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# Time Series Forecasting of Minimum and Maximum Temperatures in Ukai, Gujarat, India using SPSS Expert Modeler

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**ABSTRACT:** This research employs time series forecasting to estimate the monthly minimum and maximum temperatures of Ukai, Gujarat, India, based on historical records processed using IBM SPSS Statistics. The Expert Modeler identified Simple Seasonal Models as the most appropriate for both datasets. Model performance was strong, achieving R-squared values of 0.871 for minimum temperatures and 0.927 for maximum temperatures. Projections extend through December 2027, offering useful information for regional climate assessment and agricultural decision-making.

## I. INTRODUCTION

Ukai is a small but strategically important town located in the Tapi district of Gujarat, India, approximately 94 km from Surat. The town is best known for the Ukai Dam, also called the Vallabh Sagar Dam, constructed across the Tapi River in 1972. It is the second-largest reservoir in Gujarat after the Sardar Sarovar Dam and plays a pivotal role in irrigation, hydroelectric power generation, and drinking water supply for the region. The Ukai Dam supports extensive agricultural activity by irrigating thousands of hectares in South Gujarat, making the area agriculturally significant.

Geographically, Ukai lies in a region with a tropical climate, characterized by hot summers, a distinct monsoon season, and mild winters. The temperature ranges from around 10°C in winter to above 42°C in peak summer. Its location near a large water body influences local microclimates, which in turn impacts agriculture, fisheries, and energy demand. The region also hosts the Ukai Thermal Power Station, an important contributor to Gujarat's electricity supply.

Given its economic and ecological importance, understanding and forecasting climatic parameters—especially temperature—is vital for agriculture planning, water resource management, energy optimization, and disaster preparedness. In this context, time series forecasting of minimum and maximum temperatures using advanced statistical tools such as SPSS Expert Modeler can provide actionable insights for local authorities, farmers, and policymakers.

## II. METHODOLOGY

### 2.1 Data Source

The dataset comprises **monthly minimum and maximum temperatures** for Ukai, spanning multiple years, with the final forecast period extending to **December 2027**.

### 2.2 Software and Tools

IBM SPSS Statistics was used for the analysis. The **Time Series Modeler** procedure was employed, with the following specifications:

- Dependent variables: *MinTemperature*, *MaxTemperature*
- Independent variable: *Date* (YEAR, MONTH format; seasonal period = 12)
- Model type: **Expert Modeler**, testing ARIMA and Exponential Smoothing options with seasonality enabled.
- Confidence level: **95%**
- Missing values: Included as valid data.

### SPSS and ARIMA Modeling:

SPSS (Statistical Package for the Social Sciences) is a versatile software widely utilized for statistical analysis across numerous disciplines, including weather prediction. Known for its intuitive interface and extensive range of statistical tools, SPSS is well-suited for working with large and complex datasets. One of its significant applications is in time series analysis, where data collected sequentially over time is examined to detect trends, recurring patterns, and correlations. In weather forecasting, SPSS can process historical meteorological data such as temperature and rainfall records, enabling researchers to create visual representations like graphs and charts for easier pattern recognition. These visual insights, combined with advanced statistical methods, allow for building predictive models that aid in forecasting future weather conditions and supporting informed decision-making.

The ARIMA (Autoregressive Integrated Moving Average) model is a widely recognized statistical approach for time series forecasting, particularly effective for datasets displaying trends or seasonal behaviors. ARIMA consists of three core components:

- **Autoregression (AR):** Uses the relationship between a current value and its past values to make predictions.
- **Integration (I):** Applies differencing to transform non-stationary data into stationary form, ensuring consistent mean and variance over time—a key requirement for accurate modeling.
- **Moving Average (MA):** Models the current observation as influenced by past forecast errors, capturing dependencies between observations and residuals.
- The development of an ARIMA model follows a structured process:
- **Model Identification:** The first stage focuses on analyzing the dataset to determine the appropriate values for the autoregressive (AR), differencing (I), and moving average (MA) terms. Statistical tools such as the autocorrelation function (ACF) and partial autocorrelation function (PACF) help in identifying these parameters.
- **Parameter Estimation:** After selecting the model structure, the next step is to estimate its parameters by fitting the model to the data. This involves optimizing the coefficients so that the difference between actual and predicted values is minimized.
- **Model Validation:** The fitted model's performance is then evaluated to ensure its accuracy and reliability. This includes comparing predicted outputs to actual observations and verifying that residuals show no significant patterns or autocorrelation.
- **Forecasting:** When the model passes validation, it can be applied to predict future values. Forecasts are generated based on the patterns and trends detected in the historical dataset.

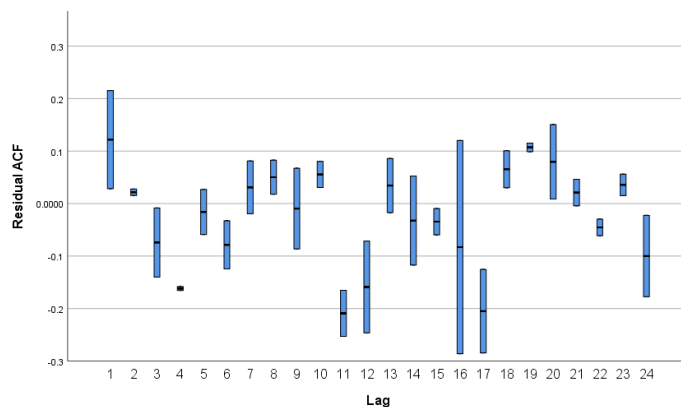
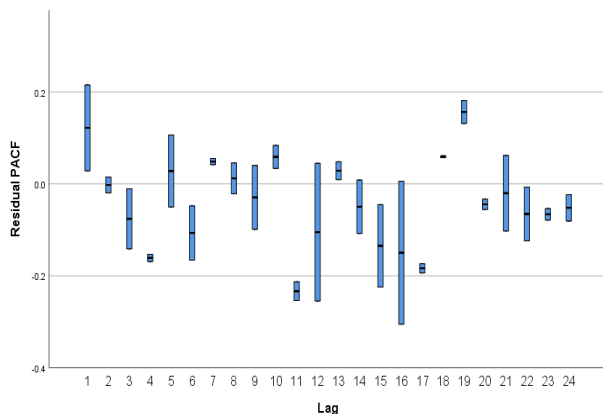
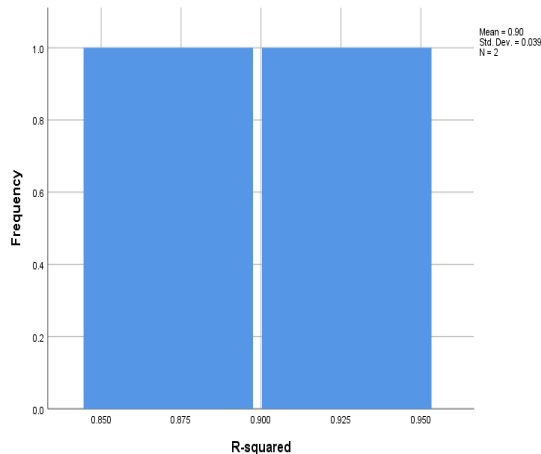
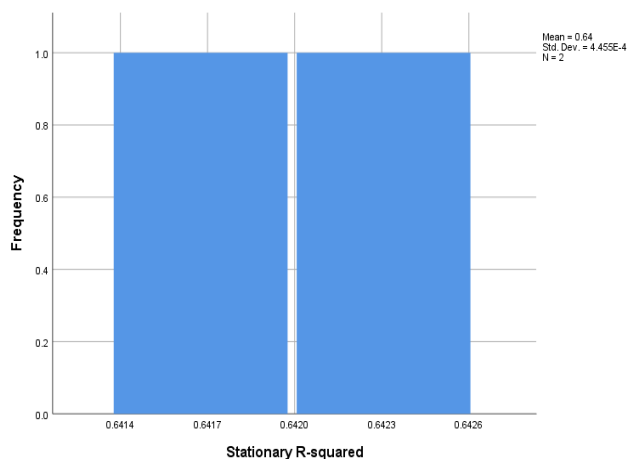
By implementing ARIMA modeling in SPSS, researchers can create dependable weather forecasting systems for areas such as the Ukai, Gujarat. These forecasts assist local communities in preparing for and adapting to potential climate variations, ultimately supporting climate resilience efforts.

