

Weather Flow

Prediction using Spatial-Temporal Graph Neural Networks

Continuous-time, diffusion-based and lightweight models on South African station data

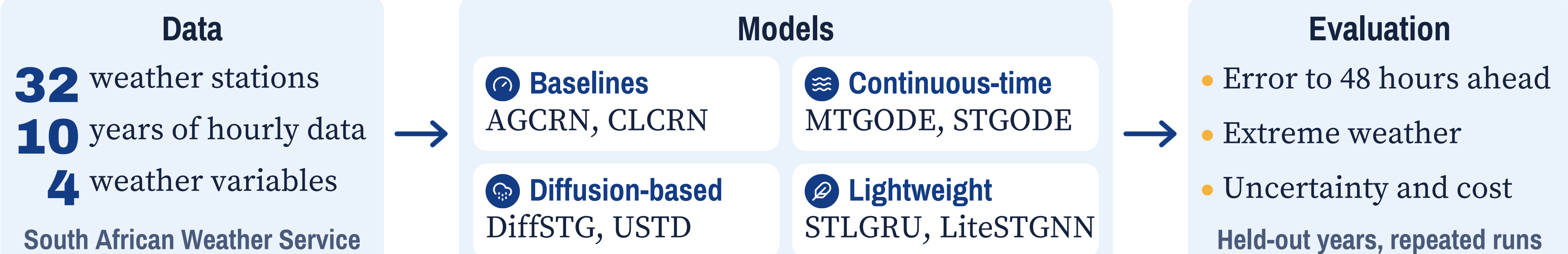
1 Overview

Weather at one station depends on its own recent past and on nearby stations. Spatial-temporal graph neural networks (STGNNs) capture both by treating stations as nodes in a graph. Prior STGNN studies successfully forecast South African weather up to 24 hours ahead. We test three newer STGNN families against the best models from that work, out to 48 hours.

2 Objectives

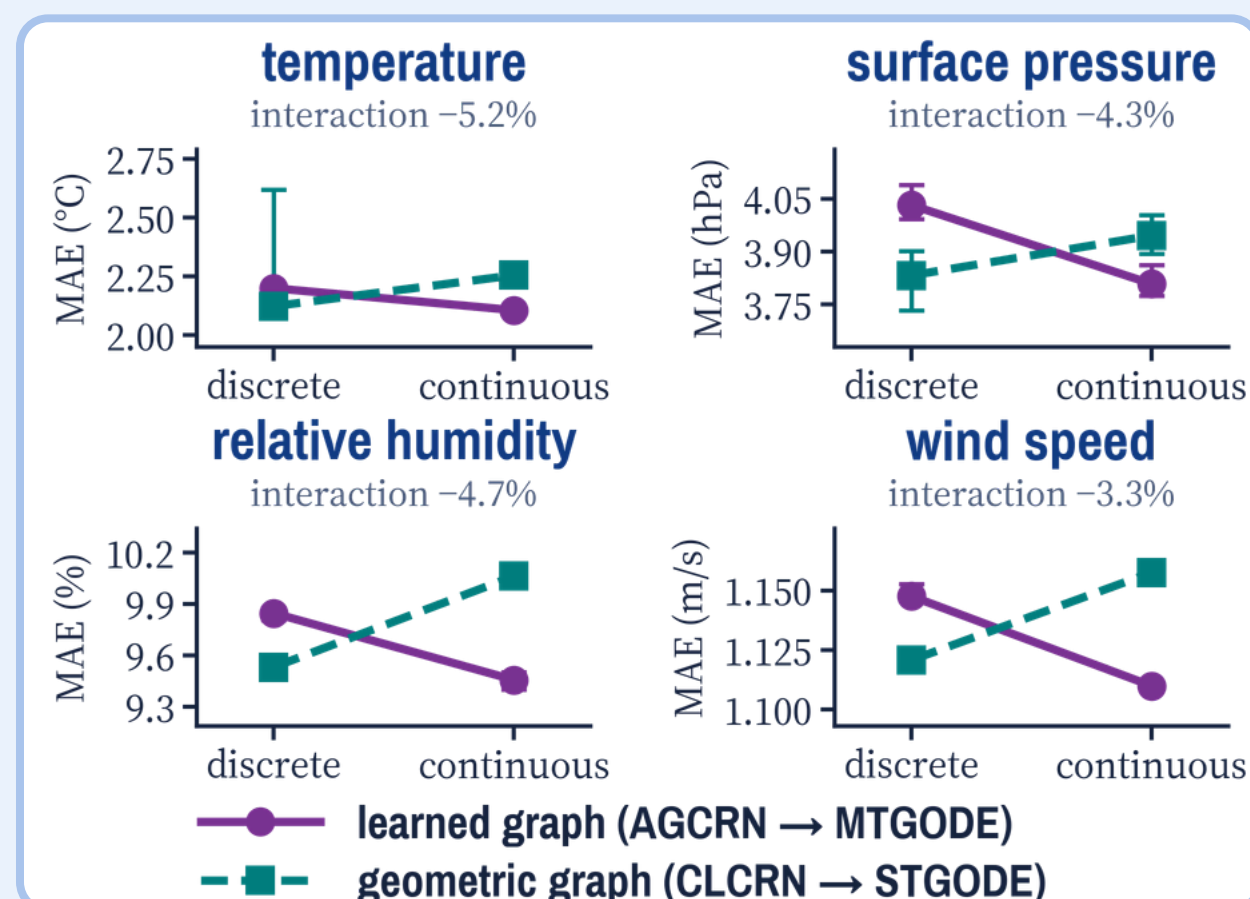
- Compare continuous-time, diffusion-based and lightweight STGNNs with the AGCRN and CLCRN baselines.
- Test how forecasts hold up as lead time grows to 48 hours and during extreme weather.

