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Analyzing the Impact of Climate Change on Temperature Trends in the United Kingdom: A Data-Driven Approach to Forecasting Future Patterns

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Introduction

Climate change threatens environmental stability, economic growth, and societal wellbeing. The UK's rising temperatures and frequent extreme weather, intensified by urbanization, impact ecosystems, agriculture, health, and infrastructure. Accurate temperature forecasting using data-driven methods, including machine learning, is crucial for adaptation and mitigation. This study analyzes UK temperature trends to deliver reliable projections supporting policy and climate resilience.

Research Questions

How effective are data-driven approaches, particularly deep learning models like LSTM, in analyzing historical UK temperature trends and forecasting future patterns to support climate change adaptation and mitigation strategies?

Methodologies

The study uses a secondary Global Temperature dataset. Data was cleaned, missing values handled and transformed into time-series format. Temperature trends were decomposed using Classical and STL decomposition. Forecasting was performed with Seasonal Naïve, SARIMA (Seasonal Autoregressive Integrated Moving Average), LSTM (Long Short-Term Memory) and Hybrid (SARIMA & LSTM) models, Forecast evaluated using MAE, RMSE, MPE, and MAPE. Results were interpreted to identify trends and implications for UK climate policies and sustainability.

Table

Table 1. Performance comparison of forecasting models

Metrix	SNaïve	SARIMA	LSTM	HYBRID
ME	0.01451	0.01215	0.08834	0.49771
RMSE	1.07511	1.10681	0.93290	1.41654
MAE	0.83441	0.84525	0.72994	1.22169
MPE	–5.57686	–5.67037	–4.49043	–14.99812
MAPE	18.78%	18.85%	15.71%	19.73%
Residual	1.0750	1.1067	0.9287	1.3262

Mathematical Formulas

$$\mathrm{ME} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \tag{1}$$

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

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

$$\mathrm{MPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right) \times 100 \tag{4}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \tag{5}$$

ME	Mean Error
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
MPE	Mean Percentage Error
MAPE	Mean Absolute Percentage Error

Figures

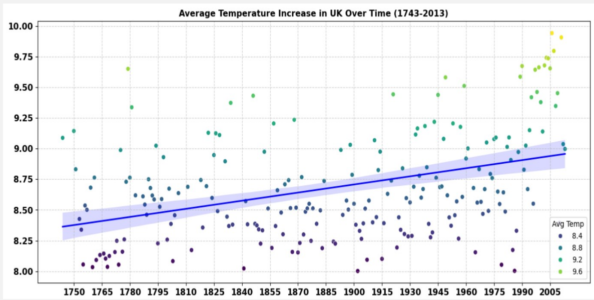

Figure 1. Scatter plot showing average temperature increase in UK over time (1743-2013)

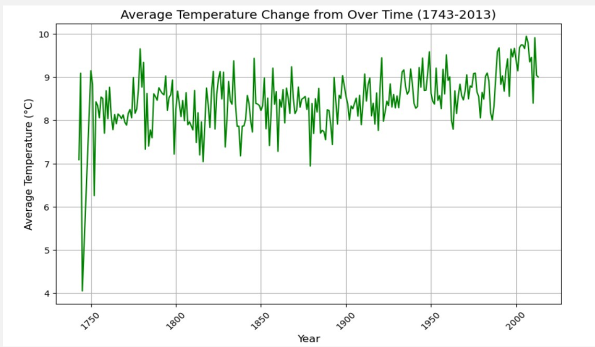

Figure 2. Line chart showing average temperature change over time (1743-2013)

