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Weather Forecasting: Using Time Series Analysis Under Different Stations Of The UK

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Abstract

Time series is a statistical tool that is used for predicting future trends based on previous trends. In this study, forecasting of three weather stations of the UK presented. For that purpose, several methods are applied to the weather station data and the best fitting model is chosen for future forecasting. For the stationarity, informal (ACF and PACF) and formal (ADF) methods were presented. A well-known technique, Box-Jenkins (ARIMA), has been implemented. The evaluation for ARIMA (Auto Regressive Integrated Moving Average) model fitting and forecasting has been done through R software using various packages. Based on the inspection of the ACF, PACF autocorrelation plots, the most appropriate orders of the ARIMA models are determined and evaluated using the AIC-criterion. In contrast to the respective models for the [1]station, ARIMA (2,0,1) and (0,1,1) for Cardiff and ARIMA (2,0,2) and (0,1,1) for Cambridge, respectively, are produced for the maximum and lowest temperatures at these stations. The annual as well as monthly analysis has been done for the validation of model. The result showed a good accordance of the projected temperature with real time data. Moreover, the ARCH/GARCH forecasting method was also presented on all three datasets. Additionally, the comparison of both ARIMA and ARCH/GARCH paradigms are presented. At the end of the study, drew a conclusion and discussed the further study gap as well.

Keywords *ARIMA modeling, Model Identification, ARCH/GARCH model.*

Introduction

Time series analysis serves two main purposes: understanding random mechanisms and forecasting future quantities based on historical data. Rainfall, monthly average temperature, and relative humidity significantly influence the likelihood of drought, impacting agriculture and economics. Weather parameter prediction aids in disaster preparedness. Linear transfer functions model relationships in time series analysis, applied to economic forecasting and quality control. Time series data comprises repeated measurements over time, from patient health monitoring to business reports on stock prices and meteorological records of wind speeds, temperature extremes, and rainfall. These diverse datasets inform decision-making across various domains (Chung et al., 2011).

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Climate change significantly impacts water resources. Predicting weather factors like precipitation, temperature, and humidity aids decision-making and risk management, optimizing water resource utilization. These variables profoundly affect hydrological cycles, crop production, and overall water usage, especially in agriculture, human endeavors, and environmental sustainability (Machiwal & Jha, 2006).

Time series, a sequential data collection, leverages human ability to perceive patterns. Tasks include content query, anomaly detection, prediction, clustering, and classification. Initially theory-driven, recent research aligns with practical applications in economics, security, genetics, medicine, and hydrology. Time series data mining illuminates' diverse real-world challenges, reflecting its evolving relevance (Esling & Agon, 2012).

Classifications of Time Series

Time series classifications hinge on criteria like time length, memory, and stationarity. Equidistant series have constant period lengths, like daily rainfall, while non-equidistant ones, like stock prices, vary. Memory distinguishes between long and short-term, affecting autocorrelation. Stationarity categorizes series as constant or varying in statistical properties over time. Forecasting in time series analysis entails model identification and future prediction, often requiring data to be stationary for accurate forecasts (Kirchgässner et al., 2012).

Components of Time Series

Time series exhibit four key components of variation:

• **Trend**: Long-term movements, like price trends in cold drinks.

• **Seasonal variation:** Predetermined patterns, seen in stock prices and exchange rates.

• **Cyclic variation:** Economic cycles, such as recessions.

• **Random variation:** Unpredictable events like floods or strikes.

These components combine mathematically in either additive or multiplicative formats.

Multiplicative Model:

$X(t) = T(t) \times C(t) \times S(t) \times R(t)$

Additive model:

$X(t) = T(t) + C(t) + S(t) + R(t)$

The multiplicative and Additive model represents time series data as the product of four components:

$T(t)$: Trend component representing long-term movements.

$C(t)$: Cyclical component depicting fluctuations due to economic cycles.

$S(t)$: Seasonal component capturing variations based on predetermined patterns.

$R(t)$: Random or irregular component representing unpredictable fluctuations. This model accounts for the interaction of these components in determining the observed values of the time series at time t.

Autocorrelation Function (ACF)

Autocorrelation Function (ACF) assesses the relationship between an observation at the current time and those at previous time points. It helps determine if the observed time series is random or exhibits a pattern. Additionally, ACF aids in identifying whether a Moving

Average (MA) model can be applied to the time series and, if so, the appropriate order of the model.

Partial Autocorrelation Function (PACF)

The correlation between observation at two-time spots given that we consider both observations are correlated to observations at other time spots. PACF provides us: Is it possible the modelling of AR model through observed time series? If yes, what will be the order?

