Sparse Local Implicit Image Function for sub-km Weather Downscaling

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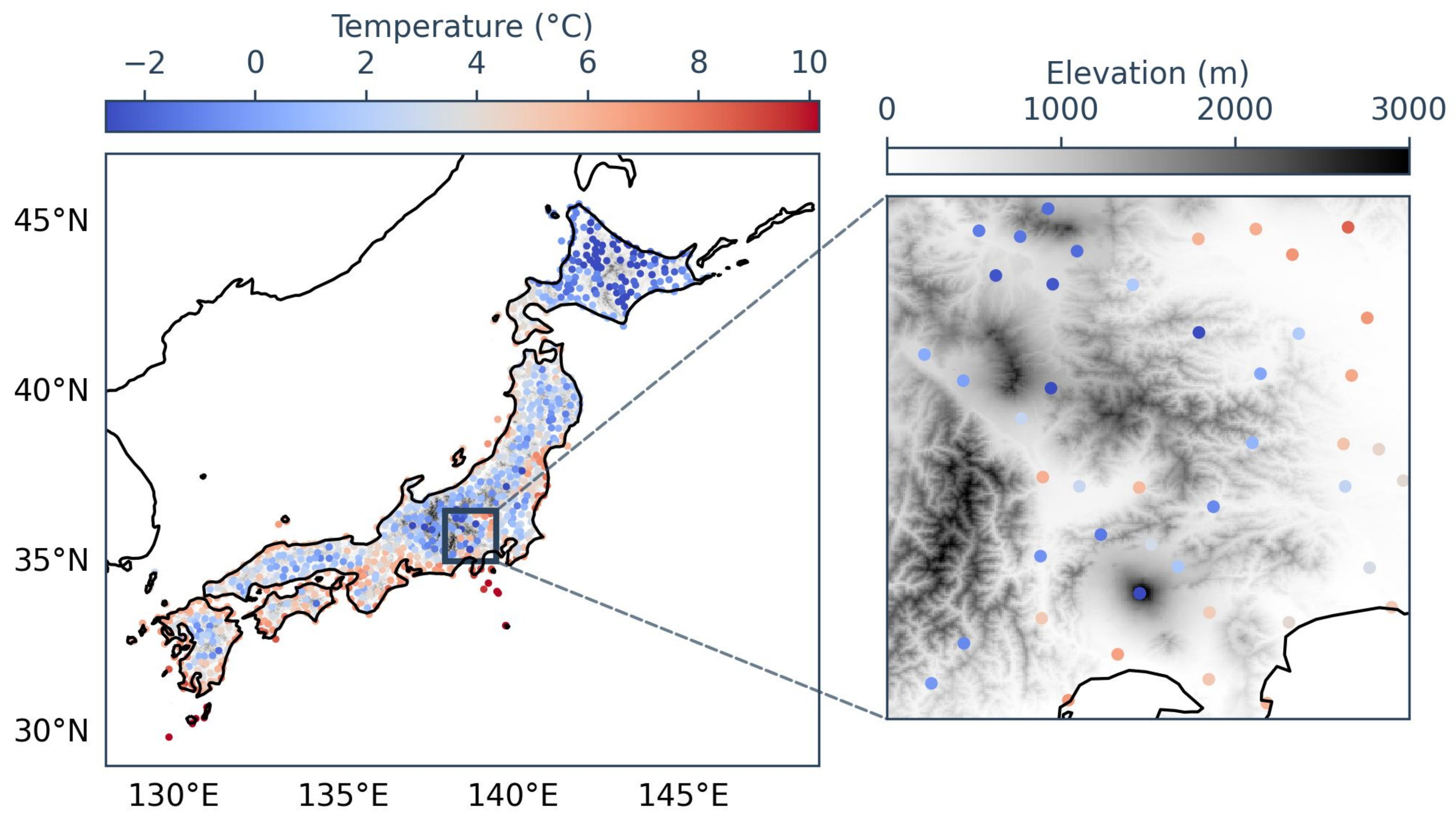
NEURAL INFORMATION PROCESSING SYSTEMS