3 Methodology



4 Results and analysis

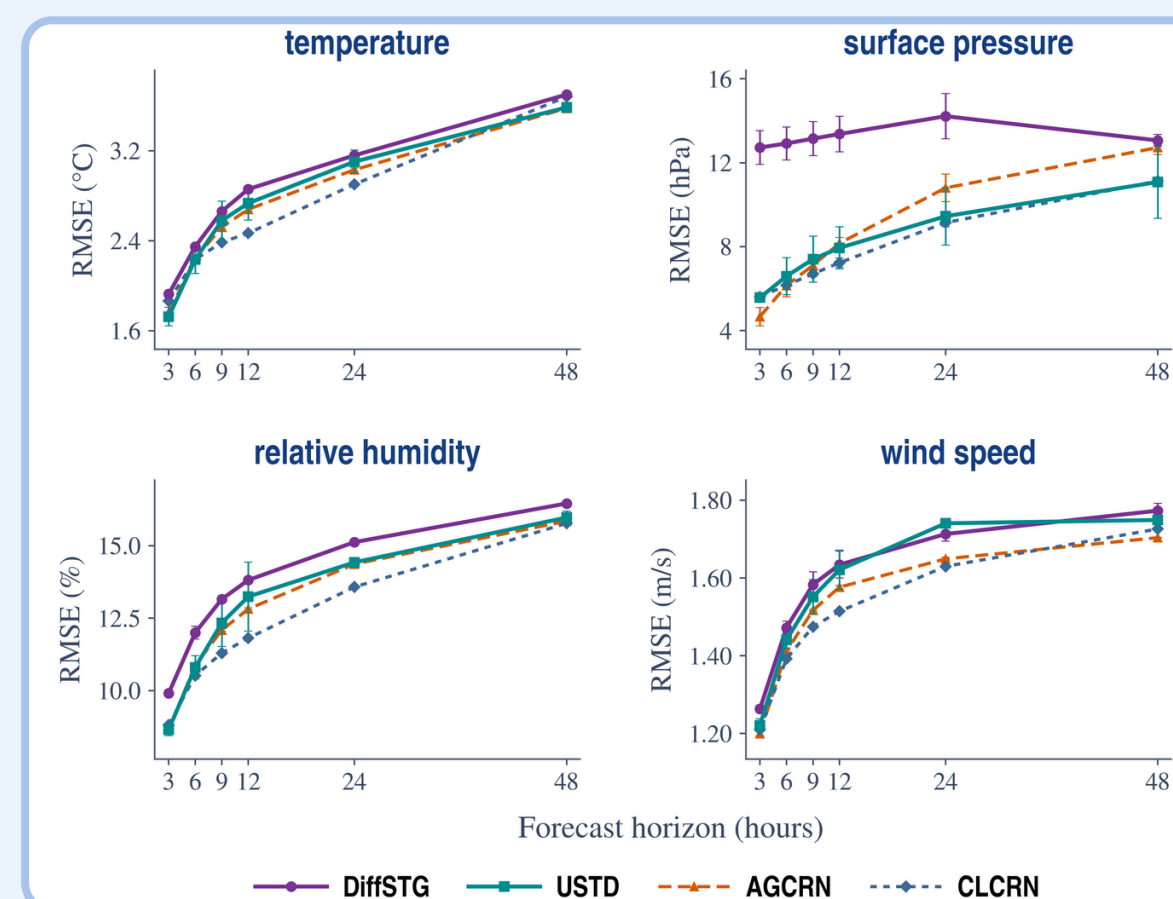
Continuous-time



The lines cross on every variable: continuous time helps with a learned graph and hurts with a geometric one.