Augmented dickey fuller (ADF) Test

It is a commonly used statistical test for the stationarity of the time series data. It belongs to the category of tests known as unit root test, this method is also check whether the data is stationary or not.

Arima Model

ARIMA is used for the modelling and forecasting of the time series data. ARIMA can measure the relationship between values in a time series data by using AR and MA approach. For the forecasting our time series data must be stationary. If time series data is stationary, then will take initial differencing to reduce the non-stationarity. By applying the method of a difference, the ARIMA model stabilizes time series data.

Model identification.

For model identification autocorrelation is very important in time series paradigm. Box-Jenkins technique recommend us model identification of ARIMA through ACF and PACF value with required differencing. Model selection criteria are guidelines that are used to choose a statistical model from a group of models based on observable data. Among the criteria for selecting a model are:

- Akaike information criteria (AIC)
- Bayesian information criteria (BIC)

Diagnostic checking

For selecting an appropriate modelling required Diagnostic, that measure a lack of fit in time series model through Ljung and Box (LB). It is a standard tool for identification of models before forecasting the data.

Objectives of study

- ARIMA models will be developed for the three temperature stations across the United Kingdom.
- Adhere to the ARCH/GARCH model specifications.
- To conduct short-term temperature forecasting on an annual basis at three specific sites within the United Kingdom.

Review of the Literature

Time series analysis involves systematically collecting data at regular intervals over a defined period. It requires extensive data to ensure reliability and accommodate seasonal variations. This method enables forecasting by leveraging past data to predict future trends, ensuring robustness in identifying patterns and trends while minimizing the impact of outliers (Brown, 2004).

Organizations leverage time series analysis to understand temporal patterns, employing data visualizations to discern seasonal trends. Time series forecasting aids in predicting future events and changes, enhancing predictive analytics. Non-stationary data, common in banking and retail, benefit from this analysis. In meteorology, time series analysis is pivotal for weather forecasting and climate change projections, utilized across various sectors and data types (Flores et al., 2012).

During the last decades, dengue viruses have spread throughout the Americas region, with an increase in the number of severe forms of dengue. The surveillance system in Guadeloupe (French West Indies) is currently operational for the detection of early outbreaks of dengue. The goal of the study was to improve this surveillance system by assessing a modelling tool to predict the occurrence of dengue epidemics few months ahead and thus to help an efficient dengue control (Gharbi et al., 2011).

The literature underscores climate change's impact on water resources, advocating for weather forecasting to inform decision-making. Key factors like precipitation, temperature, and humidity profoundly affect hydrology, agriculture, and economies. Time series analysis aids in understanding random mechanisms and forecasting. Linear transfer functions facilitate modeling for various practical applications, including economic forecasting and quality control (Cheema et al., 2011).

Various studies employ statistical models to analyze temperature and precipitation patterns across different regions. Techniques like ARIMA and SARIMA are utilized for short-term forecasting and drought prediction. These methods aid in climate zoning and anomaly detection, crucial for disaster preparedness and resource management. Studies highlight climate fluctuations and the significance of stochastic modeling for agricultural and water resource management (Lihua et al., 2010).

Material and Methods

Box-Jenkins ARIMA models: Box-Jenkins ARIMA models forecast future data points of a single time-dependent variable like temperature. Data must be stationary. Analysts eliminate variations and seasonality using moving averages, seasonal differences, and autoregressive terms. These models are valuable for understanding and predicting time series data accurately (Box et al., 2015).

The study utilizes weather variables from Abadeh Station, spanning crop years 1989–1990 to 2008–2009. After organizing distinct time series for precipitation, mean temperature, and relative humidity, the data are prepared for modeling. Time series analysis employs techniques like the (p,d,q) model, where p, d, and q represent autoregressive, differencing, and moving average values, respectively. Model selection involves assessing autocorrelation and partial autocorrelation diagrams, ensuring suitability and accuracy. If the time series is seasonal, a two-dimensional approach is adopted (Bollerslev, 1988).

The ARCH and GARCH models, short for autoregressive conditional heteroskedasticity and generalized autoregressive conditional heteroskedasticity, address volatility in time series data, crucial for risk analysis and financial decisions. Widely utilized, especially in R programming, these models provide measures like 5-standard deviation, aiding in portfolio selection and derivative pricing within financial methodologies (Liu, 2009).

