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Seasonal Autoregressive Integrated Moving Average Model for Temperature Time Series: A case study of Larisa Greece

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ABSTRACT
Forecasting temperature variations represents a fundamental challenge within meteorology and environmental sciences. Time series analysis offers a robust statistical framework for modeling climate variables. In this research, a Seasonal Autoregressive Integrated Moving Average (SARIMA) model was deployed to analyze average monthly temperature data from Larissa, Greece, spanning the years 1988 to 2021(training set). Specifically, the SARIMA (0, 0, 2)(0, 1, 1)$_{12}$ configuration was selected, using MSD and Akaike Information Criteria (AIC's). The methodology involved model identification, parameter evaluation, and diagnostic sample checking. The presentation includes a thorough overview of model selection and forecasting precision. Finally, the optimized model, having outperformed other basic benchmark models in comparative evaluation, was utilized to generate temperature predictions for the test period from January 2022 to April 2024. (test set). The empirical results demonstrated a high quality of fit, capturing the stochastic seasonal fluctuations effectively. Consequently, the SARIMA approach proved to be a highly reliable method for modeling and forecasting monthly temperature time series.
Keywords: Time Series Analysis, Decomposition, Holt-Winters, SARIMA Model, Forecasting

1. INTRODUCTION

Climate and weather play an essential role in many aspects of everyday life and human activities. Climate change has increased the need to understand and monitor changes in weather conditions. Accurate prediction of key weather parameters, such as temperature, rainfall, and wind velocity, is therefore essential for better planning, risk management, and decision-making across various sectors. For example, accurate prediction of temperature is important for energy consumption, agriculture, health, and transportation. Rainfall forecasting supports water resource management, irrigation, agriculture, and flood prevention. Wind velocity predictions are valuable for aviation, maritime activities, renewable energy, and construction. [11,22]. Weather forecasts help individuals and organizations make safer and more informed decisions risks. Therefore, reliable forecasting of key weather parameters is essential for informed decision-making, effective planning, and improving the quality of life..

Various methods have been developed to predict these weather parameters, ranging from traditional statistical approaches to modern machine-learning techniques, aiming to improve the effectiveness and

correctness of forecasting. Among them, Time Series Analysis (Winters' Method, Box-Jenkins technique), and Machine Learning models are widely used for accurate weather forecasting [5,22]. These methods differ in their ability to capture trends, seasonality, and complex patterns, making their comparison essential for identifying the most accurate approach for weather forecasting.

Autoregressive Integrated Moving Averages, ARIMA (p, d, q), models are commonly used to study trends and patterns in time-series data, but they may not perform well when the data contains regular seasonal variations, such as temperature data [19]. Seasonal Autoregressive Integrated Moving Average (SARIMA) models address this limitation by combining non-seasonal trends with seasonal patterns. The model is represented as SARIMA$(p,d,q)(P,D,Q)_s$, where the parameters (p,d,q) describe the non-seasonal and $(P,D,Q)_s$ the seasonal components of the time series, s the number of periods per season. This methodology has become a fundamental benchmark in climate and weather forecasting due to its robustness in handling and stabilizing high-variance seasonal fluctuations. [1,16]. For monthly temperature data with a yearly seasonal cycle, the seasonal period is set to (s=12). After making the series stationary through appropriate variance transformation and differencing (I), the model parameters (p,q,P,) and (Q) are initially identified using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The uppercase parameters (P), (D), and (Q) represent the orders of the seasonal autoregressive (AR), seasonal differencing (I), and seasonal moving average (MA) components, respectively. Finally, diagnostic tests are applied to evaluate the adequacy of the selected model and ensure that it can provide reliable temperature forecasts.