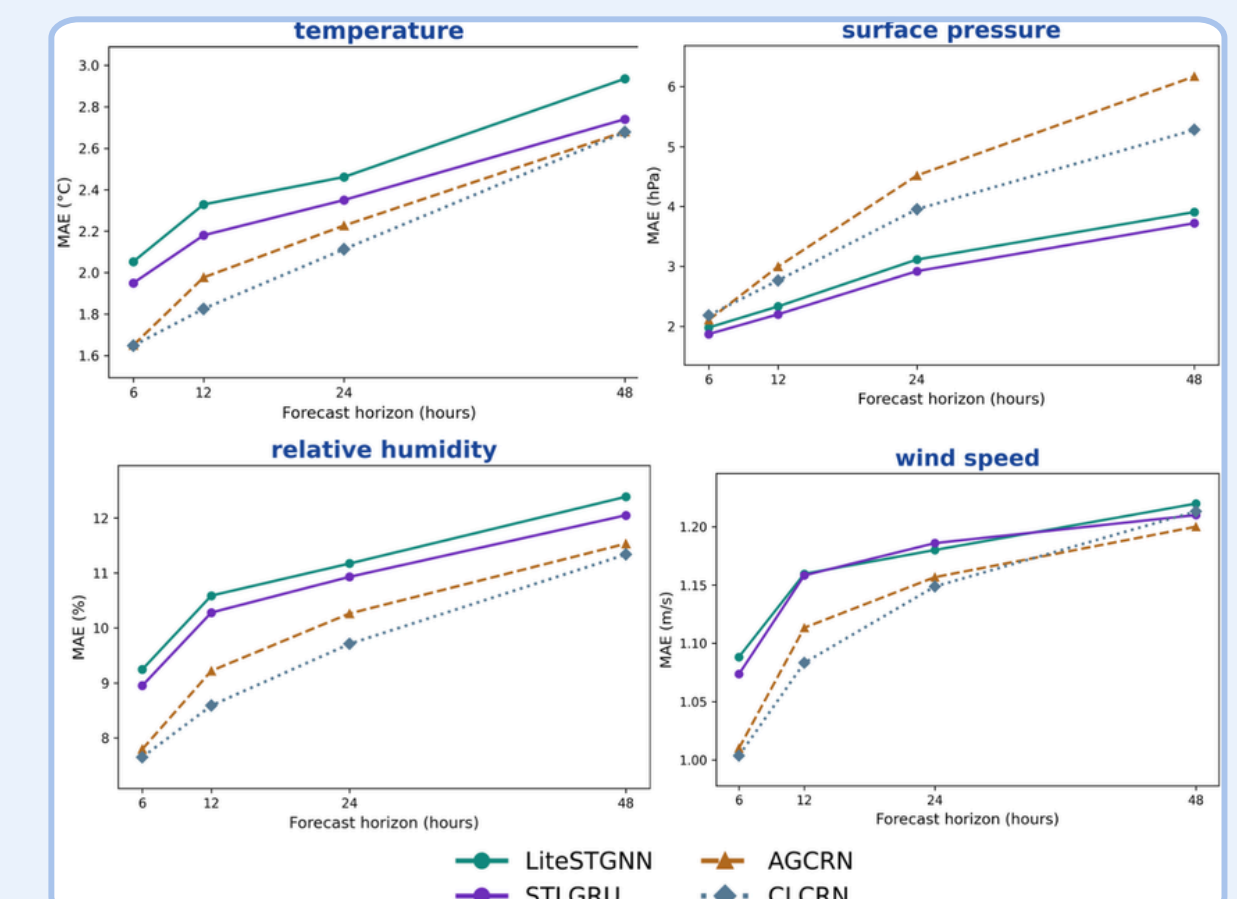
Error is **3.5x** worse on extremes
MTGODE **12x** smaller than STGODE

Diffusion-based



All models degrade as the horizon increases. CLCRN performs best on all variables, while DiffSTG performs the worst. USTD is competitive with AGCRN. DiffSTG's average pressure RMSE is **1.5x** that of USTD's.

Lightweight



Adding more capacity to a lightweight model gives diminishing returns: STLGRU is **4.1x** larger than LiteSTGNN, but its accuracy gains are but improves MAE by only **0.7–5.7%**.

5 Conclusions

A new formulations from the baseline STGNNs (AGCRN & CLCRN) pay off only with the right graph and covariates.

- 1 Diffusion models did not consistently beat the baselines; continuous-time gains depended on the graph. Lightweight performance was competitive but variable-dependent.
- 2 Models converge by 48 hours, and strong average accuracy did not guarantee accurate forecasts of extremes.