Various criteria are established to compare models, ranging from prediction error to statistics derived from residuals. AIC, BIC, and SBC assess model recognition, while methods like MPE and MSE evaluate forecasting error. The best model minimizes these statistics. AIC is favored for ARIMA models, proven effective in analyzing precipitation, temperature, and humidity interactions using R programming (Jha et al., 2016).

Model Testing and Result Analysis

Comparative Analysis of Weather Conditions Across UK Cities

The initial stage in modeling time index data involves transforming non-stationary series into stationary ones. This step is crucial as many statistical and econometric methods rely on stationarity assumptions, enabling their application only to stationary time series.

Weather Condition Bradford Station

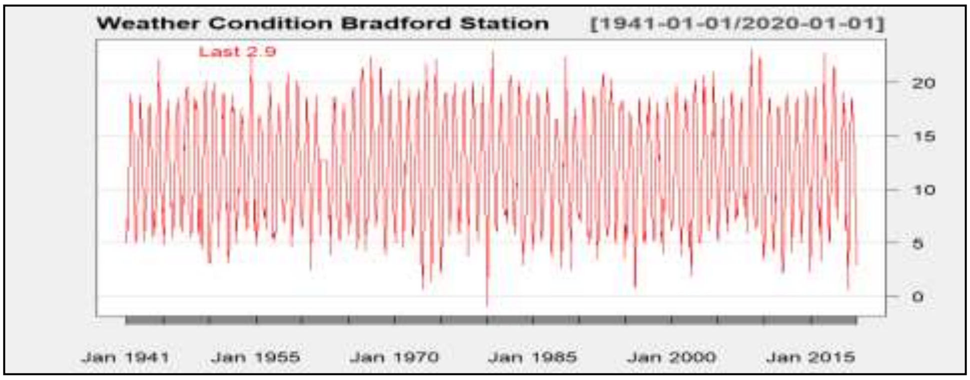

Figure 1: Time Series Plot of the Weather Condition Bradford Station.

Weather Condition Cambridge Station

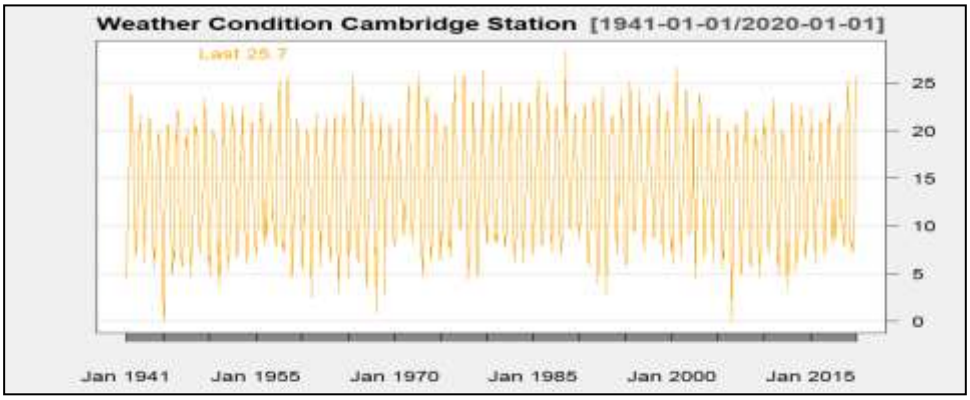

Figure 2: Time Series Plot of the Weather Cambridge Station.

Weather Condition Cardiff Station

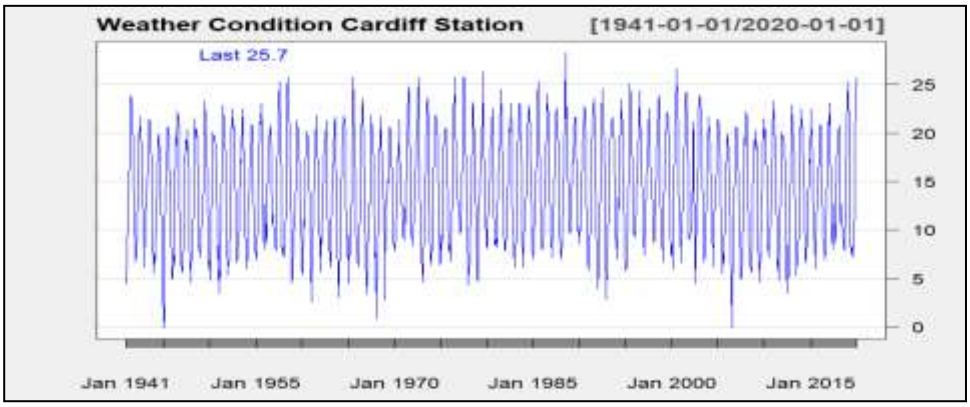

Figure 3: Time Series Plot of the Weather Cardiff Station.

