A proposal for spatially consistent weather forecast downscaling via generative deep learning

David Landry, Anastase Charantonis and Claire Monteleoni

INRIA Paris

Motivation

Predicting the state of a sensor network given a weather forecast arises in multiple areas of earth sciences e.g.

- In **weather forecast downscaling**, when predicting the weather at a station given an NWP forecast.
- In **hydrology**, when predicting streamflow given an NWP forecast.

This problem is challenging because

- NWP is uncertain and provides us with an **ensemble forecast**.
- NWP models have local biases due to unresolved fine-scale phenomena.

Modeling spatial correlations

Existing downscaling methods treat stations individually. This loses cross-correlations between stations which **are vital in downstream applications.**

Generative modeling could allows us to sample the distribution of the full network of stations, but requires new model architectures.

Use case: Weather Forecast Downscaling

We consider the **weather forecast downscaling** use case. Given the output of a weather forecasting model, what is the likely state of the network of surface weather stations?

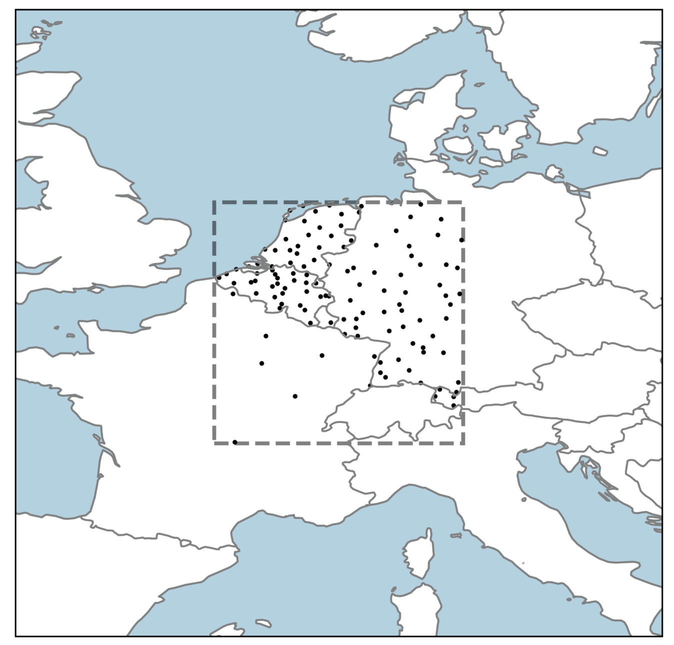
To solve this we propose a **cross-attentive transformer** trained within a **denoising diffusion** framework.

Given a weather forecast, how to model the distribution of many in situ measurements and preserve spatial correlations?

Preliminary experiments

We use the transformer architecture for non-generative downscaling of surface temperature an wind gust forecasts.

EUPPBench Dataset

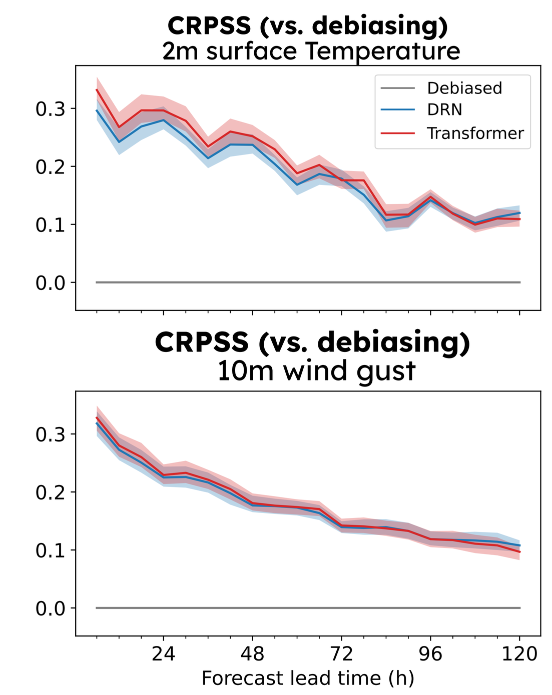


The EUPPBench dataset maps 0.25° degrees forecasts to **122 stations**.

Train/Val: 4180 reforecasts from 1997 to 2016. 11 members each.

Test: 730 forecasts in 2017 and 2018. 51 members each.

