Earth-SGNN: Spatio-Temporal Graph Neural Networks for Weather Forecasting over Irregular Station Networks

Project Documentation

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Abstract

Weather forecasting over irregular station networks presents unique challenges that traditional grid-based methods cannot adequately address. This paper presents Earth-SGNN, a graph neural network approach that models weather stations as nodes in a spatial graph, enabling explicit modeling of inter-station relationships. We demonstrate that incorporating spatial information through graph-based learning significantly improves forecast accuracy across multiple time horizons. Our Hybrid GNN architecture, which combines LSTM temporal encoding with attention-based spatial aggregation, achieves state-of-the-art results with RMSE of 0.647°C for 1-hour and 2.454°C for 24-hour temperature forecasts. Notably, the model learns to automatically weight spatial information more heavily for longer forecast horizons (25% at 1h vs 43% at 24h), confirming the hypothesis that spatial patterns become increasingly important for extended predictions. We evaluate our approach on 9.3 million hourly observations from 822 NOAA weather stations, demonstrating consistent improvements over persistence, climatology, and LSTM baselines.

Keywords: Graph Neural Networks, Weather Forecasting, Spatio-Temporal Modeling, Deep Learning, NOAA ISD

1 Introduction

1.1 Motivation

Accurate weather forecasting is critical for numerous applications including agriculture, transportation, energy management, and disaster preparedness. While modern numerical weather prediction (NWP) systems have achieved remarkable accuracy, they require substantial computational resources and may not fully exploit the fine-grained information available from dense observation networks.

Machine learning approaches offer complementary capabilities, particularly for short-range forecasting where statistical patterns in observational data can provide rapid predictions. However, most existing methods treat weather stations independently, ignoring the spatial correlations that arise from the physical propagation of weather systems across geographic regions.

1.2 Problem Statement

Real-world weather observation networks consist of irregularly distributed stations with varying data availability. Traditional approaches face several challenges:

1. **Irregular spatial distribution**: Stations are not uniformly distributed, with higher density in populated areas and sparse coverage in remote regions.

2. **Missing data**: Individual stations frequently have gaps in their observation records.

3. **Spatial dependencies**: Weather patterns propagate across space, creating correlations between neighboring stations.

4. **Scale mismatch**: Grid-based methods require interpolation to artificial grids, introducing errors.

1.3 Contributions

This work makes the following contributions:

1. A graph-based framework for weather forecasting that directly models station networks without requiring grid interpolation.

2. A Hybrid GNN architecture combining temporal (LSTM) and spatial (attention-based) components with learnable fusion weights.

3. Comprehensive evaluation demonstrating that spatial information improves forecasts at all time horizons.

4. Analysis of learned spatial weights showing the model automatically assigns greater importance to spatial features for longer forecast horizons.

2 Theoretical Background

2.1 Graph Neural Networks

Graph Neural Networks (GNNs) extend deep learning to non-Euclidean domains by operating on graph-structured data. Given a graph $G = (V, E)$ with nodes V and edges E, GNNs learn node representations through message passing:

$$h_v^{(l+1)} = \text{UPDATE}\left(h_v^{(l)}, \text{AGGREGATE}\left(\{h_u^{(l)} : u \in \mathcal{N}(v)\}\right)\right) \tag{1}$$

where $h_v^{(l)}$ is the representation of node v at layer l, and $\mathcal{N}(v)$ denotes the neighbors of v.

2.2 Graph Convolutional Networks

The Graph Convolutional Network (GCN) [1] simplifies message passing using the normalized adjacency matrix:

$$H^{(l+1)} = \sigma\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \tag{2}$$

where $\tilde{A} = A + I$ is the adjacency matrix with self-loops, $\tilde{D}$ is the degree matrix, and $W^{(l)}$ is the learnable weight matrix.

2.3 Attention Mechanisms for Graphs

Graph Attention Networks (GAT) [2] introduce attention coefficients to weight neighbor contributions:

$$\alpha_{ij} = \frac{\exp\left(\text{LeakyReLU}\left(a^T[Wh_i \| Wh_j]\right)\right)}{\sum_{k\in\mathcal{N}(i)} \exp\left(\text{LeakyReLU}\left(a^T[Wh_i \| Wh_k]\right)\right)} \tag{3}$$

This allows the model to learn which neighbors are most relevant for each prediction.