Based on Figures 1, 2, and 3, it's evident there's no discernible trend in the time series, though some seasonal effects are apparent. Hence, we conclude the time series is stationary. To confirm, we conduct an Augmented Dickey-Fuller Test for stationarity.

Table.1: Augmented Dickey- Fuller Test three different station of the UK

Station	Dickey-Fuller	Lag Order	P-value
Bradford	-11.32	9	0.01
Cambridge	-9.5726	9	0.01
Cardiff	-10.303	9	0.01

In Table 1, Augmented Dickey-Fuller Tests were performed on three UK stations (Bradford, Cambridge, Cardiff) to evaluate stationarity. Results indicate low p-values (0.01), signifying significance. With p-values below the 0.05 threshold, we affirm that each station's time series is stationary, indicating stable and consistent data behavior.

ARIMA model:

ARIMA models analyze Time Series data by combining Auto Regressive (AR) and Moving Average (MA) components. The AR part predicts based on past values, while the MA part accounts for residual influences, capturing sudden variations or "shocks" in the data.

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}.$$

Plotting ACF and PACF

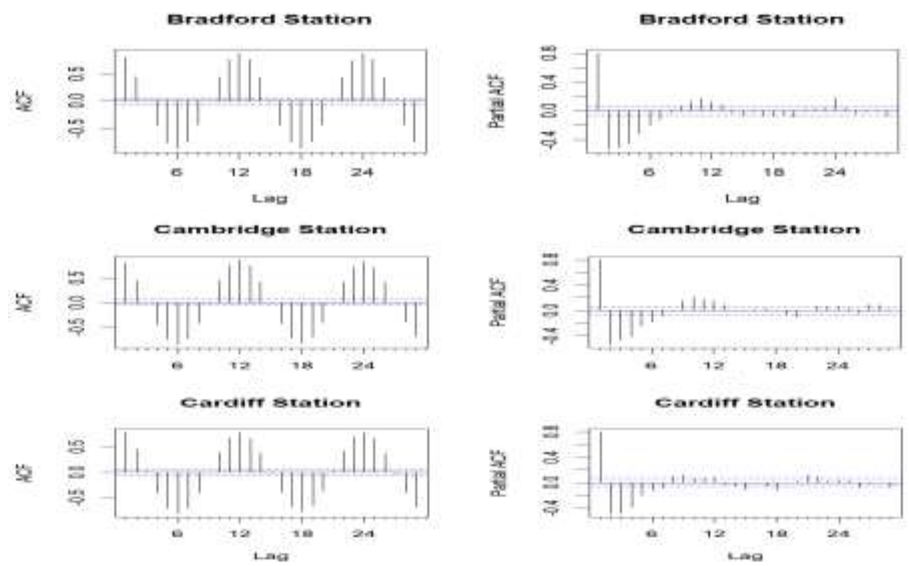

Figure 4: ACF and PACF plots of three cities of the UK

In Figure 4, correlogram analysis of Bradford station indicates an AR model, with ACF plot tailing off and PACF cutoff at lag 2, suggesting AR (2). For Cardiff and Cambridge Stations, similar patterns suggest AR (2). Additionally, ACF cutoff at lag 1 hints at MA (1). While spikes exist beyond the threshold, simplicity favors lower lags and significant spikes, like at lag 1.

Table.2: Estimated SARIMA model three different station of the UK

	Bradford Station		Cambridge Station		Cardiff Station	
Coefficients	ARIMA (1,0,0) (2,1,0)	S. E	ARIMA (2,0,2) (0,1,1)	S. E	ARIMA (2,0,1) (0,1,1)	S. E

AR (1)	0.3255	0.0310	1.6799	0.0179	1.4480	0.0453
AR (2)			-0.9486	0.0176	-0.5689	0.0302
SAR (1)	-0.7199	0.0317				
SAR (2)	-0.3140	0.0321				
MA (1)			-1.3054	0.0435	-0.8522	0.0474
MA (2)			0.5971	0.0388		
SMA (1)			-0.8730	0.0243	-0.8762	0.0176
Variance	3.35		4.253		3.793	

Table 2 presents estimated SARIMA models for three UK stations. Bradford Station's model indicates ARIMA (1,0,0) (2,1,0), while Cambridge and Cardiff Stations suggest ARIMA (2,0,2)(0,1,1). Significant coefficients include AR (1) for Bradford, AR(2) for Cambridge, and MA(1) for Cardiff. Variance values are 3.35, 4.253, and 3.793, respectively.