### 2.3 Model Selection

The Expert Modeler identified Simple Seasonal models for both minimum and maximum temperatures, based on evaluation metrics such as:

- Stationary R-squared
- R-squared
- Root Mean Squared Error (RMSE)
- Mean Absolute Percentage Error (MAPE)
- Bayesian Information Criterion (BIC)

### III. RESULTS



### Model Summary

#### Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile		
					5	10	25
Stationary R-squared	.642	.000	.642	.642	.642	.642	.642
R-squared	.899	.039	.871	.927	.871	.871	.871
RMSE	1.339	.408	1.050	1.628	1.050	1.050	1.050
MAPE	4.208	2.348	2.548	5.868	2.548	2.548	2.548
MaxAPE	15.714	11.045	7.904	23.524	7.904	7.904	7.904
MAE	.995	.240	.825	1.165	.825	.825	.825
MaxAE	3.456	1.649	2.290	4.622	2.290	2.290	2.290
Normalized BIC	.673	.619	.235	1.111	.235	.235	.235

**Model Fit**

Fit Statistic	Percentile			
	50	75	90	95
Stationary R-squared	.642	.642	.642	.642
R-squared	.899	.927	.927	.927
RMSE	1.339	1.628	1.628	1.628
MAPE	4.208	5.868	5.868	5.868
MaxAPE	15.714	23.524	23.524	23.524
MAE	.995	1.165	1.165	1.165
MaxAE	3.456	4.622	4.622	4.622
Normalized BIC	.673	1.111	1.111	1.111

**Model Statistics**

Model	Number Predictors	Model Fit statistics			
		of Stationary R-squared	R-squared	RMSE	MAPE
Min Temperature-Model_1	0	.642	.871	1.628	5.868
Max Temperature-Model_2	0	.642	.927	1.050	2.548