Sanity check: marginal in situ downscaling



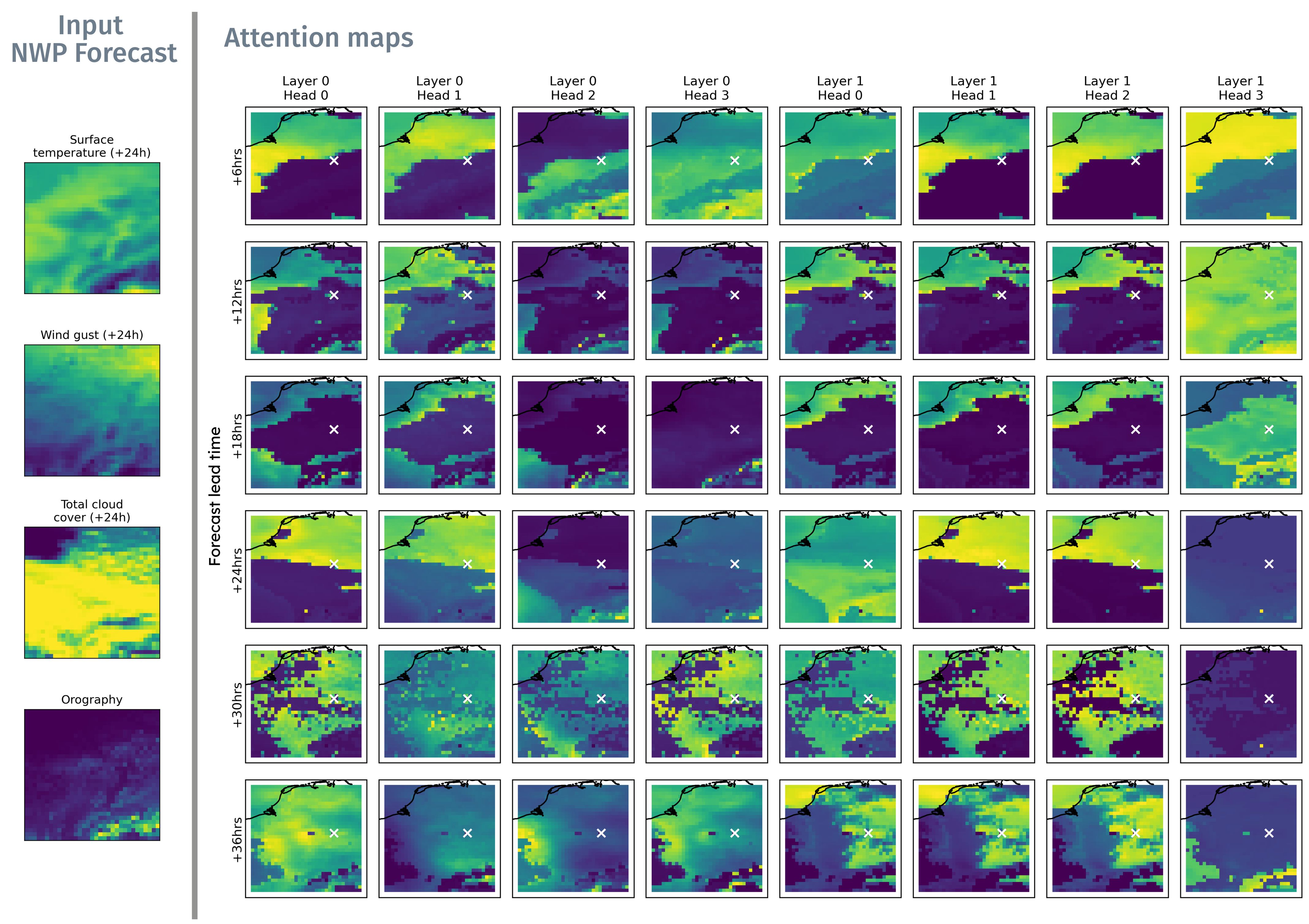
The transformer is equivalent to SOTA for non-generative postprocessing.

The transformer can plausibly be extended for spatially consistent generative modeling, while the DRN cannot needs architectural modifications.

What does the transformer learn?

We study the **cross-attention** between gridpoints and the Frankfurt/Main during downscaling. Forecast initialized on 2008-02-27T00.

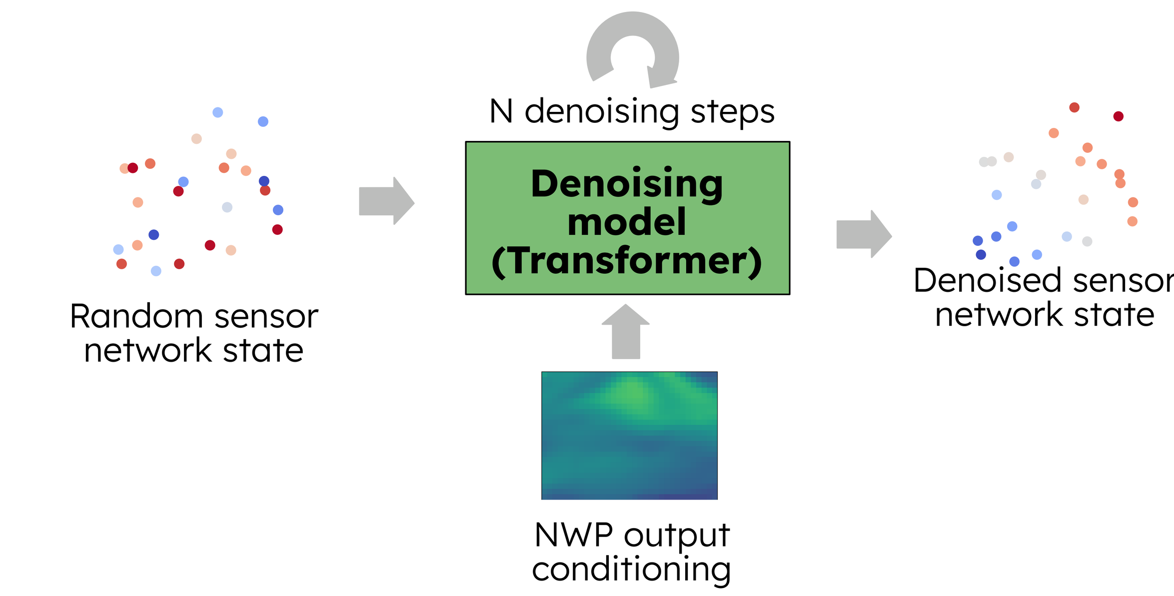
The transformer attends to spatial structures spanning the full domain.