Figures

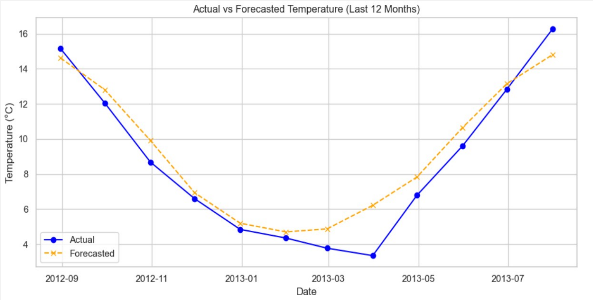

Figure 3. SNaïve forecast and actual data plot

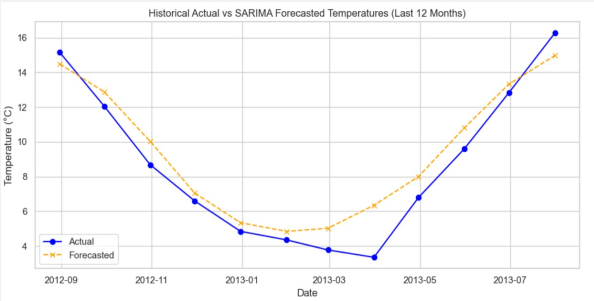

Figure 4. SARIMA forecast and actual data plot

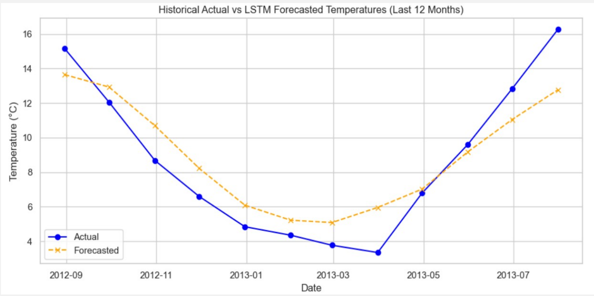

Figure 5. LSTM forecast and actual data plot

Web-App Development

The web application, built with Python, Flask, and React Native, integrates the best-performing pre-trained LSTM model from this research. It transforms the model into a practical, user-friendly platform, enabling researchers, environmental analysts, and policymakers to interactively forecast future temperatures from historical trends, bridging the gap between technical research and real-world usability.

Figures

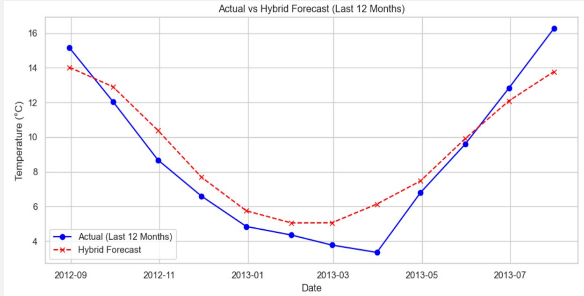

Figure 6. Hybrid (SARIMA + LSTM) forecast and actual data plot

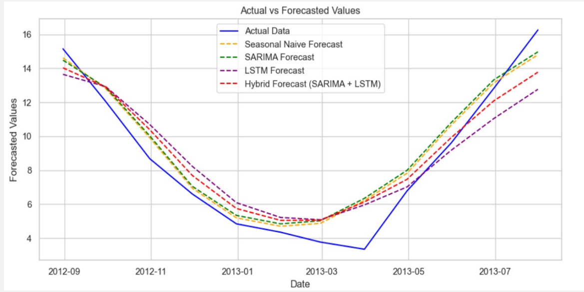

Figure 7. Comparison of various models

Conclusion

This study evaluated various temperature forecasting models (Table 1 & Figure 7), including SNaïve, SARIMA, LSTM, and a Hybrid SARIMA-LSTM model. While the SNaïve (Figure 3) model offered simplicity, it lacked adaptability to trends. SARIMA (Figure 4) performed moderately well by capturing seasonal patterns but struggled with complex dynamics. The LSTM model (Figure 5) outperformed all others, achieving the lowest error metrics, highlighting its strength in modeling non-linear temporal dependencies. Surprisingly, the Hybrid model (Figure 6) did not surpass the LSTM alone.

Temperature trend analysis from 1743 to 2013 (Figures 1 & 2) revealed a sustained long-term warming, with a significant acceleration post-1980s marked by more frequent unusually warm years. This pattern aligns with global climate change and reflects the influence of industrialization and greenhouse gas emissions.

These findings reinforce the need for robust climate mitigation strategies and demonstrate the effectiveness of deep learning for forecasting complex climate data while recognizing the value of simpler models for benchmarking.