A Graph Neural Network Approach for Localized and High-Resolution Temperature Forecasting

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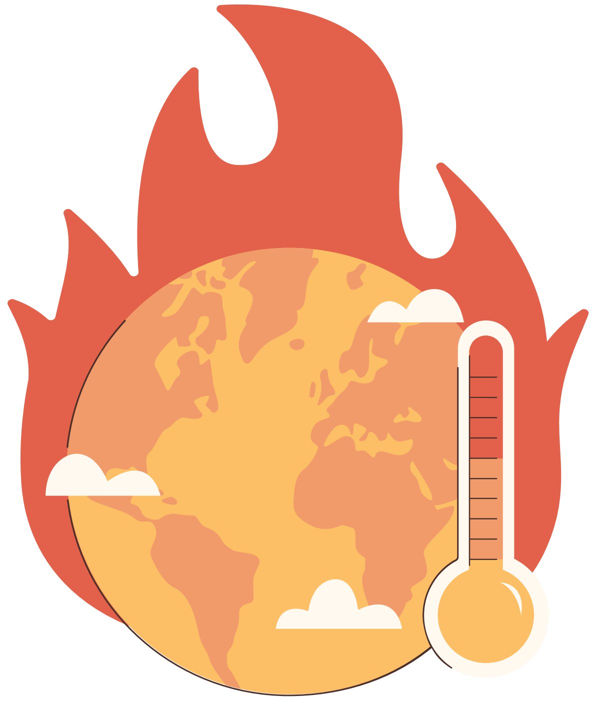
489,000

HEAT-RELATED DEATHS PER YEAR [6]

[6] Q. Z. et al. (2021).

HEATWAVES

- Threaten health, ecosystems, and economies worldwide.
- Impacts are uneven: low-income, racialized, and Global South communities are most exposed, despite minimal contribution to emissions [4, 2].

[4] Parsons et al. (2024), [2] Deivanayagam et al. (2023)

EXISTING SOLUTIONS

- Most operational forecasts run at 10–30 km.
    - Smooth over urban heat islands and neighborhood “hot spots.”
    - Lead to systematic underestimation of heat risk in precisely those marginalized areas most in need of targeted interventions.

GraphCast: Learning skillful medium-range global weather forecasting [7]

Remi Lam, Alvaro Sanchez-Gonzalez, Matthew Willson, Peter Wirnsberger, Meire Fortunato, Ferran Alet, Suman Ravuri, Timo Ewalds, Zach Eaton-Rosen, Weihua Hu, Alexander Merose, Stephan Hoyer, George Holland, Oriol Vinyals, Jacklynn Stott, Alexander Pritzel, Shakir Mohamed, Peter Battaglia

FourCastNet: A Global Data-driven High-resolution Weather Model using Adaptive Fourier Neural Operators [8]