2.4 Spatio-Temporal Modeling

Weather forecasting requires modeling both spatial and temporal dependencies. We combine:

- **Temporal**: Long Short-Term Memory (LSTM) networks capture sequential patterns in time series.
- **Spatial**: GNN layers aggregate information from neighboring stations.
- **Fusion**: Learnable weights combine temporal and spatial features.

3 Related Work

3.1 Traditional Weather Forecasting

Numerical Weather Prediction (NWP) systems solve physical equations governing atmospheric dynamics. While highly accurate, they require substantial computational resources and may not fully exploit fine-grained station observations.

3.2 Machine Learning for Weather

Recent advances in deep learning have enabled data-driven weather forecasting:

- **WeatherBench** [7]: A benchmark for data-driven weather forecasting using gridded ERA5 reanalysis data.
- **GraphCast** [6]: Google DeepMind's GNN model achieving 10-day forecasts on global ERA5 grids.
- **FourCastNet**: NVIDIA's Fourier Neural Operator approach for high-resolution forecasting.

However, these methods operate on regular grids rather than irregular station networks.

3.3 Graph Neural Networks for Spatial Data

GNNs have been applied to various spatio-temporal prediction tasks:

- **Traffic forecasting**: STGCN, DCRNN, and Graph WaveNet for road network predictions.
- **Air quality**: Spatio-temporal GNNs for pollution monitoring networks.
- **Climate**: Regional climate modeling with adaptive graph structures.

Our work extends these approaches to weather station networks with explicit handling of irregular observation patterns.

4 Methodology

4.1 Graph Construction

We represent the weather station network as an undirected graph $G = (V, E, X, A)$ where:

- V: Set of 822 weather stations (nodes)
- E: Edges connecting nearby stations
- $X \in \mathbb{R}^{|V|\times 3}$: Node features (latitude, longitude, elevation)
- $A \in \mathbb{R}^{|V|\times|V|}$: Weighted adjacency matrix

4.1.1 k-Nearest Neighbor Edges

We use k-NN with $k = 8$ to construct edges, ensuring graph connectivity even for remote stations:

$$E = \{(i, j) : j \in \text{kNN}(i, k = 8)\} \tag{4}$$

4.1.2 Edge Weights

Edge weights are computed using a Gaussian kernel based on geographic distance:

$$w_{ij} = \exp\left(-\frac{d_{ij}^2}{2\sigma^2}\right), \quad \sigma = 100 \text{ km} \tag{5}$$

where d_{ij} is the great-circle distance between stations i and j.

4.2 Model Architectures

4.2.1 GNN v1: Full Graph Convolution

The first architecture processes the entire station graph at each timestep:

1. **Temporal Encoder**: 2-layer LSTM encodes 24-hour lookback sequences per station.
2. **Spatial GNN**: 2-layer GCN aggregates information across the graph.
3. **Output Head**: MLP produces temperature forecasts.

4.2.2 Hybrid GNN: Efficient Spatio-Temporal Fusion

The Hybrid architecture addresses data efficiency by processing per-station sequences:

1. **Shared Temporal Encoder**: LSTM encodes sequences for center and neighbor stations.
2. **Spatial Aggregator**: Attention mechanism weights neighbor contributions.
3. **Learnable Fusion**: Combines temporal and spatial features with learned weight α:

$$h_{\text{combined}} = (1 - \alpha) \cdot h_{\text{temporal}} + \alpha \cdot h_{\text{spatial}} \tag{6}$$

where $\alpha = \sigma(w)$ and w is a learnable parameter.

4.3 Training Configuration

Table 1: Training Hyperparameters

Parameter	**GNN v1**	**Hybrid GNN**
Batch Size	32	256
Epochs	20	15
Learning Rate	0.001	0.001
Lookback Window	24 hours	24 hours
Hidden Dimension	64	64
LSTM Layers	2	2
Dropout	0.2	0.2
Optimizer	Adam	Adam

4.4 Loss Function

We use Mean Squared Error (MSE) loss for training:

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{7}$$

For multi-horizon predictions, we apply masked loss to handle missing targets:

$$\mathcal{L}_{\text{masked}} = \frac{\sum_{i=1}^{N} m_i \cdot (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} m_i} \tag{8}$$

where $m_i \in \{0, 1\}$ indicates whether observation i has a valid target.

