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

Data Management

Data Cleaning

- Removed measurements beyond 2025-09-30
- Forward-filled missing values
- Excluded variables with poor data quality (Sea Level Pressure, Global Radiation)

Data Splitting

Year-based split (no data leakage):

- **Train:** 1957-2017 (60 years)
- **Validation:** 2018-2022 (5 years)
- **Test:** 2023-2025 (current data)

Why year-based splitting?

- Preserves temporal ordering
- Tests generalization to future, unseen data
- Models cannot "peek" into the future during training

Methods Overview

Linear Regression

Diego Garces

Muhammad Fakhar

Random Forest

Yuqi Fang

Deepak Sorout

Neural Network

Ali Cem Çakmak

Linear Regression

Three Approaches

Simple Linear Regression:

$$TG_t = \beta_0 + \beta_1 TG_{t-1} + \epsilon$$

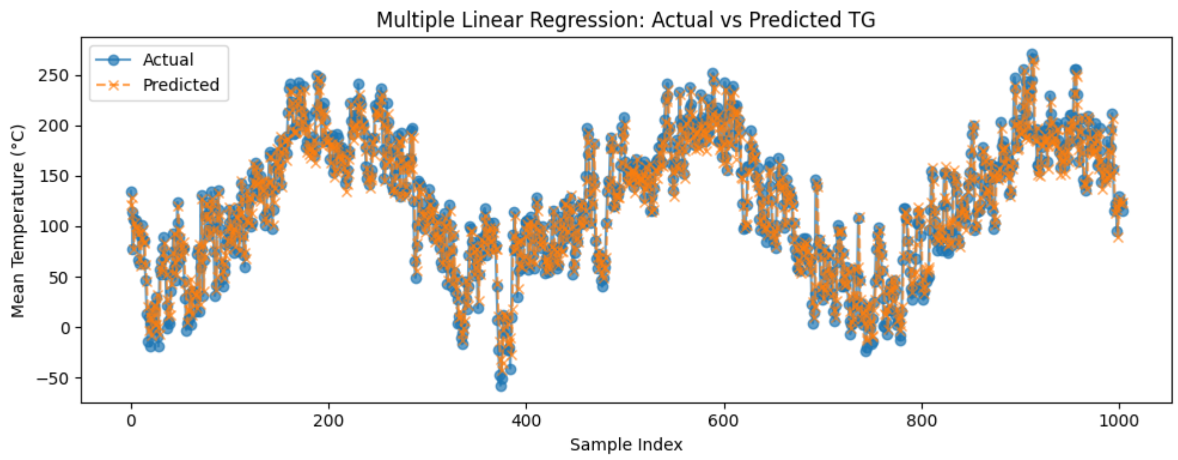
Multiple Linear Regression:

$$TG_t = \beta_0 + \beta_1 TN_{t-1} + \beta_2 TX_{t-1} + \beta_3 TG_{t-1} + \epsilon$$

Rolling Window Linear Regression:

$$TG_t = \beta_0 + \beta_1 TN_{t-1} + \beta_2 TX_{t-1} + \beta_3 TG_{t-1} + \beta_4 TG_{3d} + \epsilon$$

Results



Experiment	MAE	RMSE	R^2
Simple	1.76°C	2.26°C	0.880
Multiple	1.72°C	2.22°C	0.885
Rolling Window	1.72°C	2.22°C	0.884

Key Observations:

- Moving from simple to multiple regression improved all metrics
- More information → provides context about the stability of the weather
- Adding the 3-day average adds more noise than signal

Fitted Models

Simple Linear Regression:

$$TG_t = 0.62 + 0.93TG_{t-1} + \epsilon$$

Multiple Linear Regression:

$$TG_t = 0.07 - 0.12TN_{t-1} + 0.07TX_{t-1} + 0.96TG_{t-1} + \epsilon$$

Rolling Window Linear Regression:

$$TG_t = 0.02 + 0.15TN_{t-1} + 0.035TX_{t-1} + 0.94TG_{t-1} + 0.093TG_{3d} + \epsilon$$

The coefficient for yesterday's mean temperature is the strongest baseline predictor.