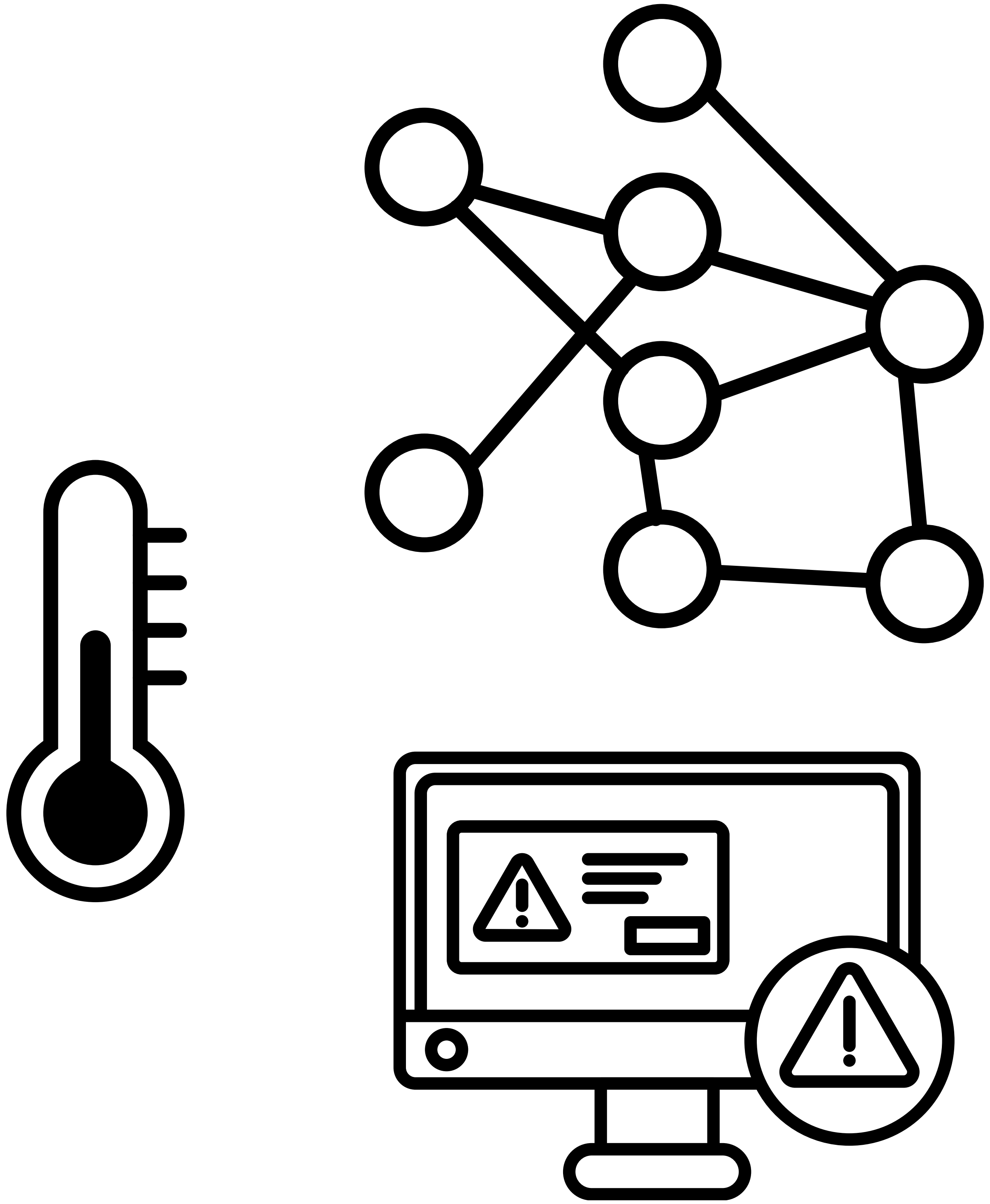
Jaideep Pathak, Shashank Subramanian, Peter Harrington, Sanjeev Raja, Ashesh Chattopadhyay, Morteza Mardani, Thorsten Kurth, David Hall, Zongyi Li, Kamyar Azizzadenesheli, Pedram Hassanzadeh, Karthik Kashinath, Animashree Anandkumar

[7] Lam et al. (2023), [8] Pathak et al. (2022)

OUR CONTRIBUTION

- We introduce a high-resolution (2.5 km) Graph Neural Network framework that produces localized temperature forecasts 1–48 hours ahead.

- Can be post-processed to match local heatwave definitions, supporting equitable early-warning workflows.



DATA

- We use NOAA's URMA dataset (2.5 km, hourly).
- We predict 2-meter air temperature as a low-level signal.
- We focus on Southwestern Ontario across three nested domains, which cover mixed land types (urban, farmland, forest, water).

Region A

~ 44km by 33km

Region B

~ 111km by 163km

Region C

~ 333km by 243km

DATA

- Data from resource-limited regions is often sparse, inconsistent, and difficult to align with information-rich datasets.

