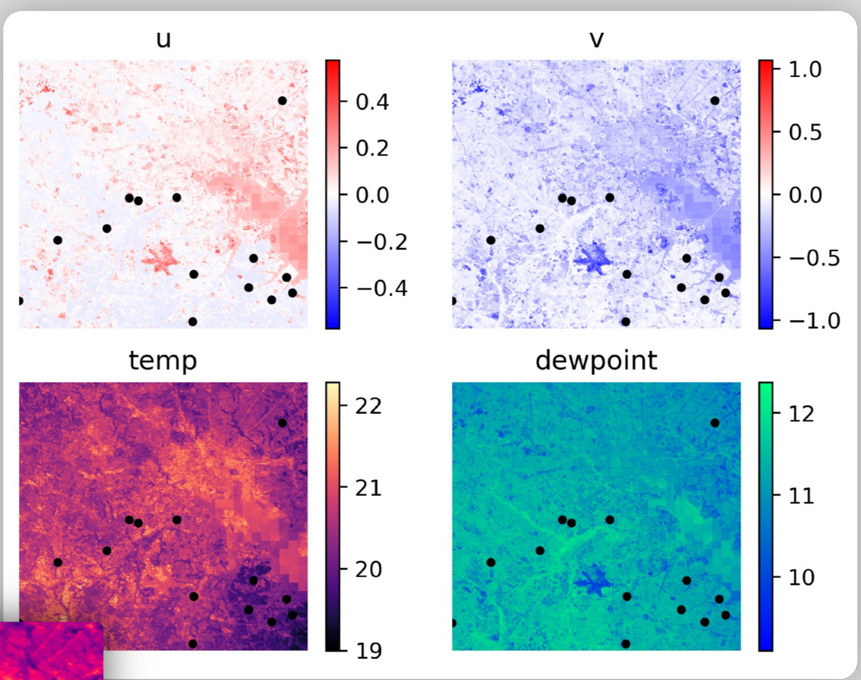
Transformer T + S2 A	1.69	1.851	1.898
Transformer T + S2 A + Delaunay (D)	**1.639**	**1.833**	**1.828**
Transformer T + S2 A + Nearest N. (NN)	1.69	1.859	1.906
Transformer T + S2 A + D + NN	1.728	1.867	1.982

optimized backbone

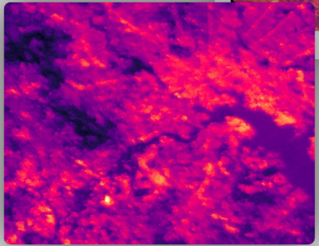
Biggest improvements along the coast



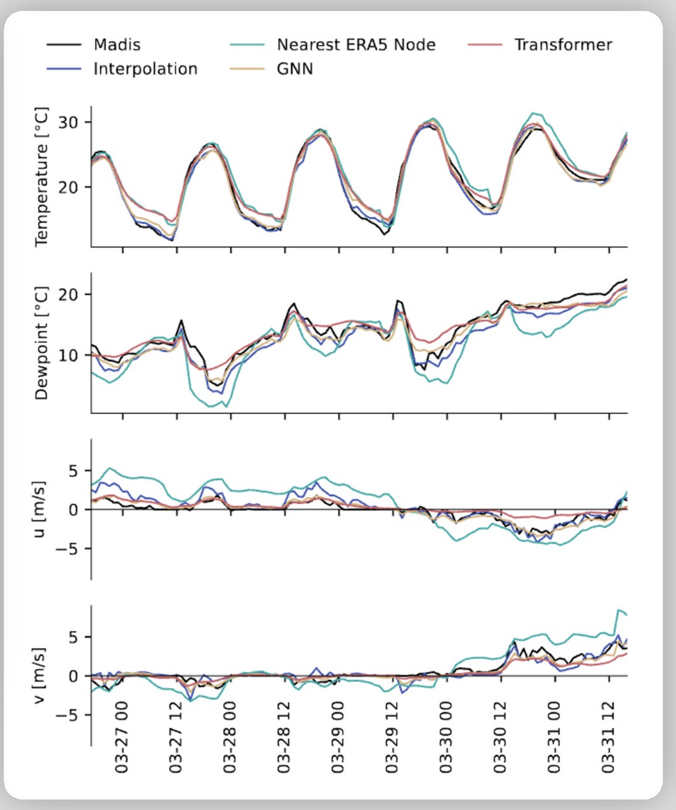
Inference at native satellite resolution and in time