Random Forest

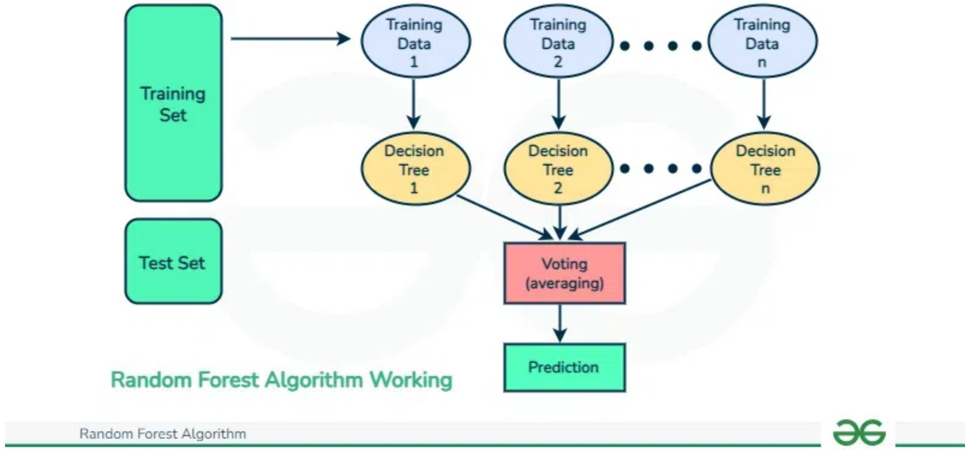
"The Wisdom of the Crowds"

Process:

- **Many Trees:** 100 independent decision trees
- **Randomness:** Each tree sees random subset of data & features
- **Averaging:** Final Prediction = Average of all 100 trees

Why:

- Reduces overfitting
- Lowers prediction variance
- Good for non-linear relationships



Source: GeeksforGeeks

Methodology

Autoregression (temporal dependencies)

- Past **15 days** of data → predict today (TG)

Features:

- 10 Weather variables: TG, TN, TX, RR, SS, HU, FG, FX, CC, SD
- Lag days: **15**
- Total features = 10 × 15 = **150 input columns**

DATE	TG_1	TG_2	TG_3	TG_4	...	TG_15	Target
10-16	108	102	97	106	...	56	139
10-17	139	108	102	97	...	57	139
10-18	139	139	108	102	...	83	174
10-19	174	139	139	108	...	58	105
10-20	105	174	139	139	...	93	77
10-21	77	105	174	139	...	108	100
10-22	100	77	105	174	...	106	77
10-23	77	100	77	105	...	105	84

Validation & Hyperparameter Tuning

Train → Test to Train → Validation → Test

Trees \ Depth	None	10
50	2.0882	2.0771
100	2.0740	**2.0737**
200	2.0768	2.0777

🏆 **Best Model:**

Trees: 100 | Depth: 10 *(RMSE: 2.0737)*

More trees ≠ Better results!

Feature Selection Experiment

The Hypothesis:

Reduce Dimensionality

- **Action:** Selected Top 30 Features
- **Expectation:** Remove noise → Better Accuracy