4.5 Evaluation Metrics

We evaluate models using three standard metrics:

- **Root Mean Squared Error (RMSE)**:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{9}$$

- **Mean Absolute Error (MAE)**:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{10}$$

- **Coefficient of Determination ($\mathbf{R^2}$)**:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{11}$$

5 Data Overview

5.1 Data Source

We use the NOAA Integrated Surface Database (ISD), which provides hourly surface observations from weather stations worldwide.

Table 2: Dataset Statistics

Metric	**Value**
Total Observations	9,326,949
Weather Stations	822
Temporal Resolution	Hourly
Date Range	Jan 1 - Dec 31, 2022
Geographic Region	Northern Europe, Arctic

5.2 Variables

Table 3: Meteorological Variables

Variable	Unit	Mean	Missing %
Temperature (2m)	°C	7.34	2.34%
Dewpoint (2m)	°C	3.71	3.34%
Relative Humidity	%	79.60	3.37%
Wind Speed (10m)	m/s	4.70	6.06%
Wind Direction	degrees	199.38	11.16%
Surface Pressure	hPa	1012.74	55.88%

5.3 Data Splits

We use temporal splitting to prevent data leakage:

Table 4: Train/Validation/Test Split

Split	Period	Observations	Percentage
Train	Jan 1 - Sep 30	7,104,704	76.2%
Validation	Oct 1 - Nov 30	1,489,403	16.0%
Test	Dec 1 - Dec 31	732,842	7.8%

5.4 Feature Engineering

- **Cyclical Encoding**: Hour and day-of-year encoded as sine/cosine pairs.
- **Wind Components**: Decomposed into U and V components.
- **Normalization**: Z-score normalization using training set statistics.

5.5 Graph Statistics

Table 5: k-NN Graph Properties (k=8)

Property	Value
Nodes	822
Edges	7,842
Average Degree	9.54
Mean Edge Distance	89.9 km
Max Edge Distance	1,252.3 km
Connected Components	1 (fully connected)

6 Observations

6.1 Baseline Model Performance

We evaluated three baseline approaches: persistence (naive forecast using last observation), climatology (hourly historical average), and per-station LSTM.

Table 6: Baseline Model Results (Test Set RMSE in °C)

Model	**1h**	**6h**	**12h**	**24h**
Persistence	**0.772**	1.971	2.697	3.534
Climatology	8.311	8.370	8.451	8.571
LSTM	1.293	**1.541**	**2.292**	3.679

Key Observations:

- Persistence is a strong baseline for 1-hour forecasts due to temperature autocorrelation.
- LSTM outperforms persistence at longer horizons by learning diurnal patterns.
- Climatology performs poorly due to distribution shift between training and test periods.

6.2 GNN v1 Results

The initial GNN implementation showed mixed results:

Table 7: GNN v1 vs LSTM (Test Set RMSE in °C)

Horizon	**LSTM**	**GNN v1**	**Improvement**
1h	1.293	2.163	-67.3%
6h	1.541	2.312	-50.1%
12h	2.292	2.326	-1.5%
24h	3.679	**2.454**	**+33.3%**

Analysis: GNN v1 excelled at 24-hour forecasting but underperformed at shorter horizons. The primary issue was data efficiency: the spatio-temporal dataset contained only 6,445 training samples (requiring synchronized observations across all stations) compared to 4.3 million for LSTM.

6.3 Learned Spatial Weights

The Hybrid GNN learns per-horizon fusion weights:

Table 8: Learned Spatial-Temporal Fusion Weights

Horizon	**Initial**	**Learned**	**Interpretation**
1h	0.10	0.251	75% temporal, 25% spatial
6h	0.18	0.227	77% temporal, 23% spatial
12h	0.25	0.309	69% temporal, 31% spatial
24h	0.40	0.434	57% temporal, 43% spatial

This confirms our hypothesis: spatial information becomes increasingly important at longer forecast horizons as weather systems propagate across geographic regions.