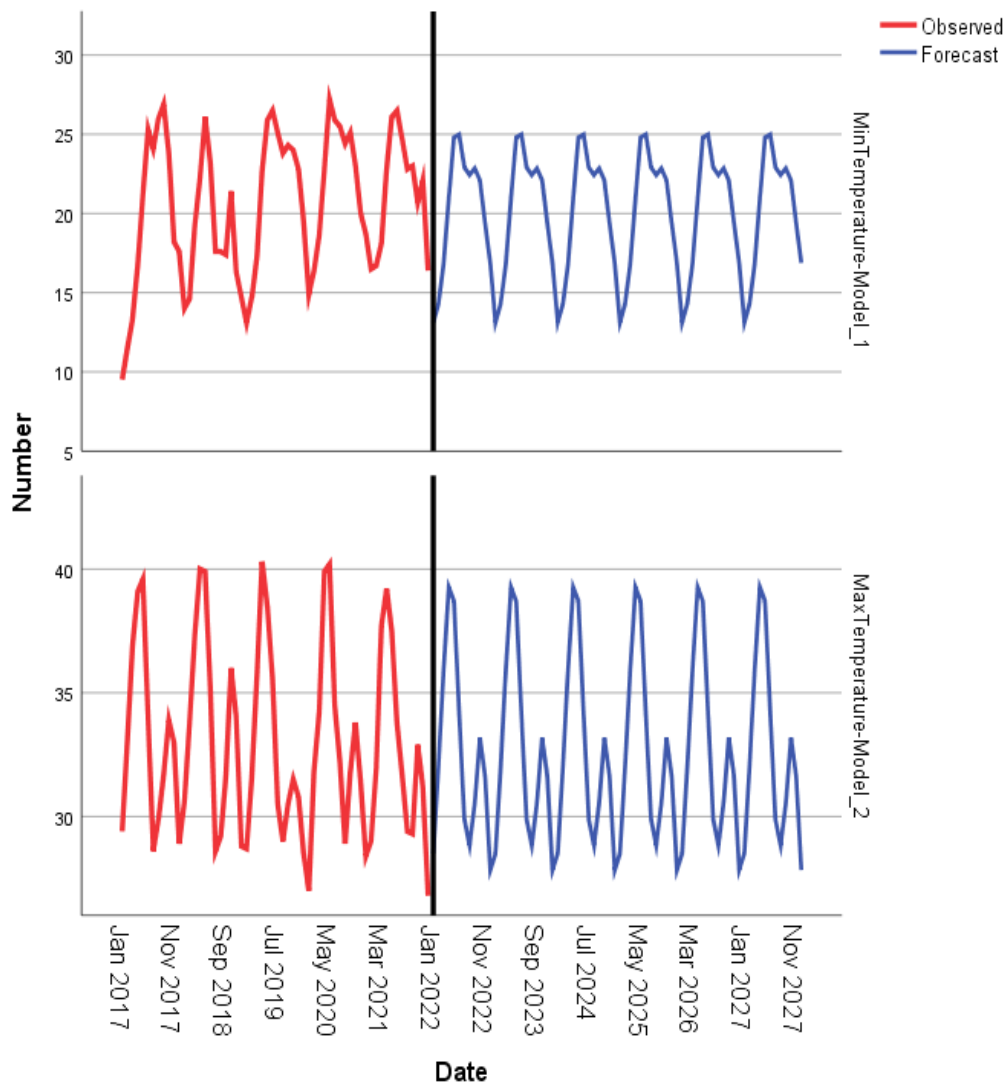
**Model Statistics**

Model	Model Fit statistics				
	MAE	MaxAPE	MaxAE	Normalized BIC	Statistics
Min Temperature-Model_1	1.165	23.524	4.622	1.111	17.773
Max Temperature-Model_2	.825	7.904	2.290	.235	25.618

**Model Statistics**

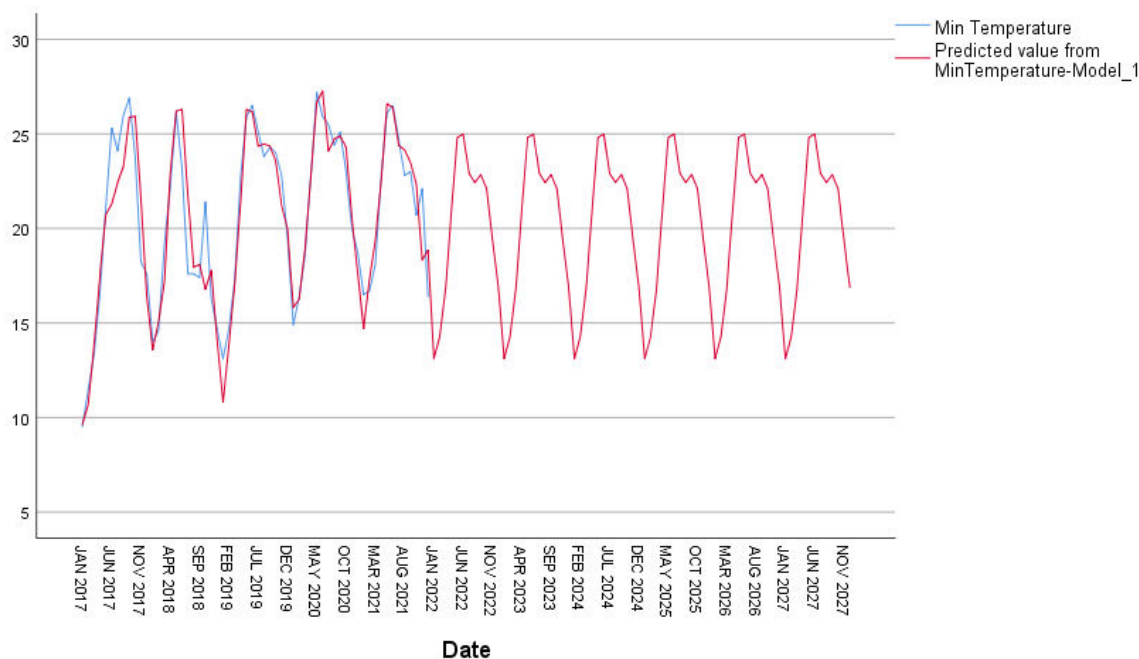
Model	Ljung-Box Q(18)	
	Sig.	Number of Outliers
Min Temperature-Model_1	.337	0
Max Temperature-Model_2	.060	0