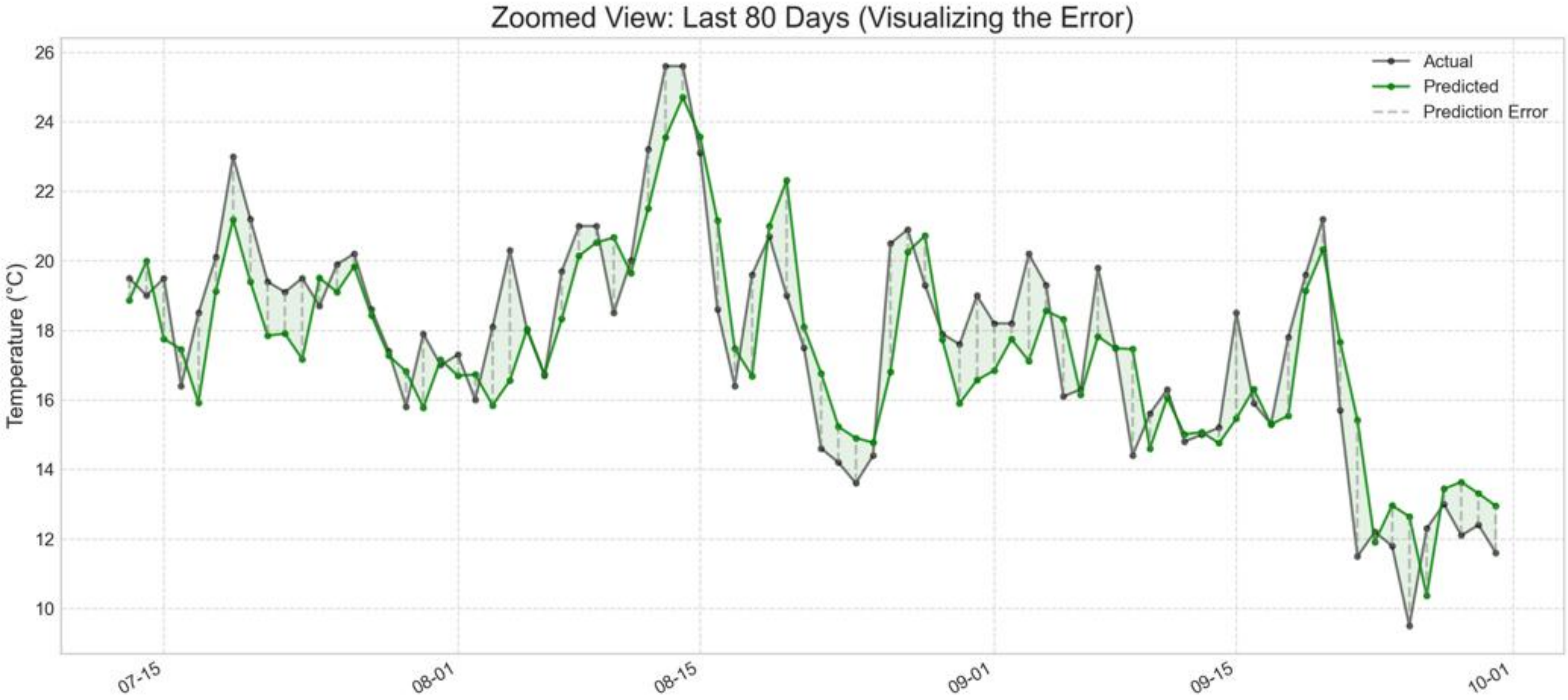
What we observed:

Performance Drop

- 🏆 Full Model (150 Feats): → lower MAE, higher R^2
- ❌ Reduced Model (30 Feats): → MAE increased, R^2 decreased

Take-away: Feature selection likely disrupted temporal continuity (breaking the trend) and lost valuable interaction effects (where features contribute jointly)