Several studies have employed Seasonal Autoregressive Integrated Moving Average (SARIMA) models to characterize, model, and forecast meteorological variables. These models are particularly suitable for weather-related time series because they can account for both temporal dependencies and recurring seasonal patterns in the observed data. Emmanuel Ayitey et al. (2021) [2], used the relatively simple seasonal model $(1,0,0)\ (1,0,0)_{12}$ to forecast the monthly temperature in Ghana's northern region (data from January 1990 to December 2020). Larry M. Ichon Jr et al. (2023) [10] analyzed the monthly mean temperature in Davao Oriental, Philippines from 2010 to 2022 using a $(0,1,3)(2,0,0)_{12}$. SARIMA model. The study does not establish a long-term climate-change trend by itself; rather, its main contribution is demonstrating the usefulness of SARIMA for short-term/seasonal temperature forecasting. Kabbilawsh et al. (2020) [12] applied SARIMA models to forecast monthly mean temperature (data from 1970-2016) using the Box–Jenkins methodology, in Kerala India. The study considered two hydroclimatic variables, namely minimum and maximum temperature, across four NEI stations. Kerala has a tropical climate characterized by strong seasonal variations associated particularly with the southwest and northeast monsoons. Temperature is important for agriculture, water resources, public health, energy demand, and hydrological modelling. The results indicated that the most appropriate SARIMA model structure varied among the stations, highlighting the presence of spatial variability in the temporal characteristics of the observed climate variables. One of the most important findings of the paper is that: $(2,1,1)\ (1,1,1)_{12}$ was identified as the ideal forecasting model for eight of the fourteen temperature time series**.** Gangshetty, et al. (2021)[9] used the SARIMA$(1,1,1)(1,1,1)_{12}$ model to forecast temperature in Pune, Maharashtra, India using meteorological observations collected from 2009 to 2020. The model was evaluated using forecasting error measures and achieved an MAE of 0.60850°C and an RMSE of 0.76233°C, substantially lower than those obtained from the conventional ARIMA model. The authors concluded that SARIMA provided more accurate temperature forecasts because it was able to account for both temporal dependence and seasonal variation in the temperature series. Chen et al. (2018)[6] applied the SARIMA$(1,1,1)(1,0,1)_{12}$ model (lowest reported AIC value of −2754.63) for forecasting monthly mean temperature in Nanjing, China (observations from 1951 to 2017). The forecasting performance of the model was subsequently evaluated using observations from 2015–2017. The reported mean squared errors were 0.84 for 2015, 0.89 for 2016 and 0.94 for 2017, with an overall MSE of approximately 0.89. The authors therefore concluded that SARIMA provides an effective and reasonably accurate approach for forecasting monthly temperature in Nanjing. Moreover, Datong and Goltong (2017) [7] applied ARIMA/SARIMA models to monthly temperature, rainfall and wind-velocity observations from Heipang

Airport, Jos Plateau, Nigeria (data interval 2011-2016). Their results demonstrated that temperature exhibited sufficient temporal and seasonal dependence to be effectively modelled using SARIMA$(1,0,0)(0,1,1)_{12}$, which produced a relatively low residual variance of 1.87. In contrast, the rainfall model, SARIMA$(0,0,0)(2,2,0)_{12}$, had a substantially larger variance of 2230, indicating greater uncertainty in rainfall forecasting. Wind velocity was found to resemble white noise and was therefore not modelled using ARIMA. The study demonstrates the importance of examining stationarity, autocorrelation and seasonality before selecting an appropriate time-series forecasting model. Kibunja et al. (2014) applied the (SARIMA) model to forecast precipitation in the Mt. Kenya region of Kenya using historical precipitation data (from 1995 up to 2010) obtained from the Kenya Meteorological Department. Three tentative SARIMA models were evaluated, and SARIMA$(1,0,1)(1,0,0)_{12}$ was selected based on the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. The selected model achieved ME, MSE, RMSE, and MAE values of −0.00537, 0.96794, 0.98384, and 0.75197, respectively. The authors concluded that SARIMA provided a suitable approach for forecasting precipitation in the Mt. Kenya region and demonstrated its potential for supporting climate-sensitive activities such as agriculture and water-resource management [13]. Wang et al. (2012) investigated the use SARIMA$(1,0,1)(0,1,1)_{12}$ model for forecasting monthly precipitation (observations covering the period 1961–2011). The authors reported that the selected model fitted the historical precipitation data well and successfully represented stochastic seasonal fluctuations, concluding that SARIMA provides an appropriate statistical approach for modelling and forecasting monthly precipitation [21].