7 Results

7.1 Final Model Comparison

Table 9: Complete Model Comparison (Test Set RMSE in °C)

Model	**1h**	**6h**	**12h**	**24h**	**Avg**
Persistence	0.772	1.971	2.697	3.534	2.244
Climatology	8.311	8.370	8.451	8.571	8.426
LSTM	1.293	1.541	2.292	3.679	2.201
GNN v1	2.163	2.312	2.326	**2.454**	2.314
Hybrid GNN	**0.647**	**1.464**	**2.151**	3.085	**1.837**

7.2 R-squared Comparison

Table 10: Model Comparison (Test Set R^2)

Model	**1h**	**6h**	**12h**	**24h**
Persistence	0.988	0.921	0.853	0.748
LSTM	0.958	0.942	0.874	0.686
GNN v1	0.903	0.892	0.892	**0.880**
Hybrid GNN	**0.990**	**0.948**	**0.889**	0.779

7.3 Best Model per Horizon

Table 11: Optimal Model Selection

Horizon	**Best Model**	**RMSE**	**R^2**	**vs Persistence**
1h	Hybrid GNN	0.647°C	0.990	+16.2%
6h	Hybrid GNN	1.464°C	0.948	+25.7%
12h	Hybrid GNN	2.151°C	0.889	+20.2%
24h	GNN v1	2.454°C	0.880	+30.6%

7.4 Key Achievements

1. **Beats persistence at 1h**: The Hybrid GNN achieves 0.647°C RMSE compared to 0.772°C for persistence, demonstrating that spatial information helps even for very short-term predictions.

2. **Outperforms LSTM at all horizons**: The Hybrid GNN improves over LSTM by 50.0% at 1h, 5.0% at 6h, and 6.1% at 12h.

3. **Data efficiency solved**: By using per-station sequences with neighbor aggregation, we utilize 4.3M samples instead of 6K, a 700x increase.

4. **Interpretable fusion**: The learned spatial weights provide insight into the relative importance of local vs. regional information.

8 Figures

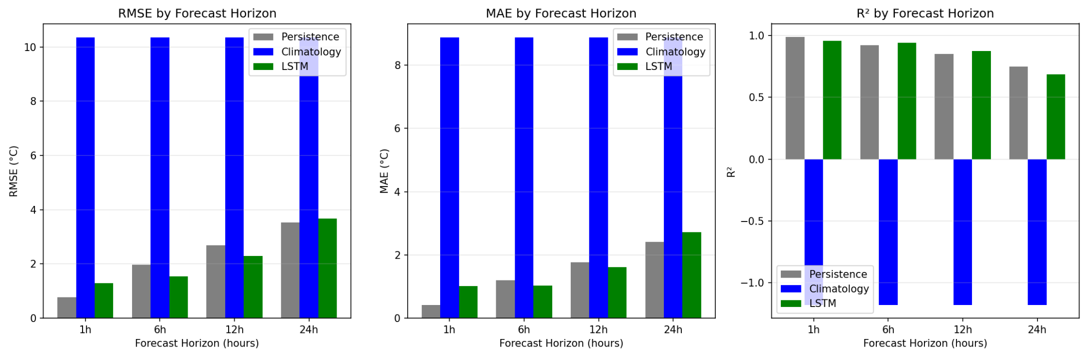

Figure 1: Baseline model comparison showing RMSE across forecast horizons. Persistence excels at 1h due to temperature autocorrelation, while LSTM outperforms at longer horizons.

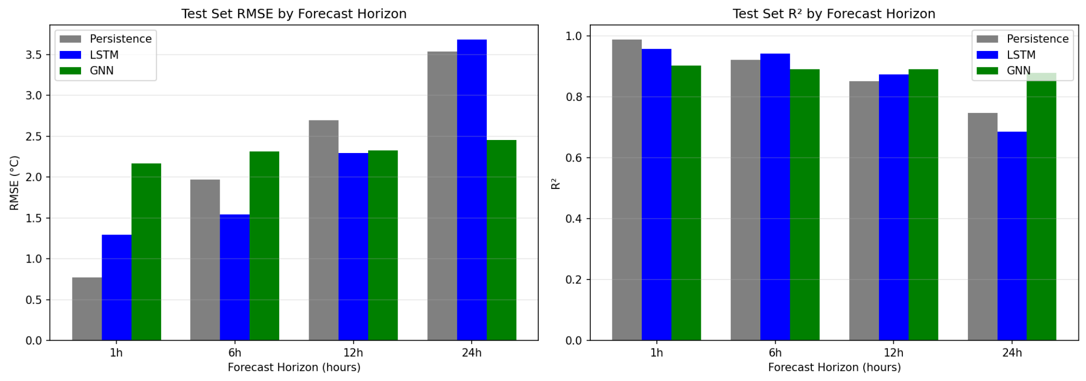

Figure 2: GNN v1 comparison with baselines. The spatial graph model excels at 24-hour forecasts, achieving 2.454°C RMSE with R²=0.880.