MAE: 1.59°C RMSE: 2.07°C R^2: 0.901



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

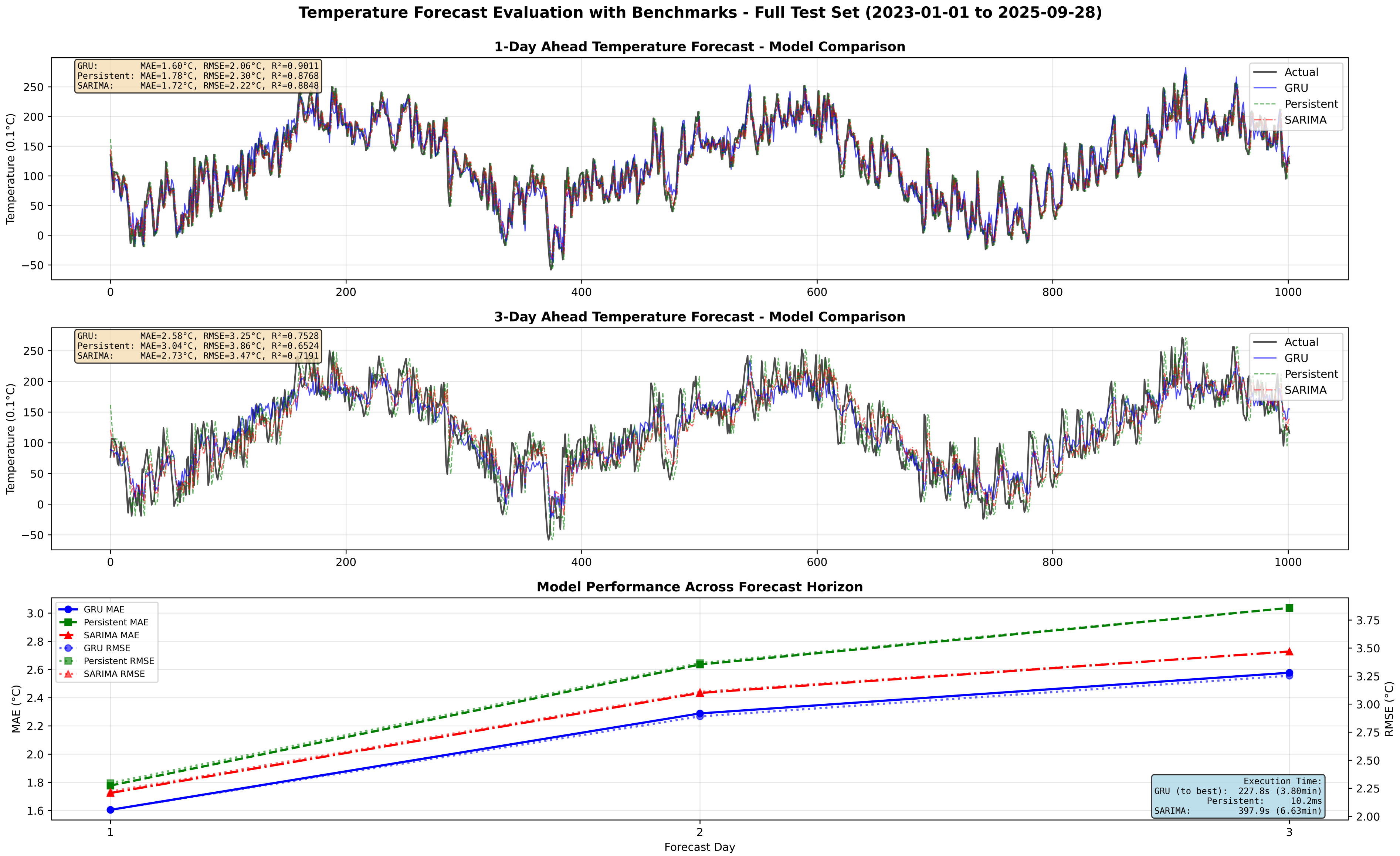
Model	Time	vs SARIMA
GRU (to best)	**227.8s**	**42.7% faster**
Persistent	10.2ms	-
SARIMA	397.9s	baseline