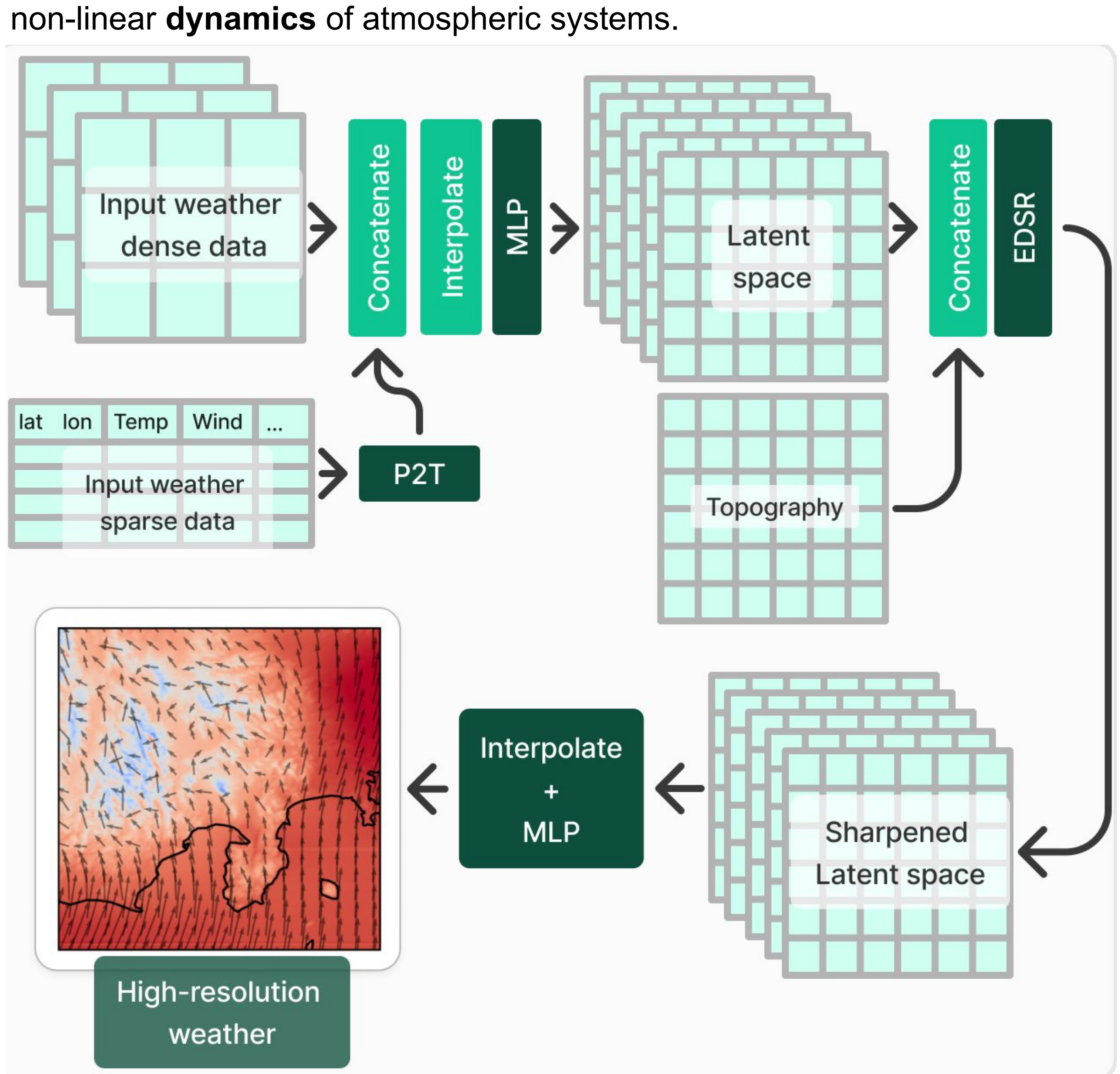
Measuring weather on-the-ground

High-resolution weather data is essential for addressing global climate change challenges. **Ground-truth weather is** captured by sparse, irregularly-spaced **weather stations** (e.g. the JMA weather station network), capturing regional biases, topographical weather effects (lapse, orographic rain), and providing higher effective spatial resolution than global gridded reanalysis datasets.



