Machine Learning for Numeric Weather Prediction

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Problem & Objective

Goal: Predict future temperature using machine learning

Approach:

- Compare 3 machine learning methods
- Predict mean daily temperature
- Evaluate on real-world data (2023-2025)

Data Source:

- European Climate Assessment & Dataset (ECA&D)
- Station: Köln-Bonn, Germany
- Period: 1957-2025 (68 years)
- Variables: 10 weather features

Methods Overview

Linear Regression

Diego Garces

Muhammad Fakhar

Random Forest

Yuqi Fang

Deepak Sorout

Neural Network

Ali Cem Çakmak

Linear Regression

[Linear Regression Content]

This section will be filled by Diego and Muhammad

Random Forest

[Random Forest Content]

This section will be filled by Yuqi and Deepak

Neural Network

Approach

Architecture:

- Sequence-to-Sequence GRU (Gated Recurrent Unit) with Attention
- Encoder-Decoder structure
- Hidden dimension: 64 units
- Single layer

Task:

- Input: 15 days of weather history
- Output: 3-day temperature forecast
- Autoregressive prediction
- Benchmarked against baselines

Benchmark Models

Persistent Model

Approach: Tomorrow = Today

$$\hat{y}_{t+1} = y_t$$

- Simplest baseline
- No training required
- Assumes weather stays constant

SARIMA Model

Approach: Statistical time series model

- Captures seasonal patterns
- Traditional forecasting method
- Widely used in meteorology

Results: Day 1 Forecast

Model	MAE (°C)	RMSE (°C)	R^2
GRU	**1.61**	**2.06**	**0.901**
Persistent	1.78	2.30	0.877
SARIMA	1.72	2.22	0.885

Key Results:

- 9.6% improvement over Persistent
- 6.4% improvement over SARIMA
- Explains 90% of variance
- Best performance on all metrics

Results: Day 3 Forecast

Model	MAE (°C)	RMSE (°C)	R^2
GRU	**2.58**	**3.26**	**0.753**
Persistent	3.04	3.86	0.652
SARIMA	2.73	3.47	0.719

Key Results:

- 15.1% improvement over Persistent
- 5.5% improvement over SARIMA
- Performance degrades gracefully
- Maintains advantage at longer horizon

Execution Time

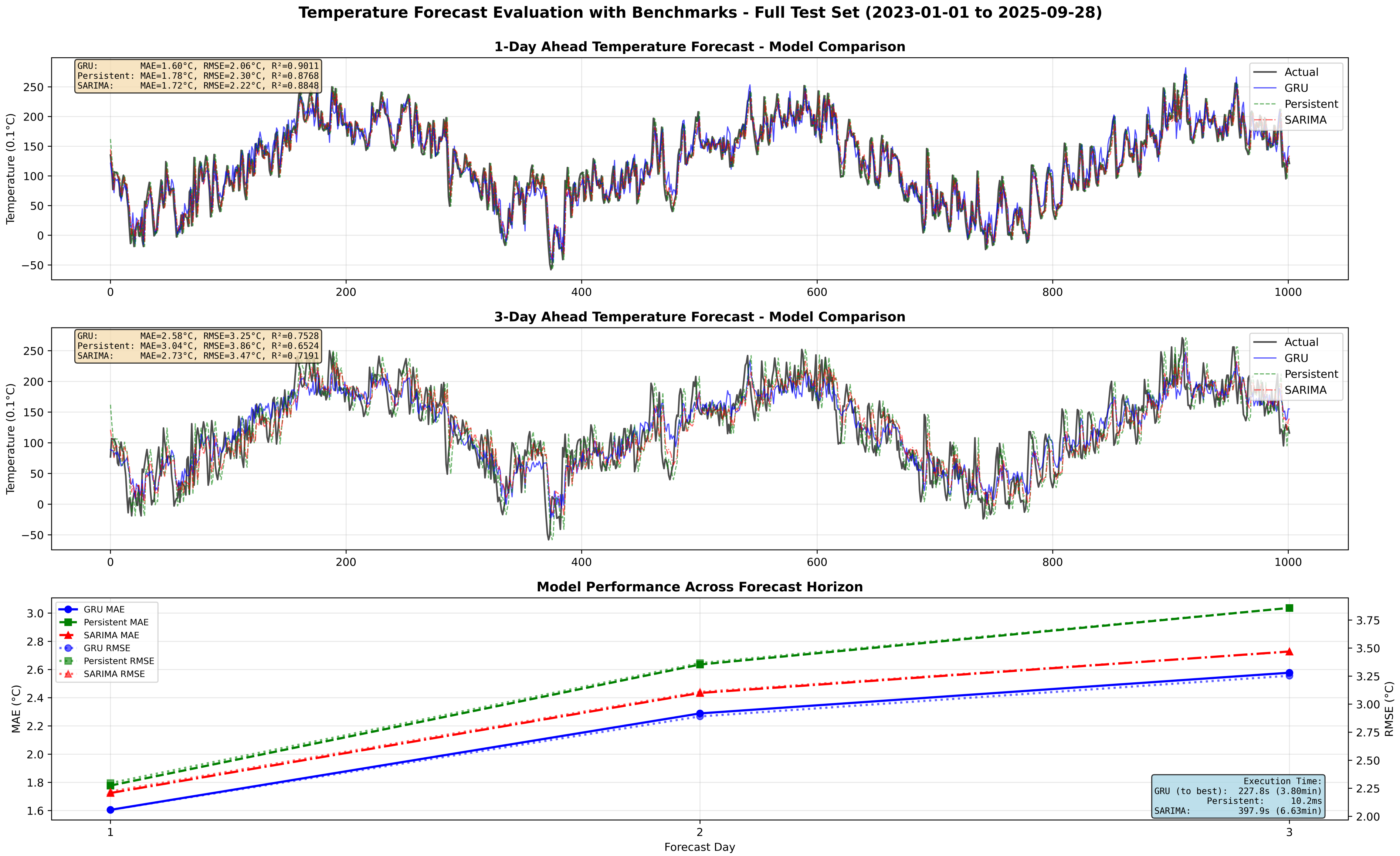
Model	Time	vs SARIMA
GRU (to best)	**227.8s**	**42.7% faster**
Persistent	10.2ms	-
SARIMA	397.9s	baseline