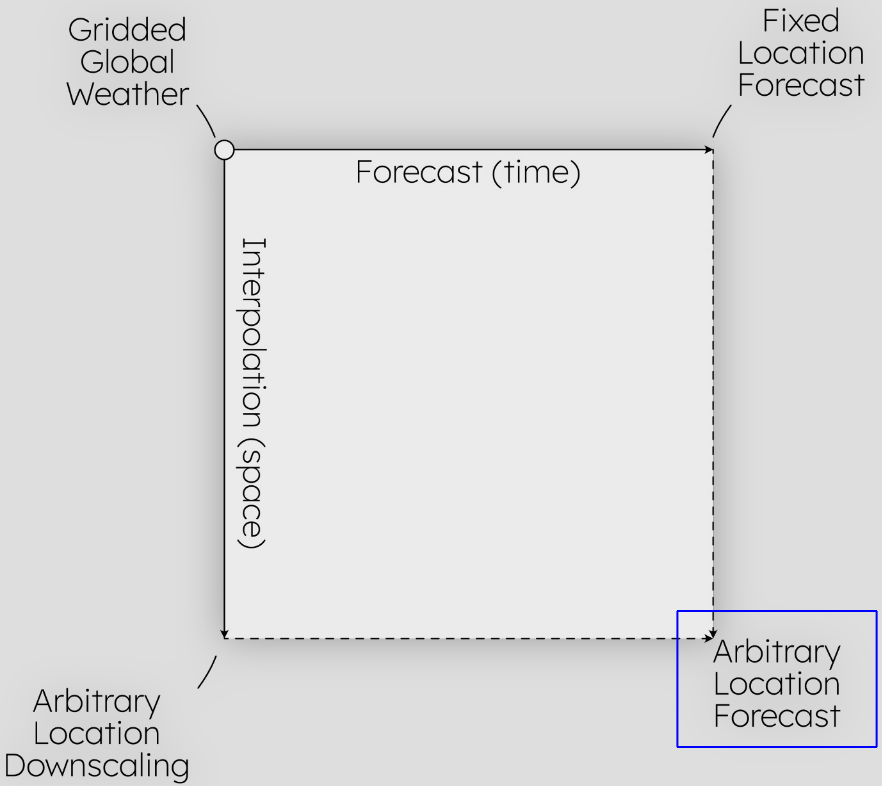
Inferred variables [10 meters]



Ecostress reference (temperature) [60 m]



What's next?


Gridded
Global
Weather
Fixed
Location
Forecast
Forecast (time)
Interpolation (space)
Arbitrary
Location
Downscaling
Arbitrary
Location
Forecast

What's next?