Table.3: Information Criteria of three ARIMA models.

Model	**AIC**	**AICc**	**BIC**
ARIMA (1,0,0) (2,1,0)	3803.	3803.9	3823.23
ARIMA (2,0,2) (0,1,1)	4037.93	4038.02	4066.98
ARIMA (2,0,1) (0,1,1)	3932.7	3932.77	3956.92

Table 3 displays the information criteria for three ARIMA models. Lower values of AIC (Akaike Information Criterion), AICc (corrected AIC), and BIC (Bayesian Information Criterion) indicate better model fit. The ARIMA (1,0,0)(2,1,0) model for Bradford has the lowest AIC, AICc, and BIC values, suggesting it provides the best goodness of fit among the

Table.4: Estimated SARIMA models accuracy.

Model	ME	RMSE	MAE	MPE	MAPE	MASE
ARIMA (1,0,0) (2,1,0)	0.0010	1.8159	1.4044	-5.2748	19.5996	0.7658
ARIMA (2,0,2) (0,1,1)	-0.0143	2.0436	1.5161	8.9244	28.9218	0.7571
ARIMA (2,0,1) (0,1,1)	0.0565	1.9311	1.4542	-1.5504	11.7526	0.6514

Table 4 provides accuracy metrics for the estimated SARIMA models. ME (Mean Error), RMSE (Root Mean Square Error), MAE (Mean Absolute Error), MPE (Mean Percent Error), MAPE (Mean Absolute Percent Error), and MASE (Mean Absolute Scaled Error) evaluate model performance. Lower values indicate better accuracy. The ARIMA (2,0,1)(0,1,1) model exhibits the lowest RMSE and MAE, suggesting it has the highest accuracy among the three models.

Five years of weather forecasts for three stations in the UK.

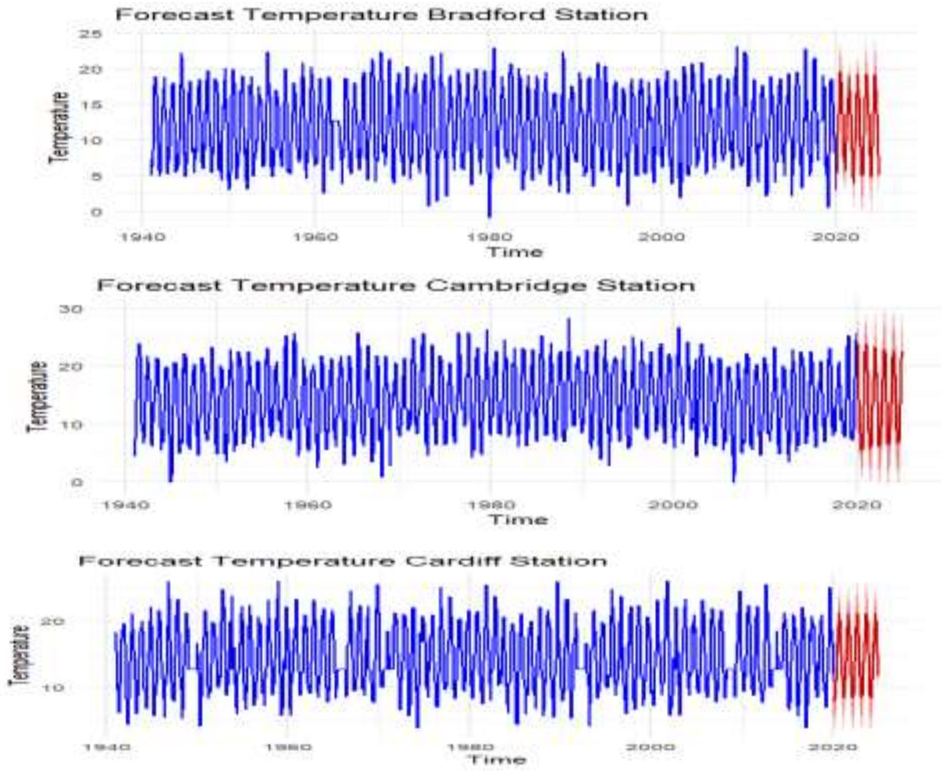

Figure 5: Forecasted Temperature three Weather Station UK.