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

6. Neural Network



Model Comparison

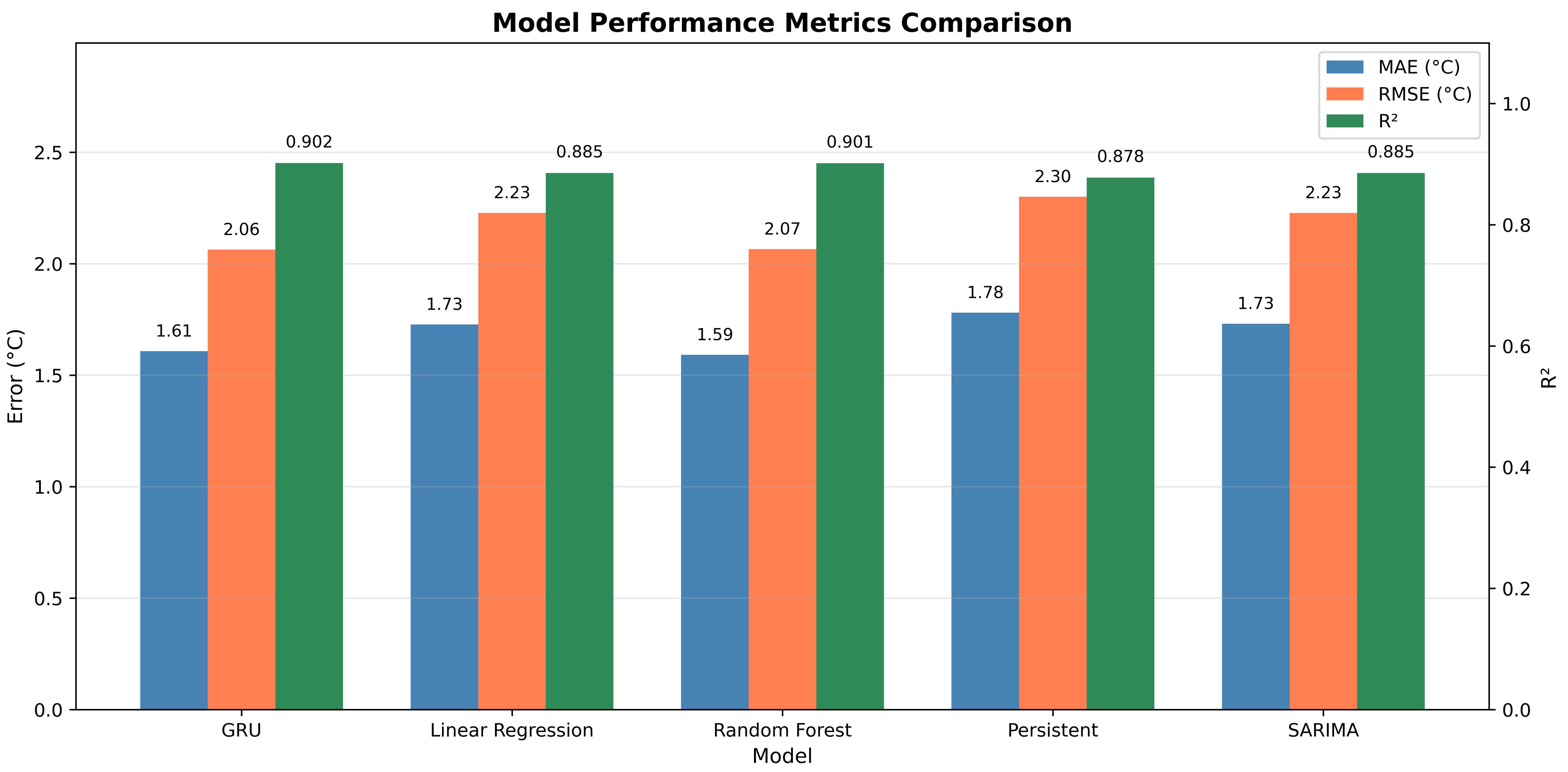