Figure 1: Left: Thessaly region, Right: Greece and Larisa.

Larissa is a city in central Greece (6th in rank), with a population of approximately 165,000 people, and the capital of the Thessaly region. Its strategic geographical location is particularly important, as it is situated in the center of the country. Thessaly is one of Greece's most important agricultural regions. Its fertile plains produce crops such as wheat, cotton, corn, and vegetables. Its climate exhibits the characteristics of the continental climate of the lowland Thessaly region, with annual differences between maximum and minimum temperatures exceeding 22°C. The mean annual temperature is 15.7°C, while the average annual precipitation in the city ranges from approximately 425 mm. There was a major storm (Daniel) occurred there in early September 2023, (especially September 5–9, 2023). The flood damaged homes, roads, farmland, and other infrastructure. It disrupted daily life and created serious risks for local communities. A total of 17 direct deaths has been attributed to the storm. In addition, a scientific study [22] examining the broader health impacts of the disaster estimated 335 excess deaths in the affected areas during the 90 days following the flooding. This event shows why accurate weather predictions are important for early preparation and safety.

2. MATERIALS AND METHODS

2.1 Seasonal ARIMA Model

The general structure of a multiplicative SARIMA (p,d,q) $(P,D,Q)_s$ model [21] formulated utilizing the lag (backshift) operator B, defined by $B^kX_t=X_{t-k}$. is expressed as follows:

$$\varphi_p(B)\Phi_P(B^s)\nabla^d\nabla_s{}^DX_t = \theta q(B)\Theta_Q(B^s)\epsilon_t \qquad (1)$$

$\phi_p(B)$: non-seasonal **AR(p)** polynomial: $\phi_p(B)=1-\phi_1B-\phi_2B_2-\cdots-\phi_pB_p$

$\Phi_P(B^s)$: seasonal **AR(P)** polynomial: $\Phi_P(B^s)=1-\Phi_1B^s-\cdots-\Phi_PB^{Ps}$

$\nabla^d=(1-B)^d$: non-seasonal differencing of order d.

$\nabla_s{}^D=(1-B^s)^D$: seasonal differencing of order D, with seasonal period s.

$\theta_q(B)$: non-seasonal **MA(q)** polynomial: $\theta_q(B)=1+\theta_1B+\cdots+\theta_qB_q$

$\Theta_Q(Bs)$: seasonal **MA(Q)** polynomial: $\Theta_Q(B^s)=1+\Theta_1B^s+\cdots+\Theta_QB^{Qs}$

ϵ_t: white-noise error term.

2.2. Source Data

For this study, monthly temperature data from Larisa, Greece gathered for time period 1/1988-4/2024. Data from 1/1988-12/2021 were used as training set (fitting performance) and data from 1/2022-4/2024 as test set for the evaluation of the prediction performance of the chosen Sarima model used to assess the temperature change in the city (Thessaly Region). Basic characteristics for Larisa weather station are summarized in Table 1.

Table 1. Basic characteristics for Larisa station

Date provision Year	Longitude	Latitude	Mean tem(°C)
1952	22.97	40.53	15.501

2.3 Stationarity of the model-differencing

Prior to conducting the analysis, the time series must be stationary, meaning that its mean and variance remain constant over time. Stationarity is a fundamental requirement for ARIMA models and represents one of their potential limitations [18]. The time series under analysis is assumed to have a constant variance over time. Therefore, the series is considered stationary with respect to its variance, and no Box–Cox [4] or other variance-stabilizing transformation is required prior to the subsequent time-series analysis (see and Figure 2). However, it may still display non-stationarity in terms of its mean level or autocorrelation structure. A primary approach for diagnosing this stationarity is through its time plot, where any underlying trend or seasonal pattern may become apparent, serving as a clear indication of its non-stationary nature.

From the time plot (Figure 2), it is evident that the temperature series exhibits strong seasonality and a slight upward trend; therefore, it cannot be considered stationary. Moreover, signs of non-stationarity are: (I) the values are not clustered around the mean (non-stationarity in the mean). (II) the variance is not constant over time (small oscillations, we ignore them) (III) the values of the time series at "nearby" time points differ only slightly (there are high correlations for small lags).