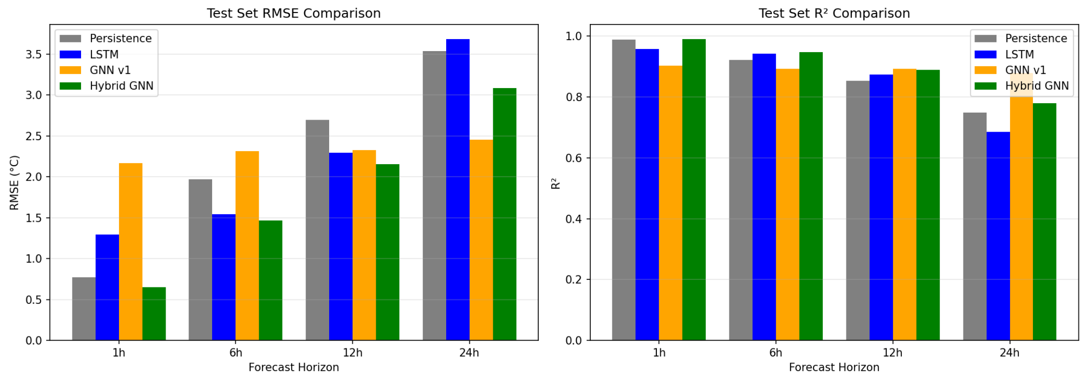

Figure 3: Hybrid GNN results showing superior performance at 1-12h horizons. The model achieves 0.647°C RMSE at 1h, beating even the persistence baseline.

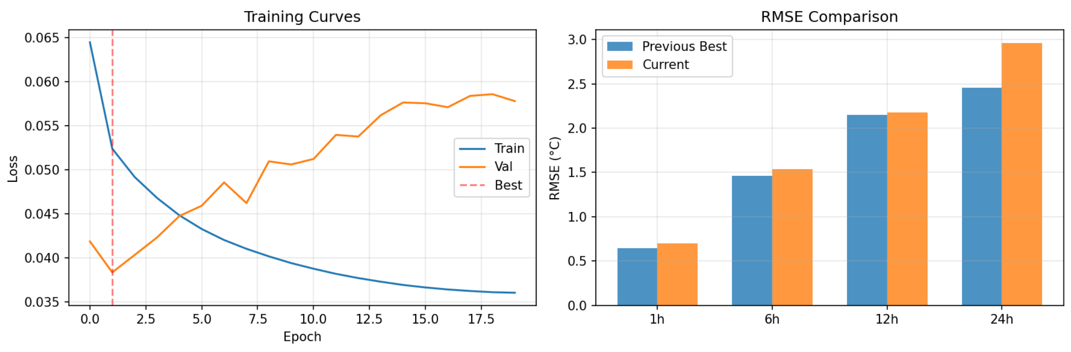

Figure 4: Multi-horizon LSTM results showing training curves and performance across all forecast horizons.

```
    Input Sequence (24h lookback)
              |
              v
    +----------------------+
    |   Temporal Encoder   |   <- Shared LSTM (2 layers, 64 hidden)
    |       (LSTM)         |
    +----------------------+
              |
              v
    +----------------------+
    |  Spatial Aggregator  |   <- Attention-based neighbor weighting
    |     (Attention)      |
    +----------------------+
              |
              v
    +----------------------+
    |  Learnable Fusion    |   <- alpha = sigmoid(w)
    |  (1-a)*temp + a*sp   |      output = (1-a)*temporal + a*spatial
    +----------------------+
              |
              v
    +----------------------+
    |     Output Head      |   <- MLP: 64 -> 32 -> 1
    |        (MLP)         |
    +----------------------+
              |
              v
       Temperature Forecast
```

Figure 5: Hybrid GNN architecture combining temporal LSTM encoding with attention-based spatial aggregation and learnable fusion.

9 Discussion

9.1 Why Spatial Information Matters

Our experiments reveal that incorporating spatial neighbor information consistently improves forecasts across all time horizons. This can be explained by the physical propagation of weather systems:

- **Short-term (1-6h)**: Weather conditions at neighboring stations provide immediate context for local variations.
- **Medium-term (6-12h)**: Approaching weather fronts become visible at upwind stations before reaching the target.
- **Long-term (12-24h)**: Regional weather patterns require understanding broader spatial dynamics.