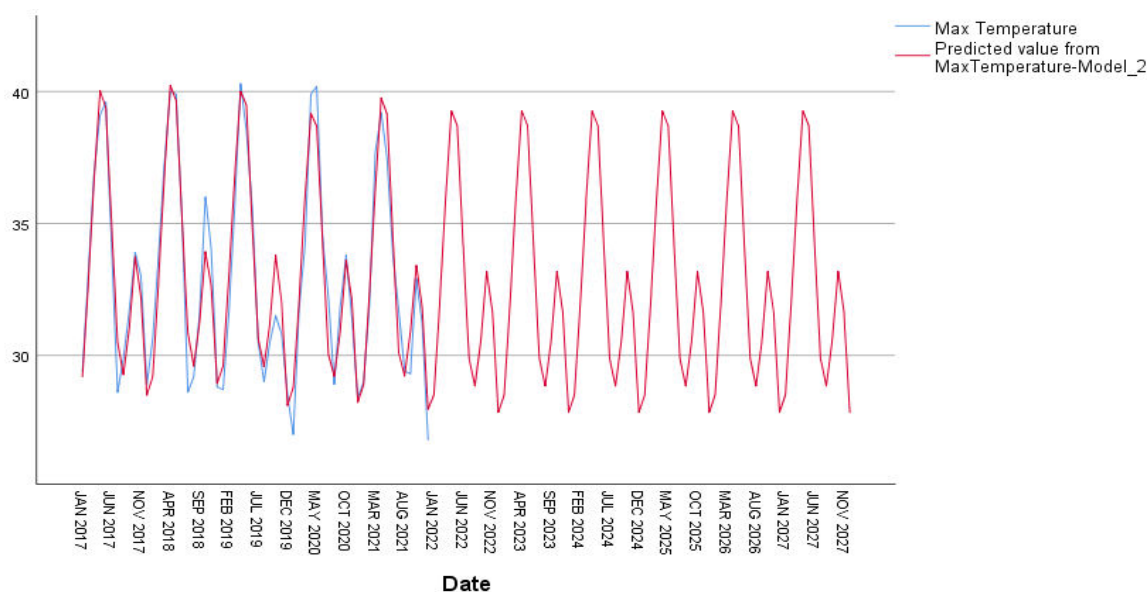
### Case Processing Summary

	Min Temperature	Predicted value from MinTemperature-Model_1
Series or Sequence Length	132	132
Number of Missing Values in the Plot	0	0
System-Missing	72	0



### Case Processing Summary

	Max Temperature	Predicted value from MaxTemperature-Model_2
Series or Sequence Length	132	132
Number of Missing Values in the Plot	0	0
	User-Missing	
	System-Missing	72
		0



**Case Processing Summary**

		Min Temperature	Max Temperature
Series Length		132	132
Number of Missing Values	User-Missing	0	0
	System-Missing	72 <sup>a</sup>	72 <sup>a</sup>
Number of Valid Values		60	60
Number of Computable First Lags		59	59