Figure 5 illustrates the combined forecasted weather temperatures for the next five years across three UK stations. It compares the forecasted temperatures for each city over the next five years with their respective temperatures recorded during the same seasons in previous years. This comparison provides insights into the expected weather trends and variations across the selected stations.

ARCH Model

An ARCH model is very similar to ARIMA, but its CH component models the previous squared residuals at each previous point in time. We are using the term "volatility" here as a proxy for variance or squared residuals. The CH model predicts a future squared residual as part of the wider ARCH model. Below we can illustrate the two components slightly differently.

$$y_t = a_0 + a_1 y_{t-1} + \cdots + a_q y_{t-q} + \epsilon_t$$

ARCH: This is the basic expanded AR component for illustration.

Table.5: ARCH Effect check all three models.

Model	LM test	Rank-based Test	P-value
ARIMA (1,0,0) (2,1,0)	24.298	38.955	Less < 0.05
ARIMA (2,0,2) (0,1,1)	28.473	26.29	Less < 0.05
ARIMA (2,0,1) (0,1,1)	23.268	50.57	Less < 0.05

Table 5 evaluates the presence of ARCH (Autoregressive Conditional Heteroskedasticity) effects in all three models using LM and Rank-based tests. P-values less than 0.05 indicate significant ARCH effects. All models exhibit significant ARCH effects, suggesting volatility clustering in the residuals.

Conditional Heteroskedasticity

From our studies of the necessary assumptions of OLS regression, we will review the concept of heteroskedasticity.

$$\hat{\epsilon}_t^2 = \hat{\alpha}_0 + \sum_{i=1}^{q} \hat{\alpha}_i \hat{\epsilon}_{t-i}^2$$

Garch Model

Generalized Autoregressive Conditional Heteroscedasticity, or GARCH, is an extension of the ARCH model that incorporates a moving average component together with the autoregressive component.

$$\mathrm{ht} = \omega + \sum \mathrm{qi}\alpha\mathrm{ie2t} - \mathrm{i} + \sum \mathrm{p1}\beta\mathrm{iht} - \mathrm{iht} = \omega + \sum \mathrm{qi}\alpha\mathrm{ie2t} - \mathrm{i} + \sum \mathrm{p1}\beta\mathrm{iht} - \mathrm{i}$$

where hthtis variance at time t, $\mathrm{et} - \mathrm{iet} - \mathrm{i}$ is the model residuals at time $\mathrm{t} - \mathrm{i}$.

Table. 6: Estimated Coefficients GARCH effects in UK Weather Stations

UK Cities	Bradford Station	Cambridge Station	Cardiff Station
	Estimation	**Estimation**	**Estimation**
GARCH	**sGARCH (1,1) ARFIMA (1,0,1)**	**sGARCH (1,1) ARFIMA (1,0,1)**	**sGARCH (1,1) ARFIMA (1,0,1)**
Mu	12.224	13.655	
ar1	0.712	0.699	0.95
ma1	0.347	0.328	0.11
omega	0.206	0.012	0.02
alpha1	0.002	0	0.00
beta1	0.972	0.999	1.00

Table 7 presents the estimated coefficients for GARCH models across three different UK stations: Bradford, Cambridge, and Cardiff. The coefficients include Mu (mean), ar1 (autoregressive term), ma1 (moving average term), omega (constant), alpha1 (ARCH term), and beta1 (GARCH term). These coefficients characterize the volatility dynamics of the weather data in each station.

Table. 7: Test Statistics SGARCH model three different station of the UK

UK Cities	Bradford Station			Cambridge Station			Cardiff Station		
GARCH	**sGARCH(1,1) ARFIMA(1,0,1)**			**sGARCH(1,1) ARFIMA(1,0,1)**			**sGARCH(1,1) ARFIMA(1,0,1)**		
Parameters	**Std. Error**	**T**	**P**	**Std. Error**	**T**	**P**	**Std. Eror**	**T**	**P**
Mu	0.36	33.932	0	0.648	21.061	0			
ar1	0.022	33.037	0	0.037	19.153	0	0.01	86.26	0.00

ma1	0.024	14.4	0	0.04	8.276	0	0.03	3.37	0.00
omega	0.038	5.446	0	0.037	0.324	0.7	0.03	0.61	0.54
alpha1	0.006	0.335	0.737	0.003	0	1	0.00	0.00	1.00
beta1	0.004	218.79	0	0	20042	0	0.00	18528.00	0.00

Table 8 displays test statistics for SGARCH models across three UK stations: Bradford, Cambridge, and Cardiff. Parameters include Mu (mean), ar1 (autoregressive term), ma1 (moving average term), omega (constant), alpha1 (ARCH term), and beta1 (GARCH term). Test statistics such as standard error, t-values, and p-values assess the significance of each parameter. Lower p-values indicate greater significance, suggesting significant effects on volatility dynamics in each station.