Performance Summary

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

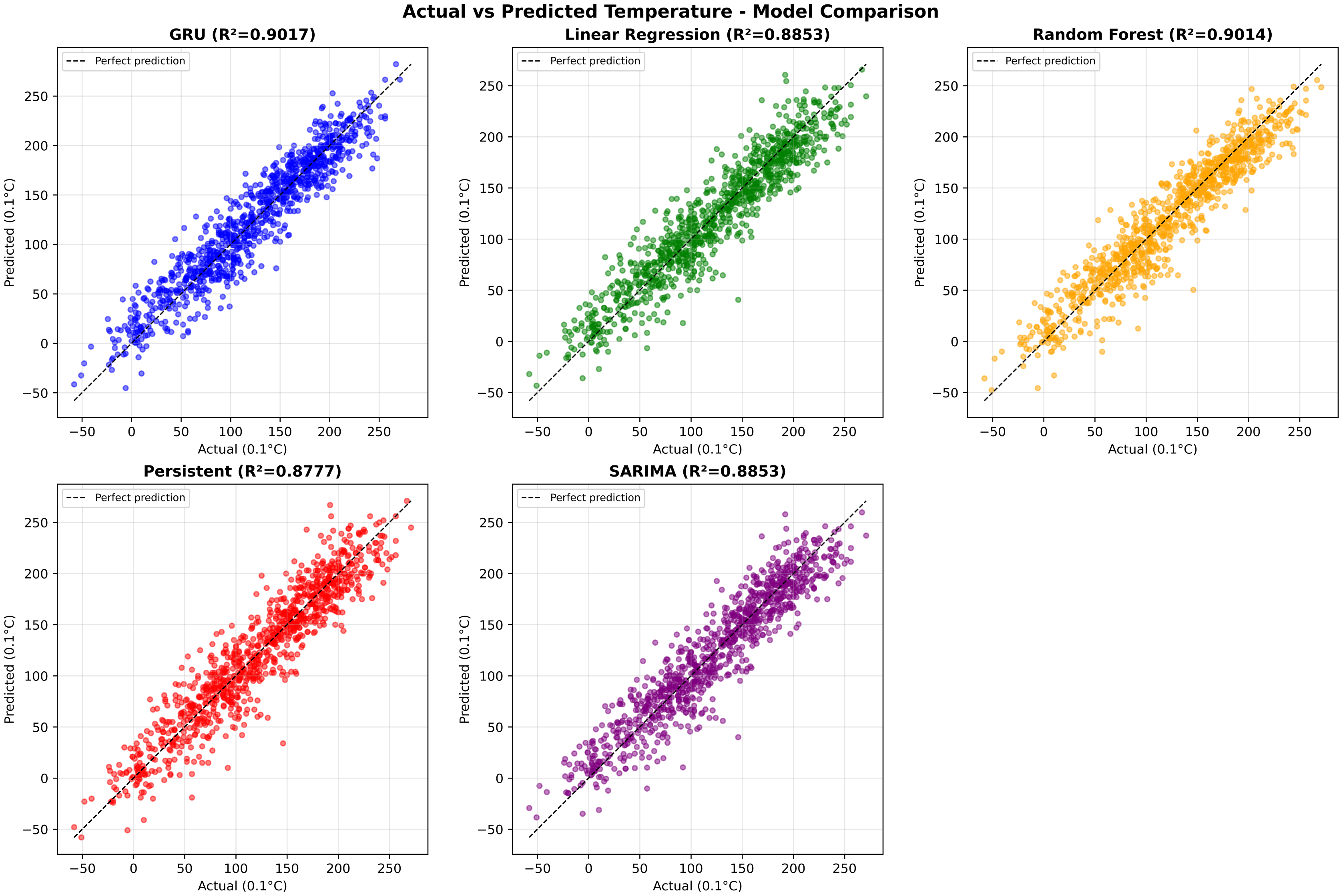
Key Observations:

- 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

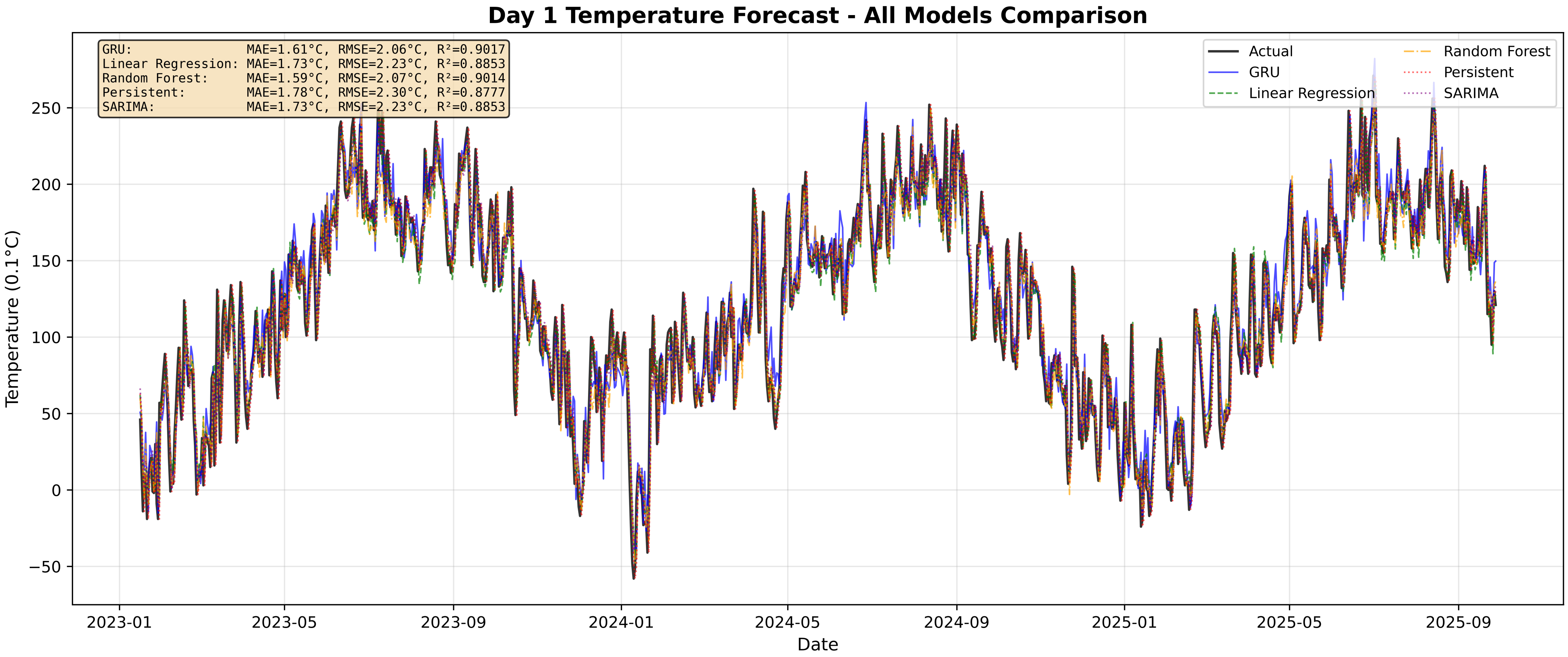
7. Model Comparison



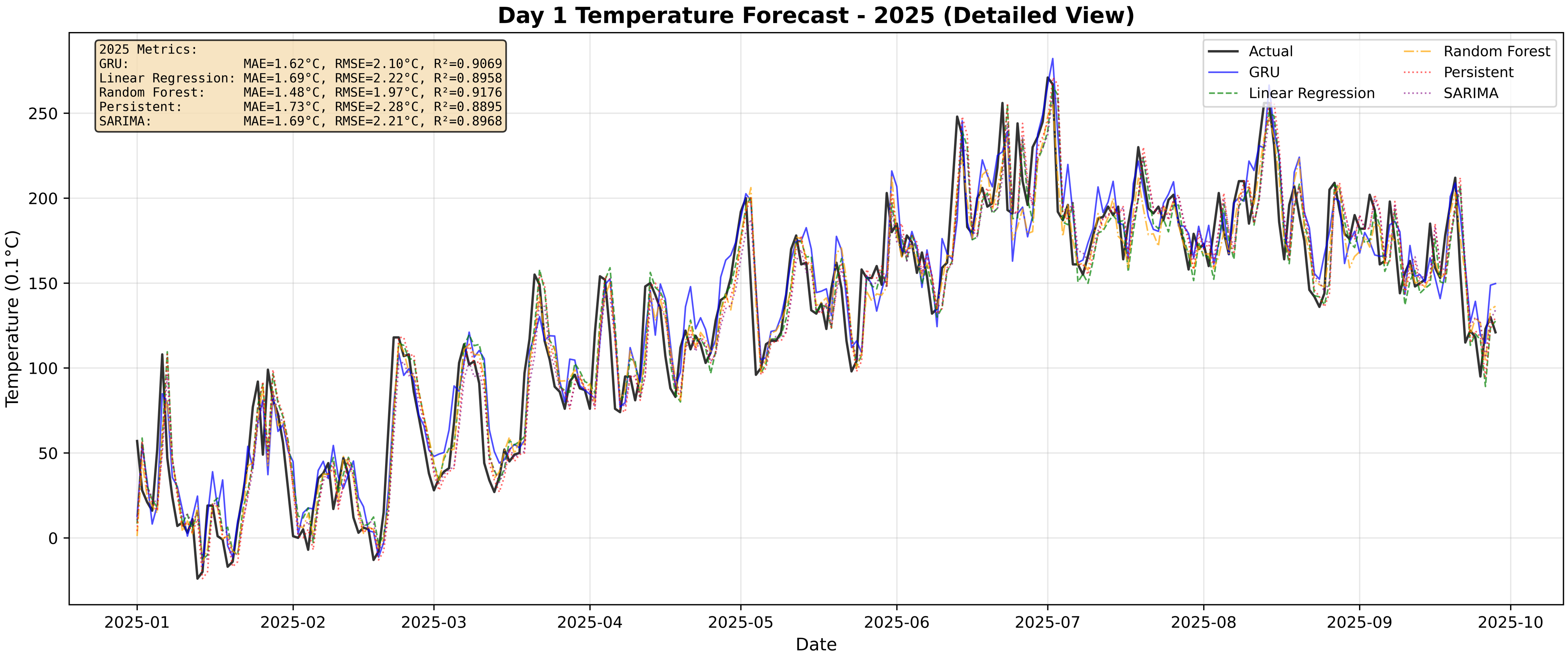
7. Model Comparison



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?