Learning continuous weather

SpLIIF can combine sparse/dense weather and topography data into a single implicit neural representation (INR), making it flexible. The linear **interpolation in latent-space captures** the **nonlinear**, continuous non-linear **dynamics** of atmospheric systems.

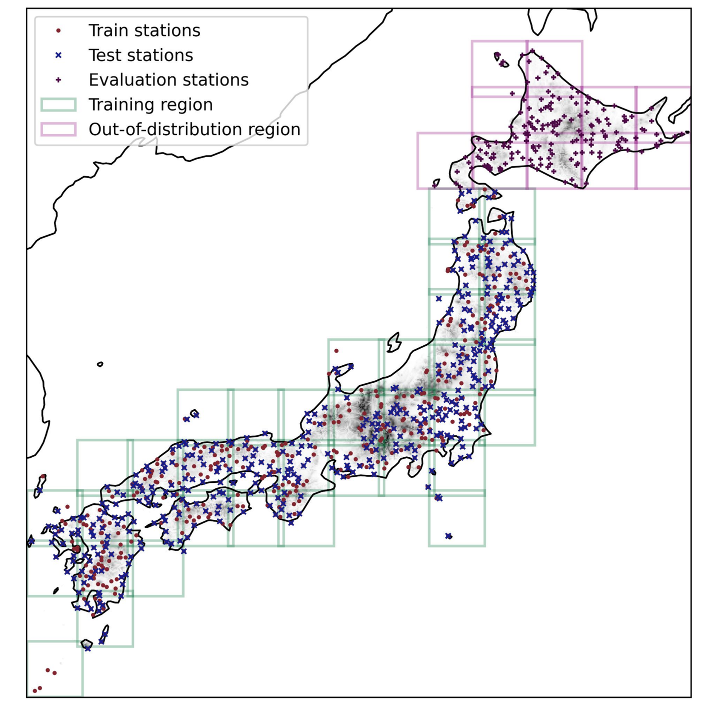


Training setup

Data: ~1300 stations (0.1° avg separation), 1 year of hourly data (2018), 30% test set, ~200 Hokkaido stations for evaluation.

Steps:

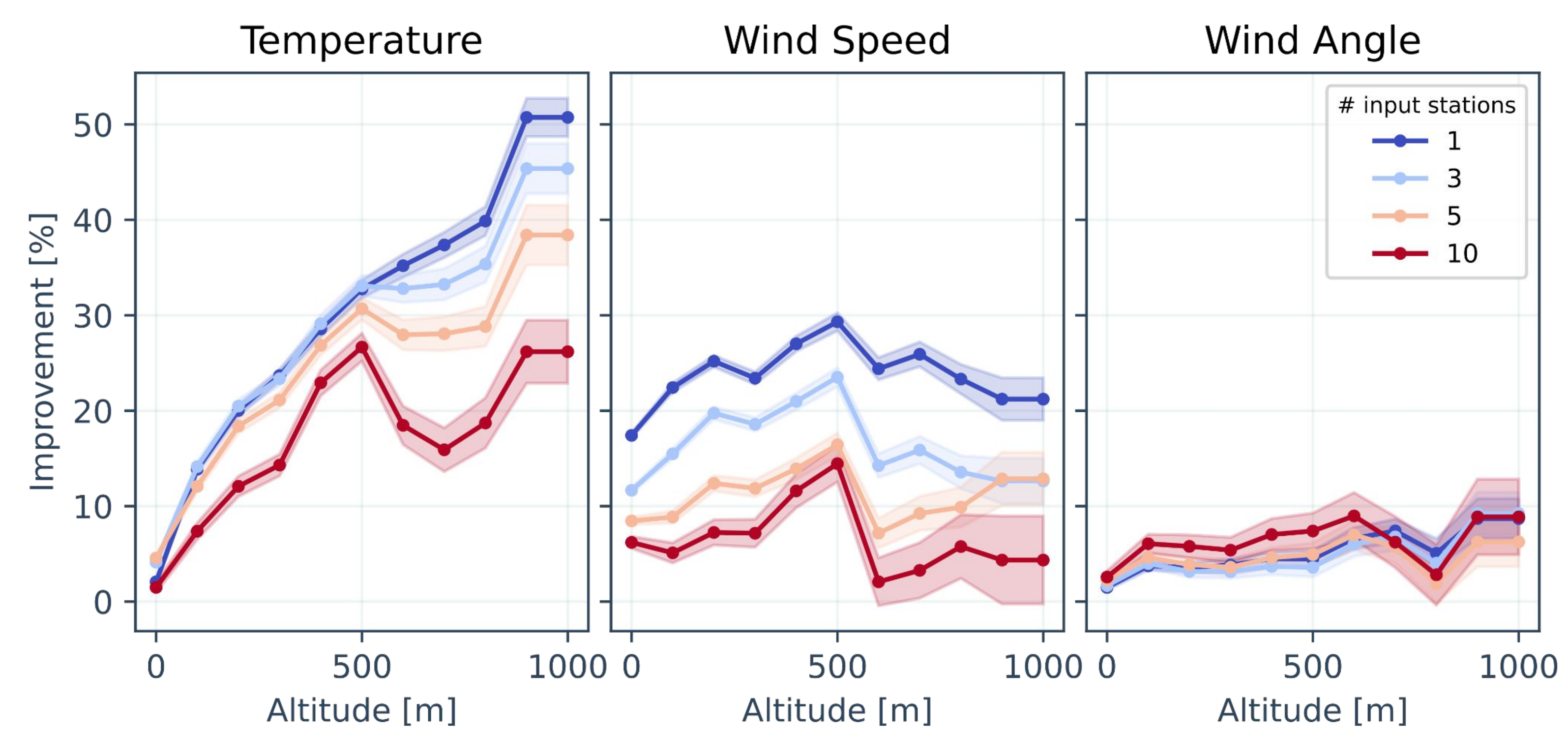
1. Split Japan in 150km wide patches
2. Use 15-20 stations per patch to generate INR.
3. Calculate L1 loss with the rest of the stations in the patch.



Comparison to baseline (test set)

Using varying numbers of input station data to generate INR, performance was evaluated against an IDW interpolation baseline, and calculated as the percentage improvement in RMSE.