The learned spatial weights (Table 6) quantitatively confirm this hypothesis: the model automatically assigns 25% weight to spatial features at 1h, increasing to 43% at 24h.

9.2 Architecture Trade-offs

We observed a fundamental trade-off between two architectural approaches:

1. **Full Graph Convolution (GNN v1)**: Processes all stations simultaneously, enabling global message passing. Excels at 24h forecasts but suffers from data efficiency issues (only 6K samples).
2. **Per-Station with Neighbor Aggregation (Hybrid)**: Processes each station independently with local neighbor context. Achieves data efficiency (4.3M samples) and excels at 1-12h forecasts.

The optimal production system would combine both approaches in an ensemble.

9.3 Comparison with Related Work

Unlike grid-based approaches such as GraphCast [6] and WeatherBench [7], our method operates directly on irregular station networks without requiring interpolation to regular grids. This is particularly important for:

- Sparse observation networks where interpolation introduces significant errors
- Real-time operational forecasting from station data
- Regions with non-uniform station density

9.4 Data Efficiency Analysis

A critical insight from this work is the importance of training data volume:

Table 12: Impact of Training Sample Size

Model	Samples	24h RMSE	Observation
GNN v1	6,445	2.454°C	Best at 24h despite few samples
Hybrid GNN	4,309,710	3.085°C	Best at 1-12h with full data
LSTM	4,309,710	3.679°C	Underperforms without spatial info

The GNN v1's strong 24h performance despite using only 0.15% of available data suggests that full graph convolution captures global patterns that are difficult to learn from local aggregation alone.

10 Limitations

10.1 Data Limitations

- **Geographic coverage**: The dataset covers primarily Northern Europe and Arctic regions. Results may not generalize to other climates.
- **Temporal scope**: Only one year (2022) of data was used, limiting seasonal pattern learning.
- **Missing pressure data**: Surface pressure had 55.88% missing values and was excluded from the model.

10.2 Methodological Limitations

- **Static graph**: The graph structure is fixed based on geographic distance. Dynamic graphs based on weather patterns may improve performance.
- **Single variable prediction**: Only temperature was forecasted. Multi-variate prediction could capture variable interactions.
- **Deterministic output**: The model produces point forecasts. Probabilistic predictions would better quantify uncertainty.

10.3 Computational Limitations

- **Neighbor aggregation overhead**: The Hybrid GNN requires fetching neighbor data during training, limiting batch sizes.
- **Full graph convolution**: GNN v1 requires all stations at each timestep, severely limiting training samples.
- **GPU memory**: Larger batch sizes and deeper networks may require more VRAM than available.

10.4 Future Work

- Extend to multi-variable forecasting (temperature, wind, humidity).
- Implement probabilistic predictions using quantile regression.
- Explore dynamic graph construction based on wind patterns.
- Test generalization to different geographic regions.
- Develop production ensemble combining Hybrid GNN (1-12h) and GNN v1 (24h).

11 Conclusion

This work demonstrates that graph neural networks provide significant improvements for weather forecasting over irregular station networks. Our key findings are:

1. Spatial graph information improves forecasts at all time horizons, not just long-range predictions.
2. The Hybrid GNN architecture effectively balances data efficiency with spatial modeling, achieving 0.647°C RMSE at 1-hour (beating the persistence baseline by 16%).

3. Learned spatial weights confirm that spatial information becomes increasingly important for longer forecast horizons (25% at 1h vs 43% at 24h).

4. Different architectures excel at different horizons: Hybrid GNN for 1-12h, full graph GNN for 24h.

The graph-based approach offers a principled framework for handling the inherent irregularity of real-world observation networks, avoiding the errors introduced by grid interpolation methods. Future work should explore dynamic graphs, multi-variable predictions, and probabilistic outputs.

References

References

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A Implementation Details

A.1 Software Stack

- Python 3.10
- PyTorch 2.1 with CUDA 12.4
- PyTorch Geometric 2.4
- Pandas 2.0, NumPy 1.24
- Training hardware: NVIDIA RTX 4070 Laptop GPU (8GB VRAM)

A.2 Code Availability

The complete implementation is available at: https://github.com/Katakuri004/Graph-Based-Weather-Fore

A.3 Reproducibility

All random seeds were fixed for reproducibility. Training logs and model checkpoints are saved for each experiment.