- We also explore language-model embeddings as an intermediate representation. Each Region A observation is transformed into a short paragraph, for example:

> temperature is 291.6 K, dew point is 283.7 K, u wind component is 4.0 m/s, v wind component is -2.1 m/s, surface pressure is 99209 Pa, … , elevation is 172.0 meters

- These descriptions are encoded using ClimateBERT [5], which become node features in the pipeline.

[5] Webersinke et al. (2022)

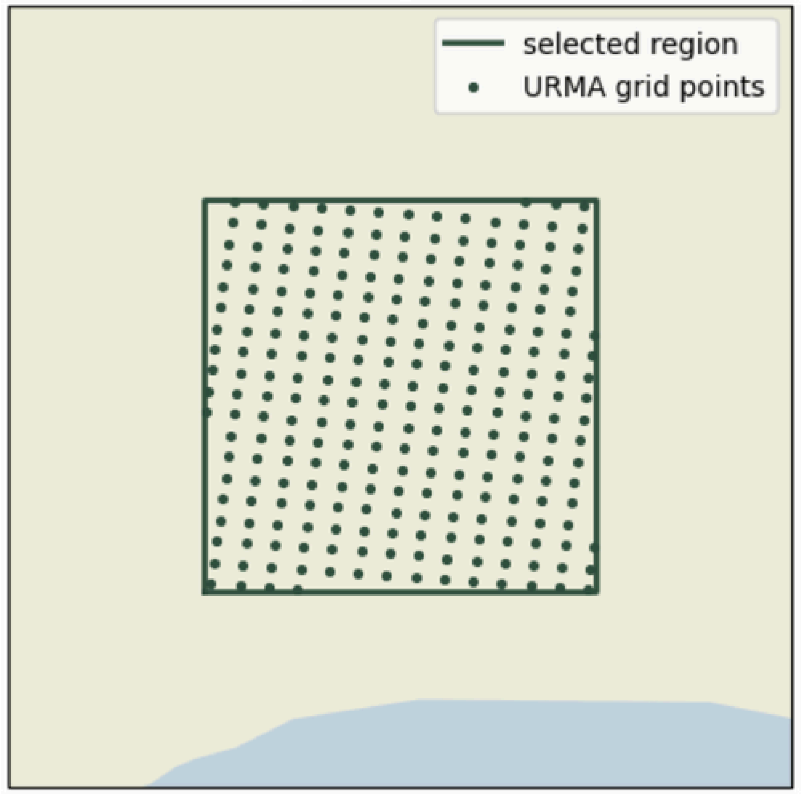
MODEL

- A hybrid Graph Convolutional Network (GCN) with a Gated Recurrent Unit (GRU) was trained for each region.

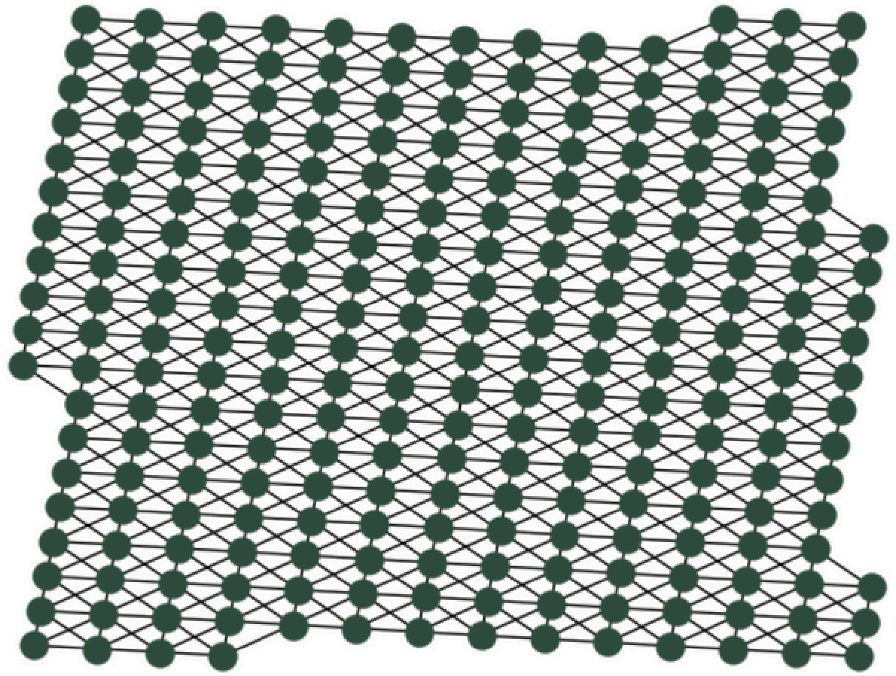
- Graph convolution layers model neighborhood effects [3].