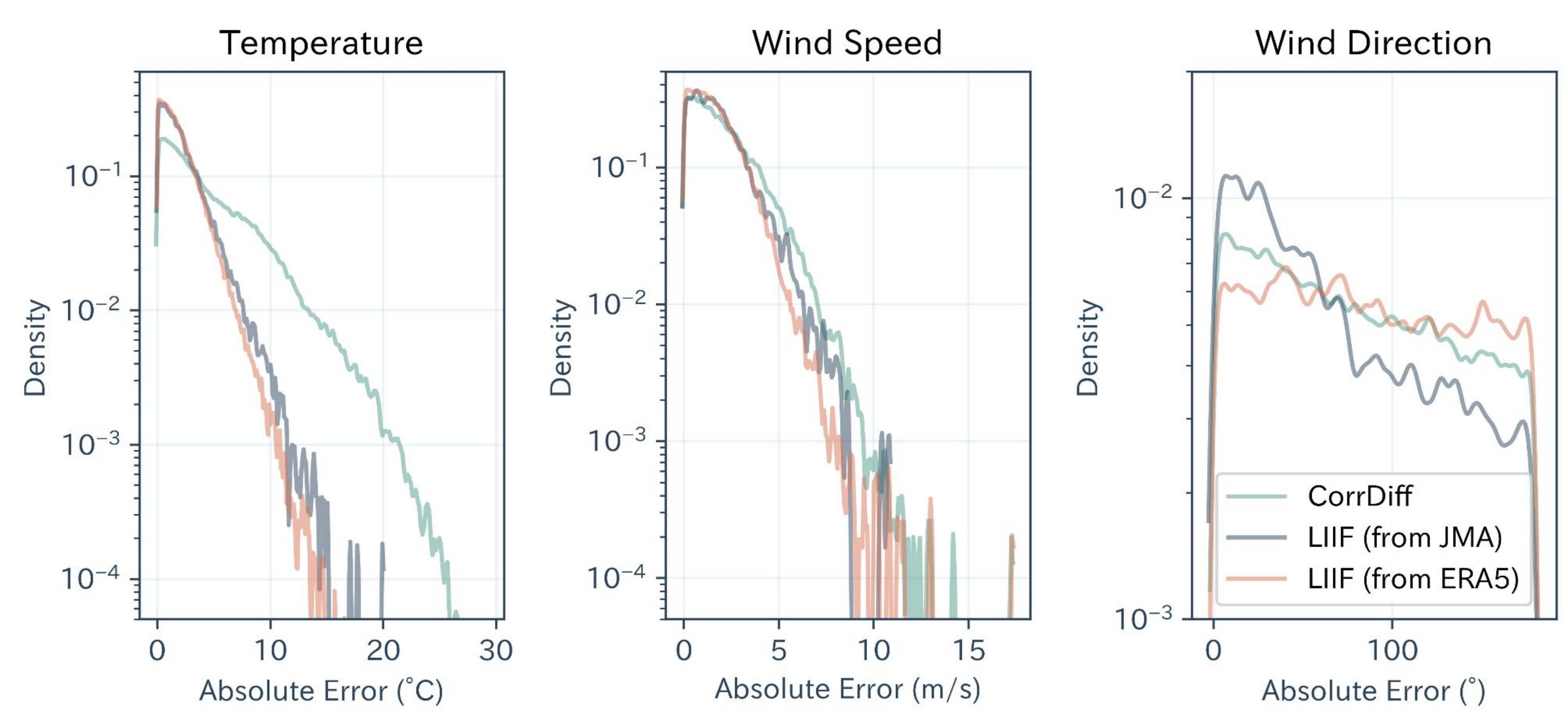
- **Temperature**: up to 50% improvements proportional to altitude
- **Wind**: ~10-30% improvements inversely proportional to number of stations



Comparison to CorrDiff (evaluation set)