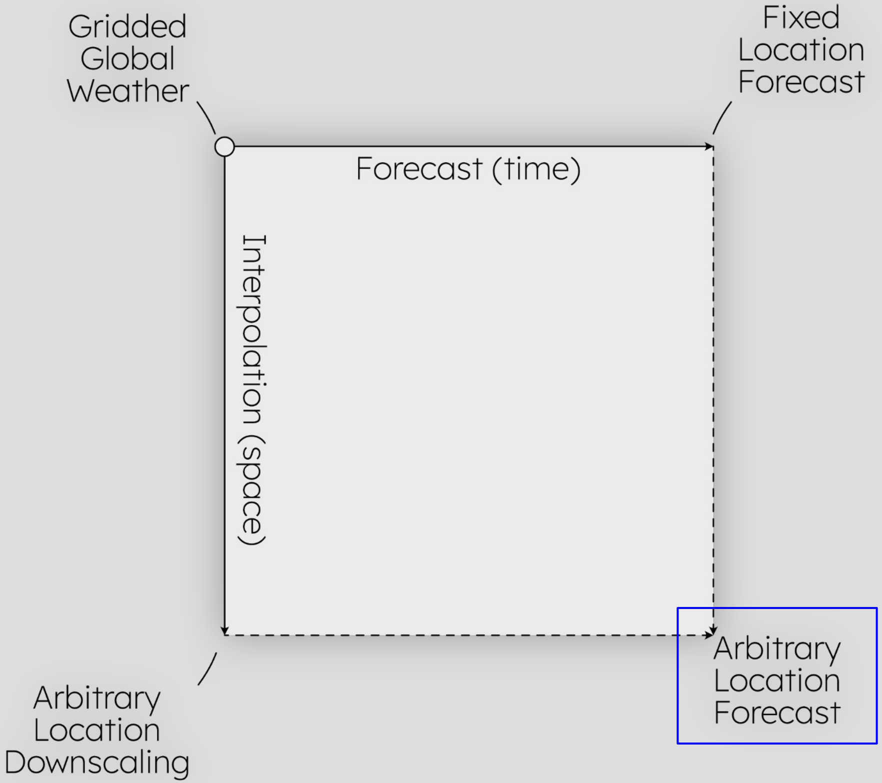
Improve Inference

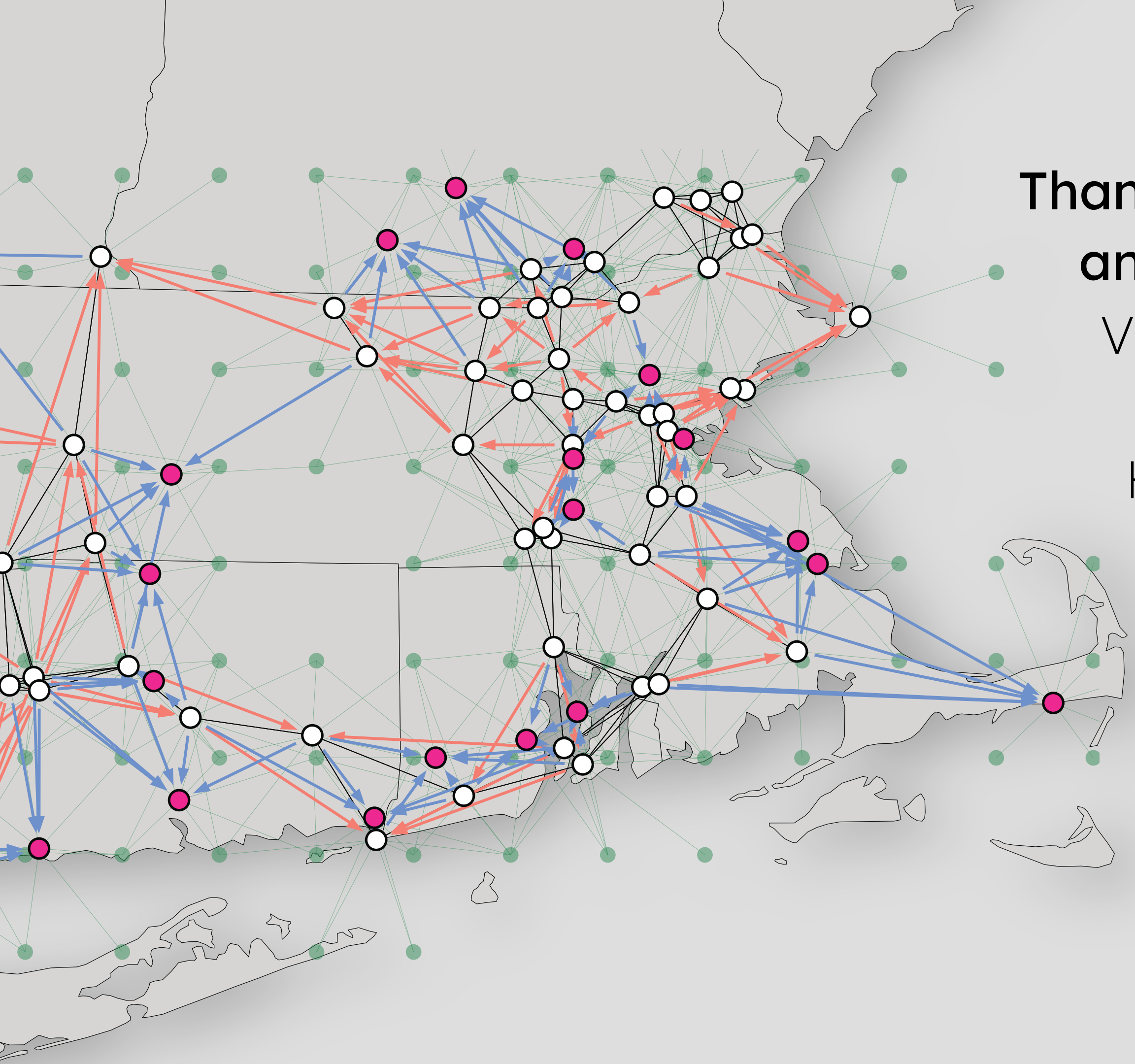
- Missing target environments

Integrate Foundation Model Embeddings

- First results: almost match performance of best results

Forecast at arbitrary locations





Thank you for your attention and for the opportunity!

Very excited to be here.

Happy to answer any Questions!

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sherwang@mit.edu