- GRUs capture temporal dependencies [1].

- The objective was to predict temperature at 1, 6, 12, 18, 24, 36, and 48h ahead from the current time.



Sample selected region.

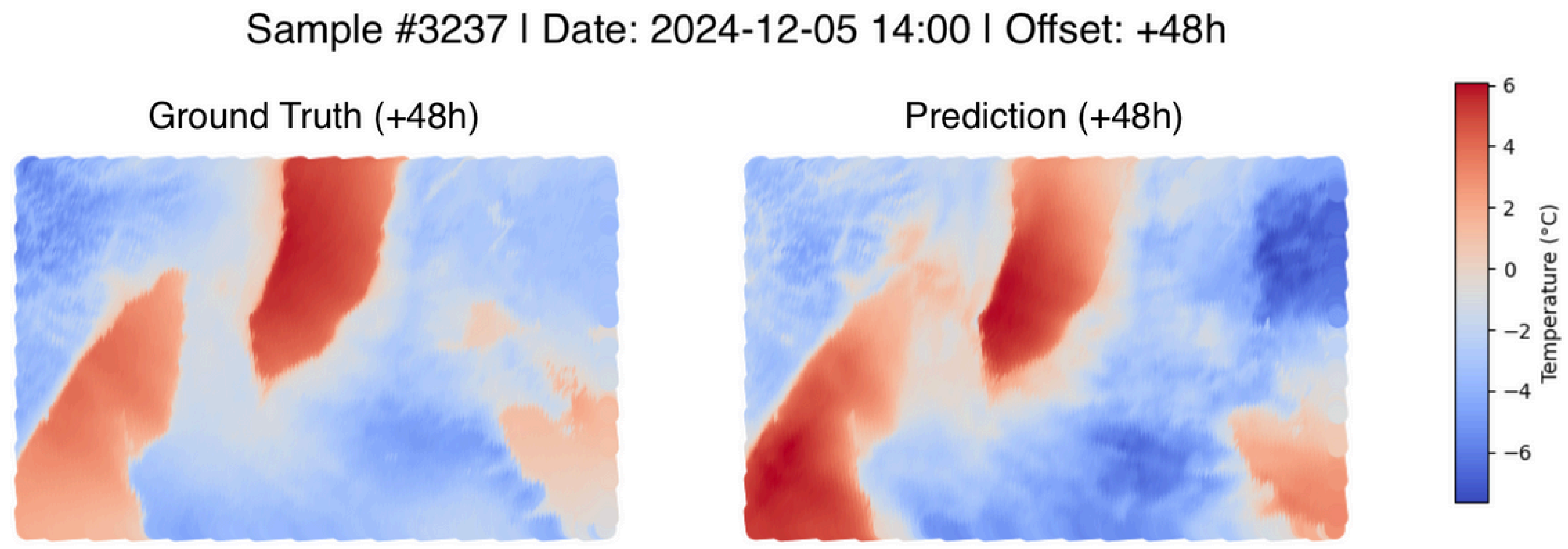


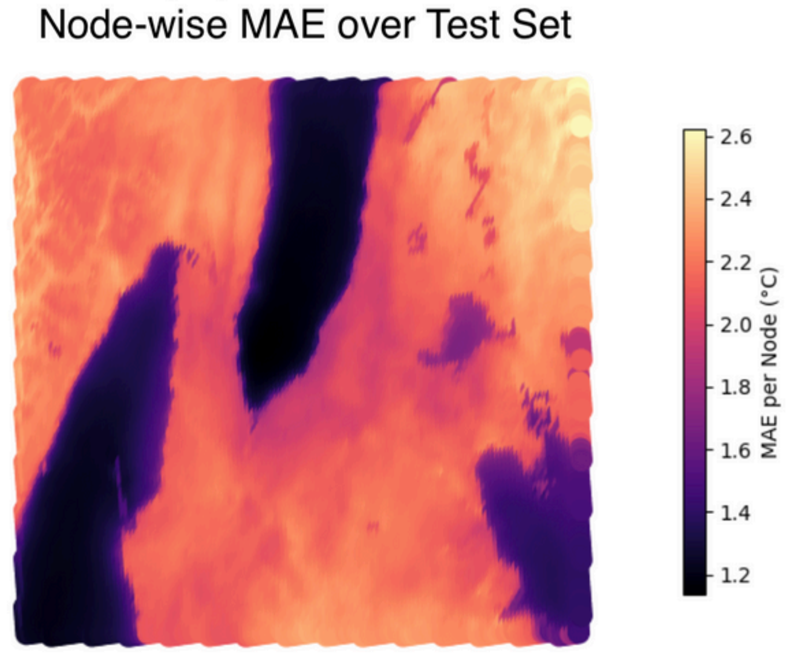
Corresponding graph.

Graph setup. Each grid point in the region is represented as a graph node with meteorological features, connected by edges to capture spatial interactions.

[3] Kipf and Welling (2017), [1] Cho et al. (2014)

RESULTS - Per-region performance





Region	Mean MAE (°C)	MAE@48h (°C)	RMSE@48h (°C)
A	2.55	3.78	4.84
B	2.48	3.73	4.84
C	1.93	2.93	3.90

- Performance improved as the spatial window expanded (Region A → Region C).
- Training on Region C strains memory, so we also sampled every 6h. The 6h model reached mean MAE 2.39, MAE@48h 3.15, and RMSE@48h 4.16.
  - i.e., modest degradations (+0.46, +0.22, +0.26) for substantially lower compute.

RESULTS - Embeddings

- Performance with embeddings shows a modest decrease in mean MAE relative to the tabular baseline.
- Control model performs noticeably worse.
- This suggests that embedding features carry meaningful signals.

Model	Mean MAE (°C)	MAE@48h (°C)	RMSE@48h (°C)
Baseline (tabular)	2.55	3.78	4.84
Embeddings (ClimateBERT)	3.34	4.34	5.54
Control (random weights)	9.11	8.89	10.49

IMPACT

- Localized forecasting is an equity issue:
  - Coarse models miss neighbourhood-level risks that disproportionately affect marginalized communities.

- Our approach offers a transferrable solution:
  - Models trained in data-rich regions can be adapted to under-monitored contexts to strengthen early warnings and resource allocation.

CONCLUSIONS

- We present a 2.5 km GCN–GRU framework for 2-meter temperature forecasting across 3 regions, and found that:
  - performance improves as spatial context increases,
  - a 6-hour sampling variant preserves most skill, and
  - an embedding approach standardizes heterogeneous inputs.

NEXT STEPS

- Building matched-resolution baseline models.
- Broadening geographic coverage to additional regions.
- Integrating with operational dashboards for practical deployment.
- Extending the framework to other climate extremes (wildfire, floods, drought).

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Climate Change AI

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Thank you!

Questions? Comments? Suggestions?
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