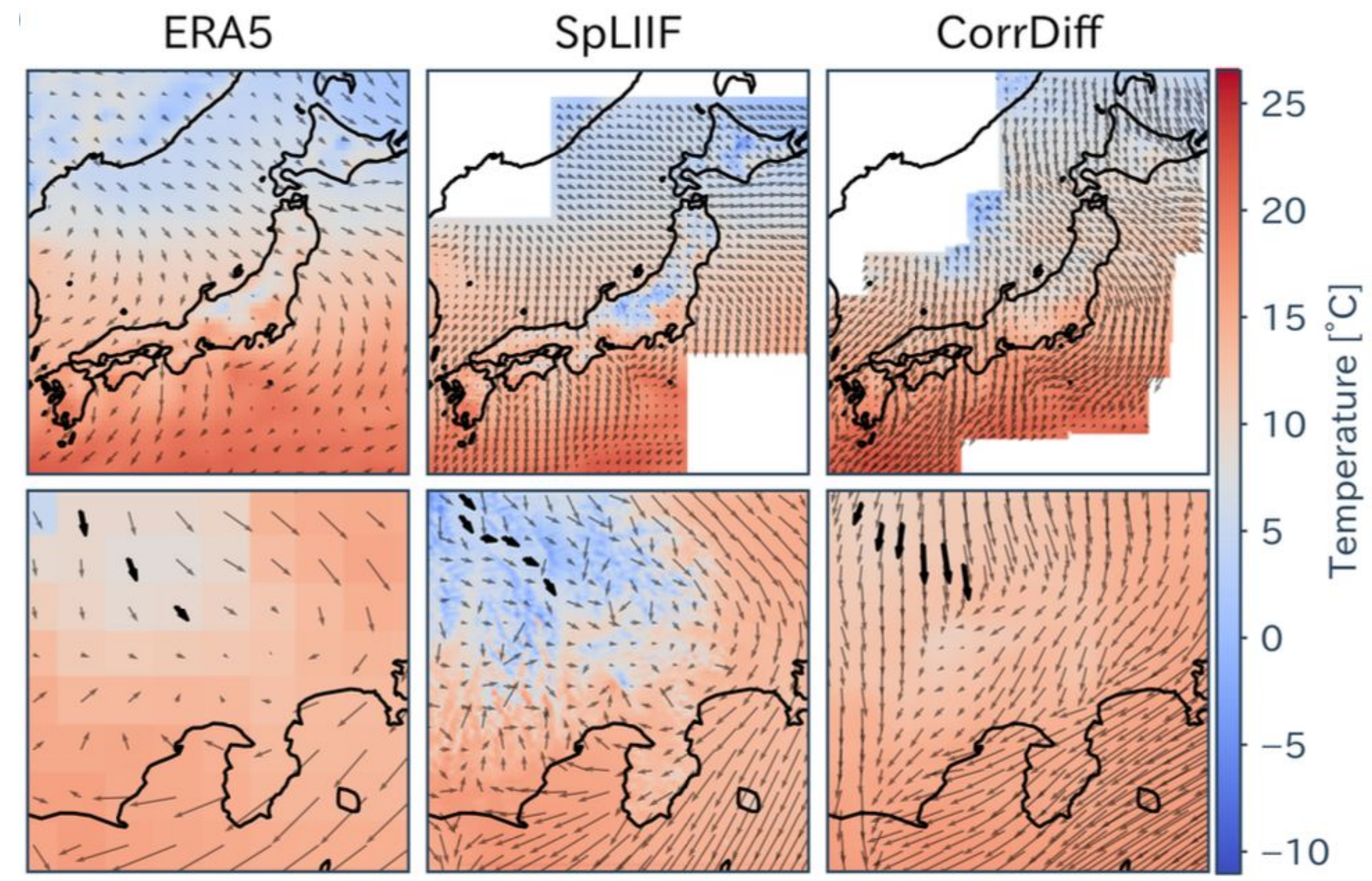
Two different INRs generated from two weather inputs: 10 JMA stations per patch or ERA5. Out-of-distribution evaluation over Hokkaido, and the error compared against the state-of-the-art diffusion model (CorrDiff):

- **Temperature**: 50% reduction in RMSE
- **Wind speed**: 20% reduction in RMSE
- **Wind direction**: 10% reduction in RMSE (for INR from JMA stations)



Example inferences

SpLIIF's downscaled maps featured more high-resolution features that correspond directly to the underlying topography, with wind directions aligning more closely with valley structures and contouring mountain ranges. These details were absent in the CorrDiff output, demonstrating SpLIIF's superior ability to capture topographically-induced weather effects.



Takeaways and future steps

- **INRs allow for flexible trainings and inferences** – we can train on weather stations but run accurate inferences from reanalysis datasets
- **In-distribution evaluation** – inclusion of topography in training means temperature predictions can be locally very accurate.
- **Out-of-distribution evaluation** – both using ERA5 and JMA stations as inputs, SpLIIF outperforms CorrDiff on temperature and wind speed predictions.
- **Future work** to include additional variables (e.g. rainfall) and comparisons to more SOTA models

References

Chen, Y., Liu, S. & Wang, X. *Learning Continuous Image Representation With Local Implicit Image Function* CVPR 2021, pp. 8628-8638

Mardani, M. et al. *Residual corrective diffusion modeling for km-scale atmospheric downscaling*, Commun Earth Environ 6, 124 (2025)

Company website

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