**Min Temperature****Autocorrelations**

Series: Min Temperature

Lag	Autocorrelation	Std. Error <sup>a</sup>	Box-Ljung Statistic		Sig. <sup>b</sup>
			Value	df	
1	.738	.126	34.294	1	.000
2	.365	.125	42.827	2	.000
3	-.038	.124	42.921	3	.000
4	-.302	.123	48.971	4	.000
5	-.413	.122	60.505	5	.000
6	-.412	.120	72.185	6	.000
7	-.358	.119	81.186	7	.000
8	-.232	.118	85.034	8	.000
9	-.011	.117	85.043	9	.000
10	.242	.116	89.395	10	.000
11	.433	.115	103.619	11	.000
12	.505	.114	123.386	12	.000
13	.356	.112	133.397	13	.000
14	.076	.111	133.865	14	.000
15	-.180	.110	136.558	15	.000
16	-.289	.109	143.606	16	.000

a. The underlying process assumed is independence (white noise).

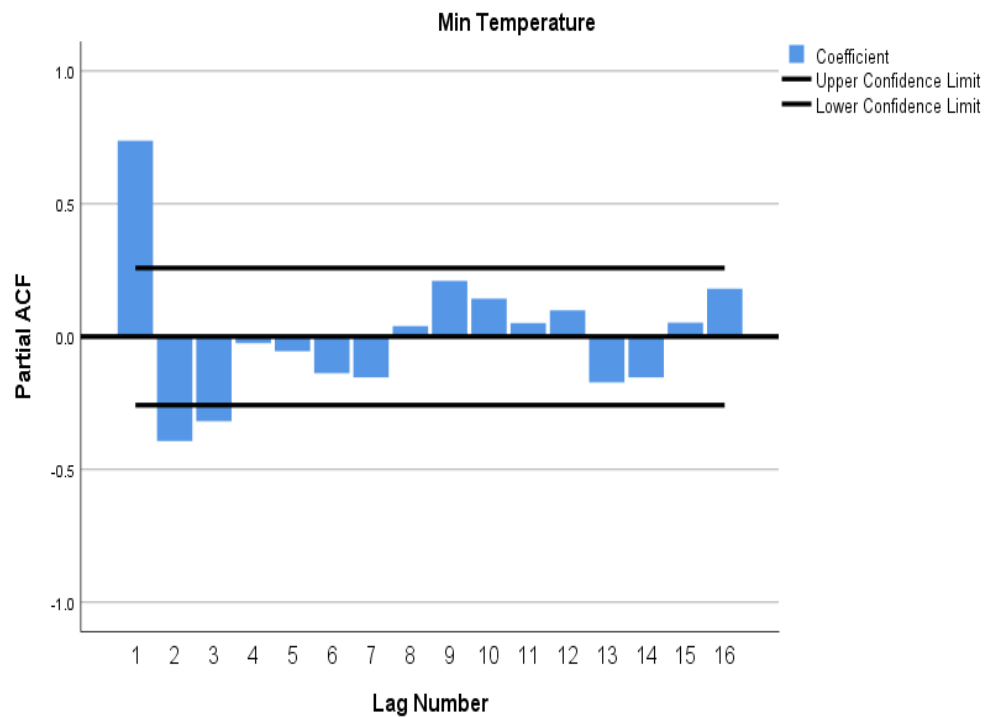
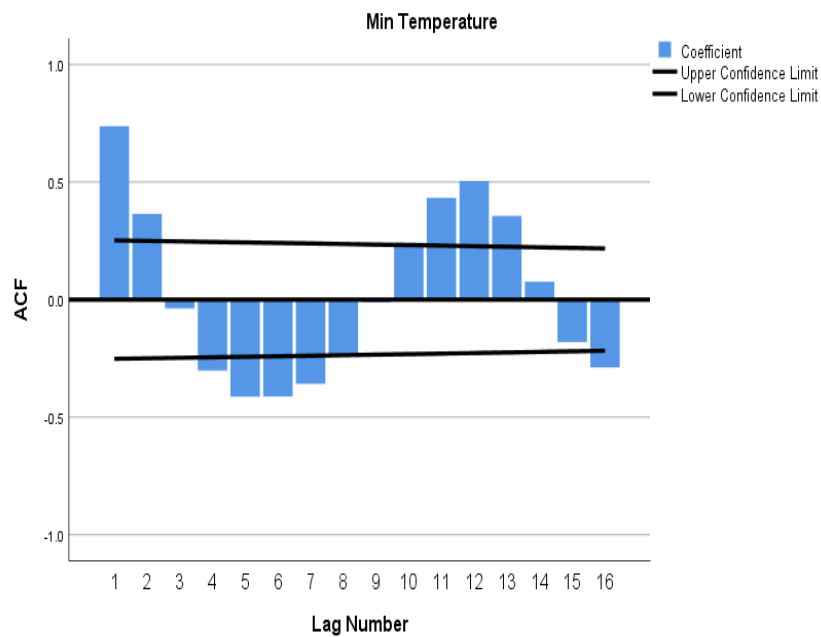
b. Based on the asymptotic chi-square approximation.