Table. 8: Model Selection Criteria SGARCH model

	Bradford	**Cambridge**	**Cardiff**
AIC	4.926	5.2448	5.7753
BIC	4.9495	5.2959	5.8009
Shibata	4.926	5.2445	5.7753
Hannan-Quinn	4.9348	5.2649	5.7851

Table 8 presents model selection criteria, including AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), Shibata, and Hannan-Quinn scores, for SGARCH models across three stations: Bradford, Cambridge, and Cardiff. Lower values indicate better model fit. These criteria aid in selecting the most suitable SGARCH model for each station.

Table.9: Forecasted SGARCH models accuracy

UK Cities	**ME**	**RMSE**	**MAE**	**MPE**	**MAPE**	**MASE**	**ACF1**
Bradford Station	-0.721	2.172	1.856	-15.411	21.545	0.399	0.613
Cambridge Station	0.7949	2.1415	1.5767	6.249	11.3036	0.0705	0.8576
Cardiff Station	-0.021	2.331	1.629	Undfine	Undfine	0.765	0.002

Table 9 presents forecasted accuracy metrics for SGARCH models in three UK cities. Bradford, Cambridge, and Cardiff. Metrics include ME (Mean Error), RMSE (Root Mean Square Error), MAE (Mean Absolute Error), MPE (Mean Percent Error), MAPE (Mean Absolute Percent Error), MASE (Mean Absolute Scaled Error), and ACF1 (Autocorrelation of Residuals at Lag 1). These metrics assess the SGARCH models' performance in volatility prediction for each city.

Table. 10: Adjusted Pearson Goodness-of-Fit Test of SGARCH models

	Bradford Station		**Cambridge Station**		**Cardiff Station**	
Group	**Statistic**	**P-value**	**Statistic**	**P-value**	**Statistic**	**P-value**
20	21.27	0.32	13.33	0.82	178.70	0.00
30	29.79	0.42	25.03	0.68	207.50	0.00

40	43.77	0.28	28.95	0.88	247.00	0.00
50	41.19	0.78	44.63	0.65	255.50	0.00
Elapsed	0.71653		0.32191		0.51142	

Table 10 presents the Adjusted Pearson Goodness-of-Fit Test results for SGARCH models at three UK stations: Bradford, Cambridge, and Cardiff. The table includes statistics and p-values for various group sizes (20, 30, 40, and 50). Lower p-values indicate better model fit, suggesting the adequacy of the SGARCH models in capturing volatility dynamics at each station.

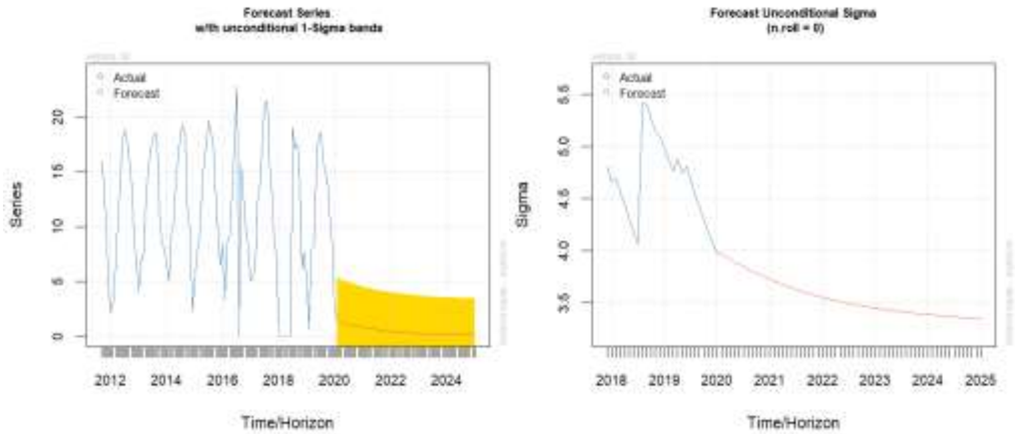

Figure 6: Forecasted Weather Series with Unconditional Sigma: Bradford.