GRU time includes full training

Key Observations:

- GRU trains in ~3.8 minutes
- Nearly twice as fast as SARIMA
- Achieves better accuracy in less time
- Persistent is instantaneous (no training)
- GRU offers best accuracy-to-time ratio

5. Neural Network



Model Comparison

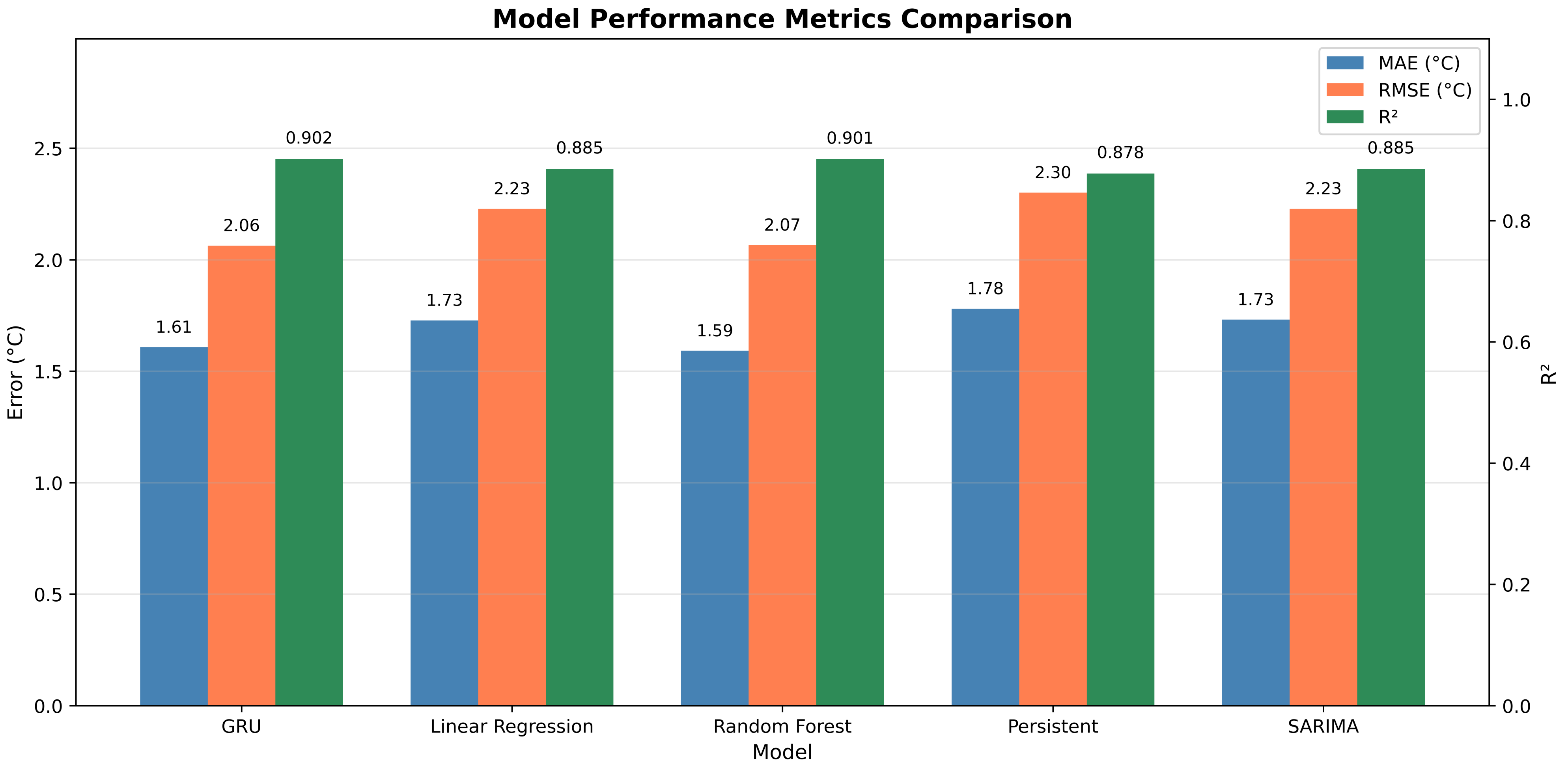
Performance Summary

Model	MAE (°C)	RMSE (°C)	R^2
Random Forest	**1.59**	2.07	0.901
GRU	1.61	**2.06**	**0.902**
Linear Regression	1.73	2.23	0.885
SARIMA	1.73	2.23	0.885
Persistent	1.78	2.30	0.878

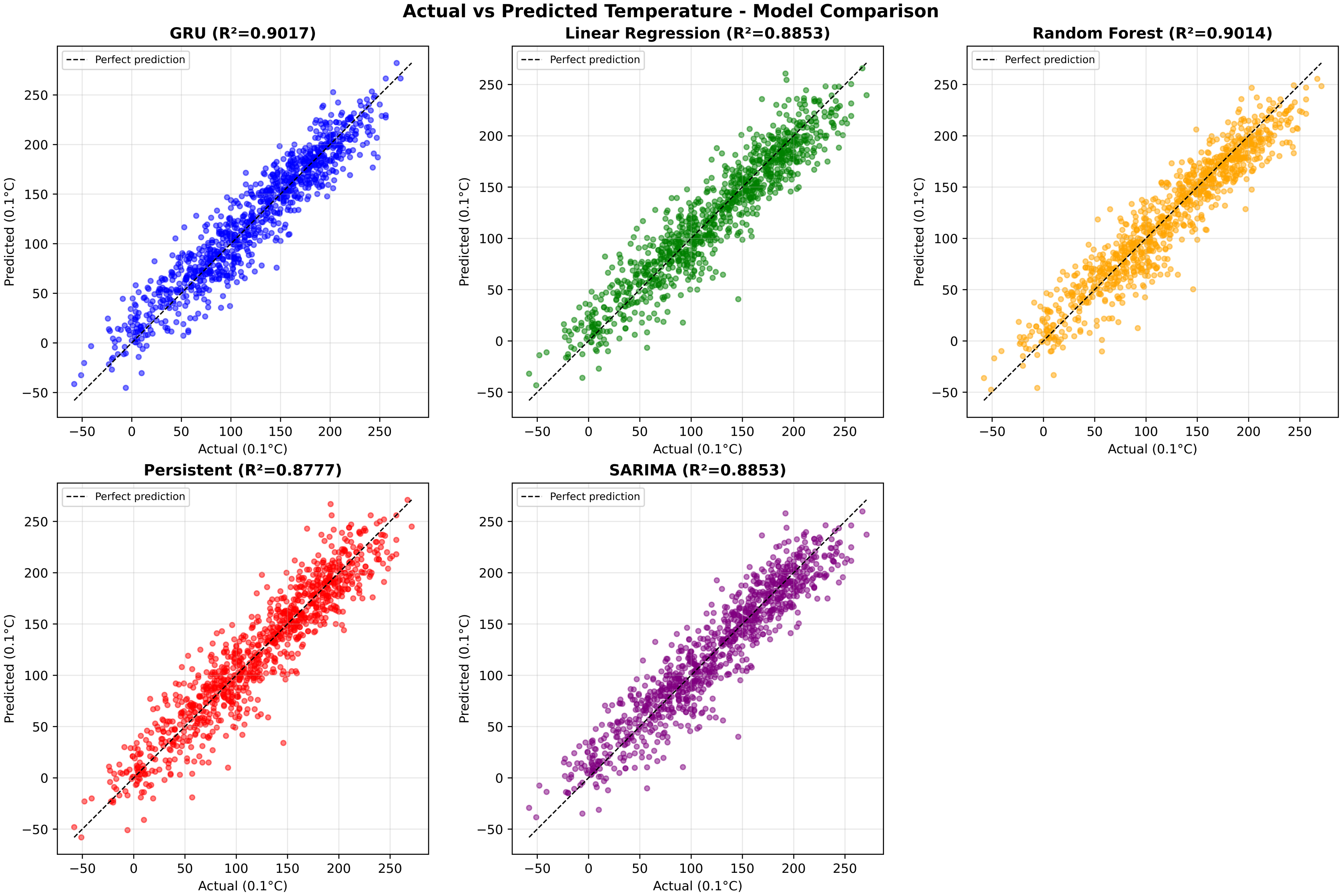
Key Observations:

- GRU and RF achieve comparable top performance
- Both ML models outperform traditional methods
- 10% improvement over Persistent baseline
- 7% improvement over SARIMA baseline
- All models maintain R^2 > 0.87

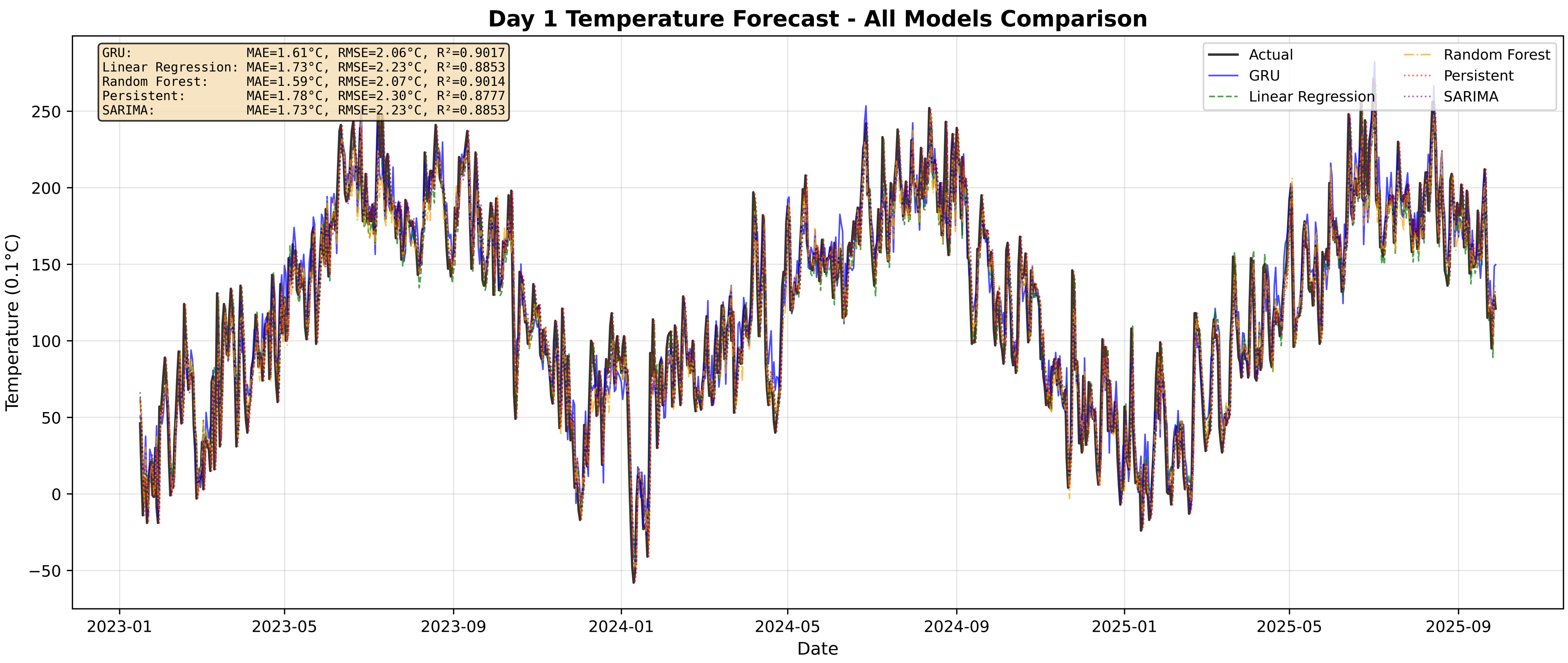
6. Model Comparison



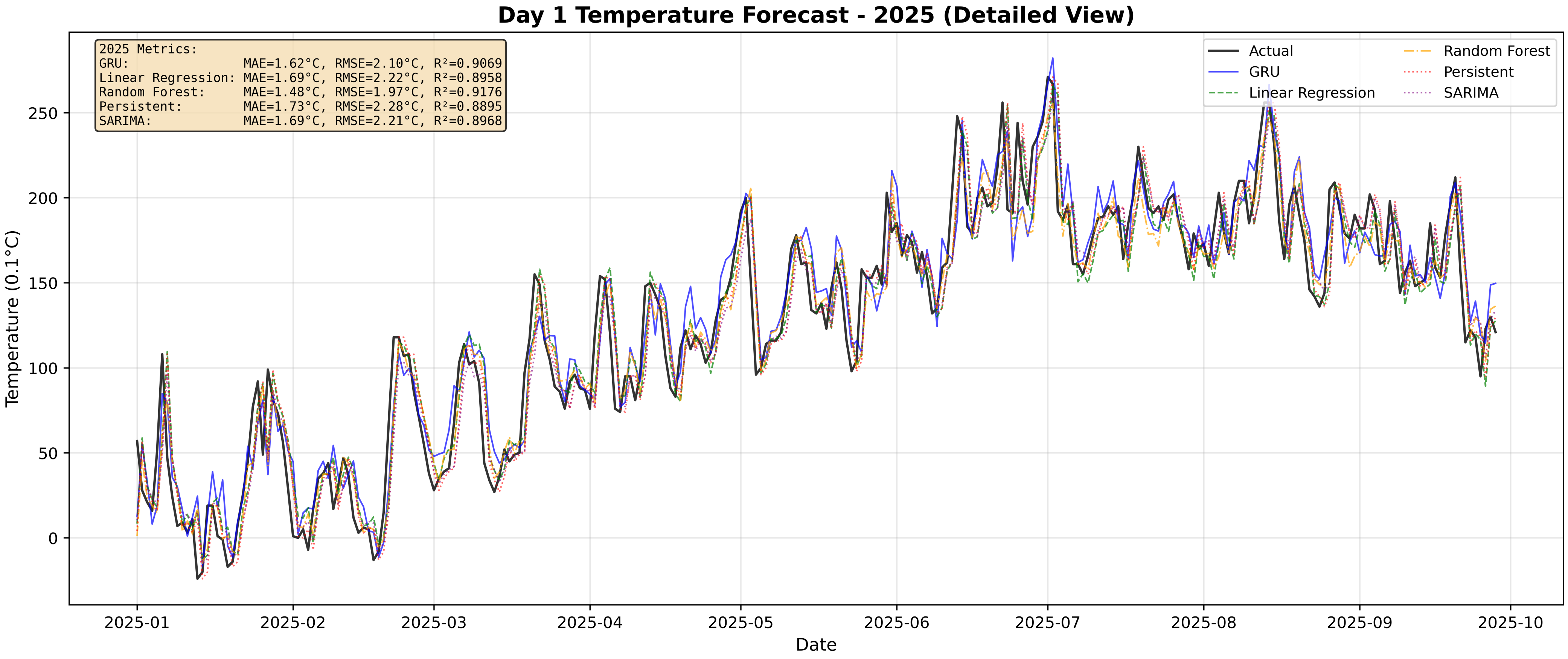
6. Model Comparison



All Models: Time Series (Full Range)



All Models: Time Series (2025 Detail)



Conclusion

Key Findings:

- GRU and Random Forest achieved top performance ($R^2 > 0.90$)
- All ML methods outperformed presistent by 3-12%
- GRU: Better accuracy-to-time ratio (43% faster than SARIMA)

Future Directions:

- Multi-station data for spatial patterns
- Extend forecast horizon beyond 3 days
- Ensemble methods combining approaches

Questions?