### Partial Autocorrelations

Series: Max Temperature

Lag	Partial Autocorrelation	Std. Error
1	.618	.129
2	-.617	.129
3	-.057	.129
4	.018	.129
5	.081	.129
6	-.419	.129
7	-.366	.129
8	-.239	.129
9	-.104	.129
10	.207	.129
11	.158	.129
12	.238	.129
13	-.077	.129
14	.002	.129
15	.075	.129
16	-.095	.129



**Max Temperature****Autocorrelations**

Series: Max Temperature

Lag	Autocorrelation	Std. Error <sup>a</sup>	Box-Ljung Statistic Value	df	Sig. <sup>b</sup>
1	.618	.126	24.083	1	.000
2	.000	.125	24.083	2	.000
3	-.403	.124	34.685	3	.000
4	-.417	.123	46.250	4	.000
5	-.139	.122	47.556	5	.000
6	-.003	.120	47.557	6	.000
7	-.163	.119	49.429	7	.000
8	-.392	.118	60.404	8	.000
9	-.393	.117	71.688	9	.000
10	.002	.116	71.688	10	.000
11	.512	.115	91.572	11	.000
12	.748	.114	134.964	12	.000
13	.501	.112	154.849	13	.000
14	-.004	.111	154.850	14	.000
15	-.322	.110	163.448	15	.000
16	-.324	.109	172.310	16	.000