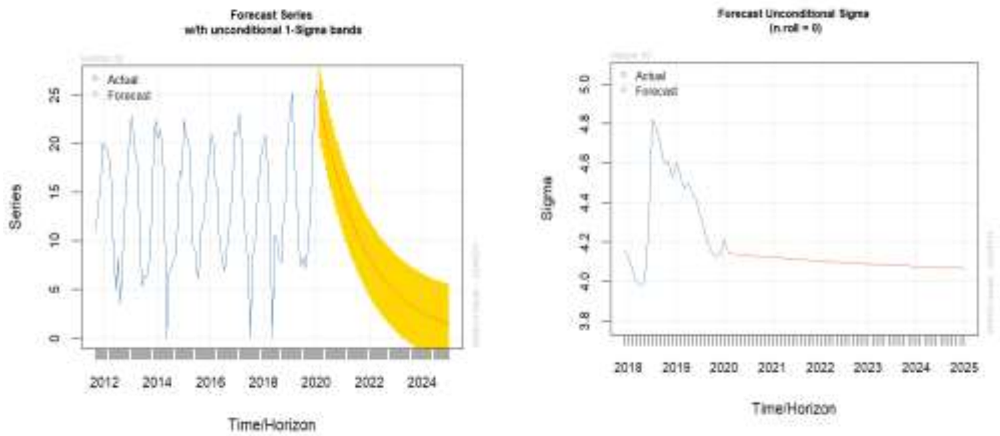

Figure 7: Forecasted Weather Series with Unconditional Sigma: Cambridge.

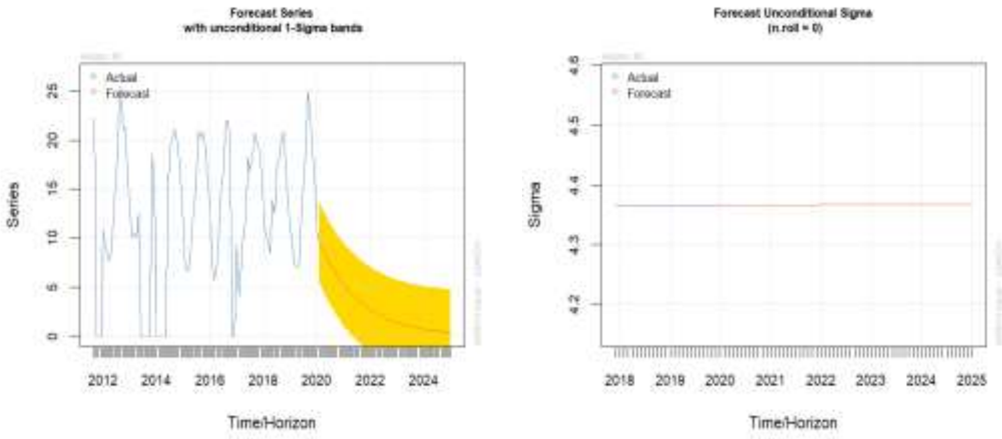

Figure 8: Forecasted Weather Series with Unconditional Sigma: Bradford.

In Figure 6, the forecasted weather series with unconditional sigma for Bradford shows a downward trend. Similarly, Figure 7 depicts forecasted downward trends for unconditional sigma in Cambridge. Figure 8 also displays forecasted downward trends for unconditional sigma in Cardiff.

Conclusion

The time domain method stands as a crucial tool in analyzing financial time series, notably in forecasting using ARIMA-ARCH/GARCH models. ARIMA, while adept at linear analysis, lacks immediacy in reflecting recent shifts, necessitating frequent parameter updates with new data. Its unconditional variance remains static, requiring series stationarity, often through transformations like log conversion.

Complementing ARIMA, ARCH/GARCH assesses series volatility, effectively modeling ARIMA's noise term. By integrating current data, it calculates conditional variances, facilitating precise future forecasts. Mixed-model forecasting intervals are narrower than ARIMA alone, enhancing accuracy.

ARCH and GARCH models find broad application, notably in finance, where risk assessment plays a pivotal role in decision-making. In asset pricing, portfolio optimization, and risk management, understanding the interplay between risk and return is paramount. This paper underscores the significance of robust risk measurement methods, providing a foundation for informed economic decisions. Through meticulous analysis, ARCH and GARCH models offer a statistical framework for testing and exhibiting various asset pricing and portfolio theories.

Recommendations

In order to validate SDSM effectively, it's imperative to consider additional parameters such as precipitation, pressure, solar radiation, and relative humidity. This comprehensive approach ensures a thorough analysis of the model's performance and enhances its predictive skills. Calculated biases from this study offer valuable insights for evaluating future scenarios generated by the model, extending the analysis to include maximum temperature as well.

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