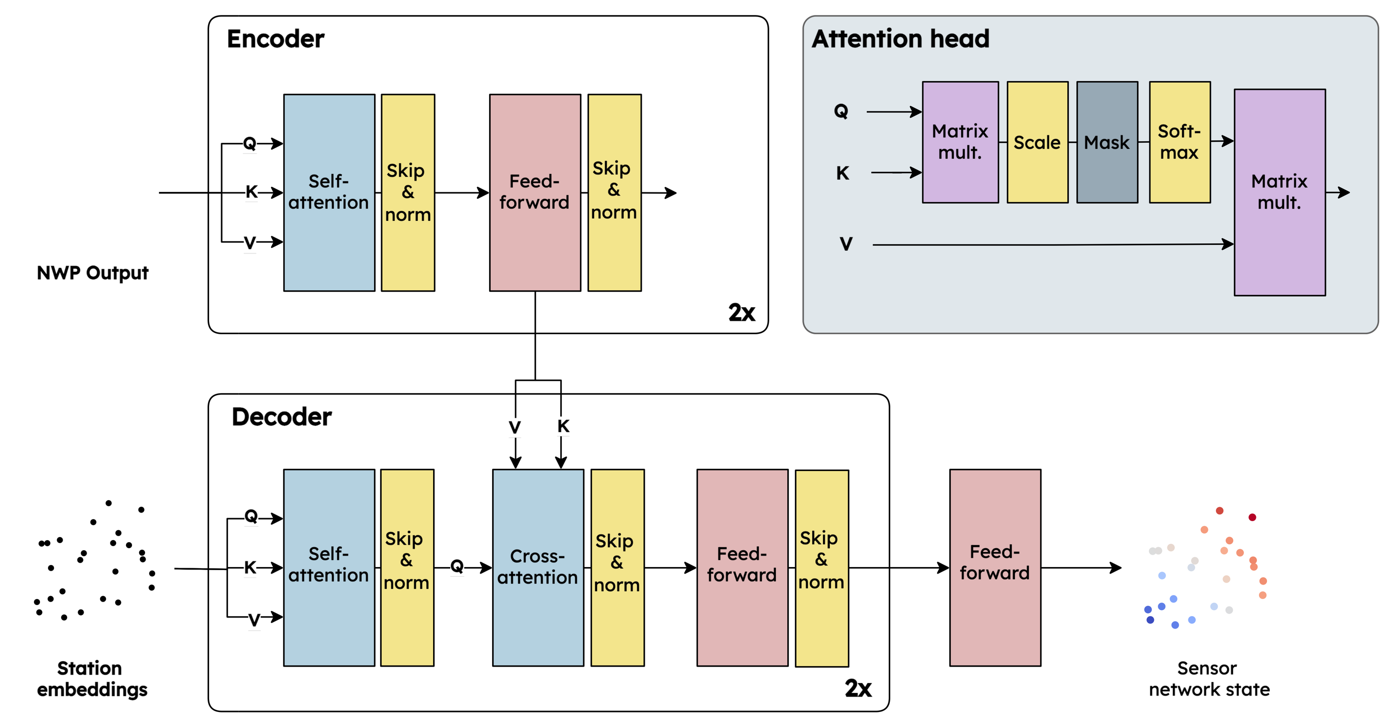
Prospective generative model

We propose using the **denoising diffusion framework** to sample spatially consistent states for the network of weather stations conditioned on the NWP model output.

The sensor network state progressively goes from a random gaussian distribution (which we can sample) to a denoised, coherent state (which we cannot sample easily).



Transformer architecture



Outlook

The transformer network successfully models spatial structures to perform weather forecast downscaling.

The next step is to integrate it into a diffusion framework.

Challenges and uncertainties

We have a **high-dimensional conditioning** (the NWP forecast) with a **lower-dimensional** target (the station network state), which is unusual.

Evaluation of multivariate ensemble forecasts is still a methodological challenge **[Chen2024]**.

Demonstrate the benefits of a generative approach in downstream applications (hydrology, power production/consumption forecasting).

References

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