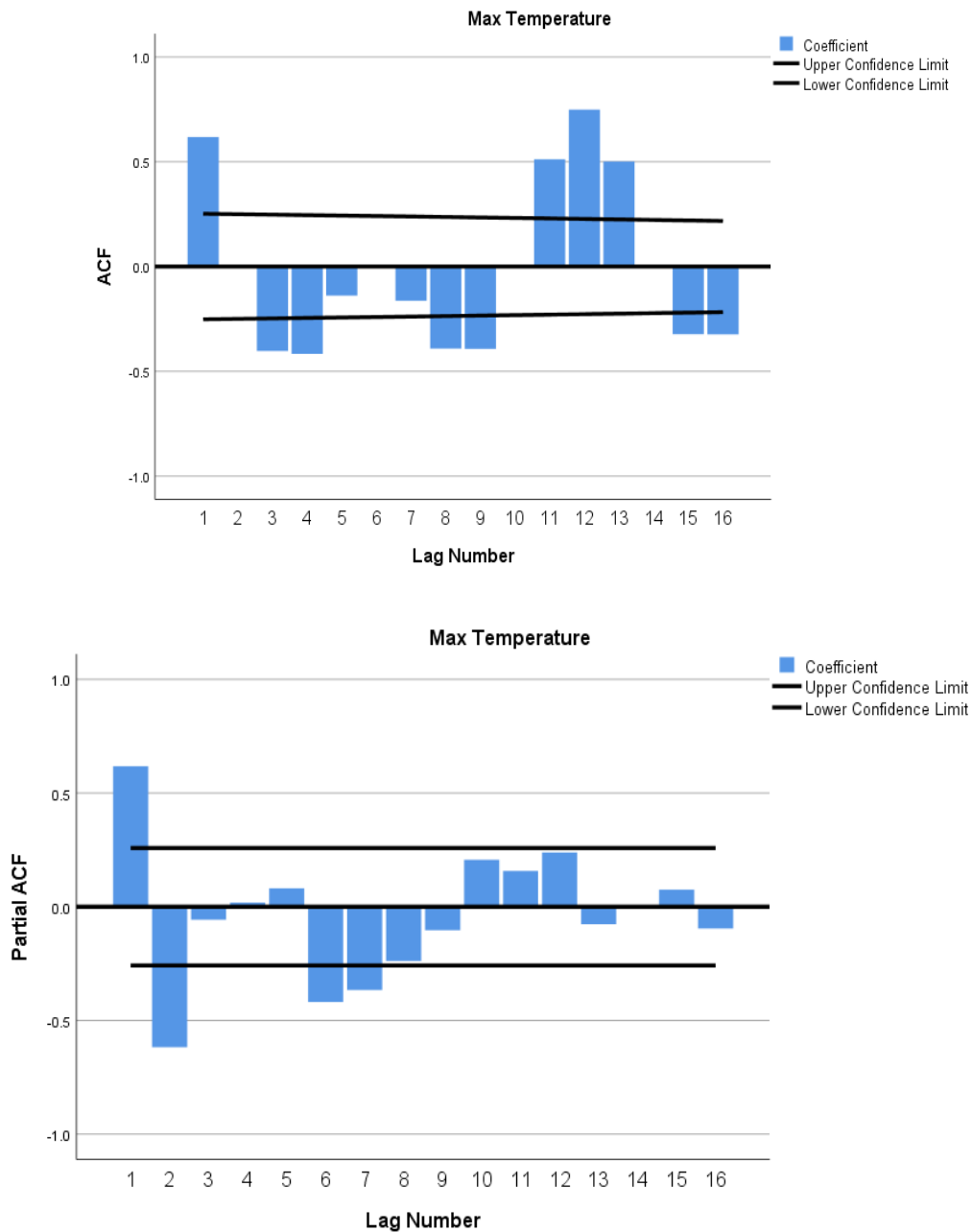
a. The underlying process assumed is independence (white noise).

b. Based on the asymptotic chi-square approximation.

**Partial Autocorrelations**

Series: Max Temperature

Lag	Partial Autocorrelation	Std. Error
1	.618	.129
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10	.207	.129
11	.158	.129
12	.238	.129
13	-.077	.129
14	.002	.129
15	.075	.129
16	-.095	.129



#### IV. DISCUSSION

The strong  $R^2$  values and comparatively low MAPE demonstrate that the Simple Seasonal model accurately reflects the recurring temperature patterns observed in Ukai. The smaller RMSE and MAPE for maximum temperatures indicate that predictions for daily highs are more precise than those for daily lows.

These forecasting insights are valuable for local agricultural planning, enabling farmers to better align their sowing and harvesting schedules with expected weather conditions. Furthermore, anticipated temperature trends can support energy management strategies, particularly in forecasting cooling requirements, and assist public health officials in preparing for potential extreme temperature events.

## V. CONCLUSION

This study effectively utilized the SPSS Expert Modeler to project monthly minimum and maximum temperatures in Ukai, Gujarat, through December 2027. The Simple Seasonal models demonstrated strong forecasting performance, accurately representing the area's characteristic yearly temperature fluctuations. These projections offer practical benefits for agricultural planning, water resource management, energy usage forecasting, and climate adaptation efforts, contributing to the region's sustainable development goals.

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