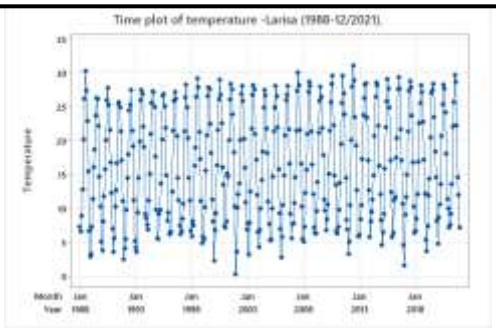
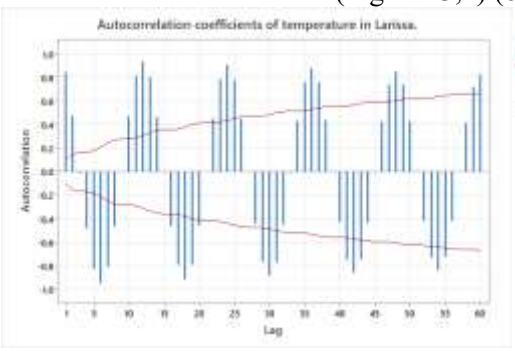


Figure 2: Time plot of temperature -Larisa (1988-12/2021).

A second approach to examining the stationarity of a t.s. is through its autocorrelation diagram (correlogram), which plots the autocorrelation coefficient for each lag of order (k). The function defined in this manner is called the Autocorrelation Function (ACF) and is instrumental in determining the order of the potential models that correspond to the given time series. If the autocorrelation coefficients "decay slowly toward zero" (remaining statistically significant), it serves as an indication of non-stationarity, whereas an exponential or sinusoidal rapid convergence indicates stationarity. Furthermore, the approximate 95% confidence bounds, given by ± 1.96/√T, are based on the asymptotic normality of the estimated autocorrelation coefficients.

The non-stationarity, for our data, can also be observed from the autocorrelation and partial autocorrelation coefficients of the time series (Figures 3,4) (60 lags) and tables 1,2 (10 lags).

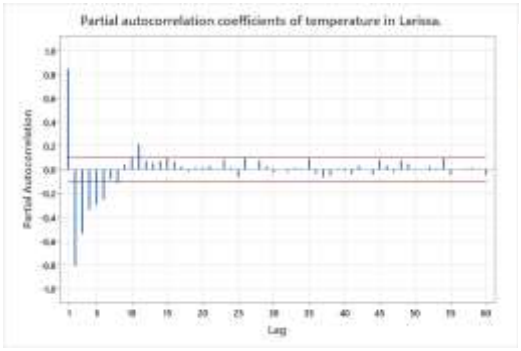


Autocorrelations

Lag	ACF	T	LBQ
1	0,842409	17,02	291,67
2	0,475543	6,18	384,85
3	-0,010018	-0,12	384,89
4	-0,482427	-5,75	481,26
5	-0,821488	-9,08	761,37
6	-0,940999	-8,78	1129,84
7	-0,806008	-6,41	1400,84
8	-0,461424	-3,35	1489,88
9	0,006406	0,05	1489,90
10	0,471129	3,33	1583,19

Figure 3: Autocorrelation coefficients of temperature in Larissa.

Table 2: Autocorrelation coefficients of temperature in Larissa (10 lags).



Partial Autocorrelations

Lag	PACF	T
1	0,842409	17,02
2	-0,806313	-16,29
3	-0,535386	-10,81
4	-0,337668	-6,82
5	0,291732	5,89
6	-0,249218	-5,03
7	-0,080393	-1,62
8	-0,110841	-2,24
9	0,043914	0,89
10	0,103823	2,10

Figure 4: Partial autocorrelation coefficients of temperature in Larissa.

Table 3: Partial autocorrelation coefficients of temperature in Larissa (10 lags).

In Figure 3 (or Table 2**),** we observe that the autocorrelation coefficients do not "decay exponentially to zero"**.** They are statistically significant, i.e. their values lie outside the significance bounds, with *t*-values greater than 2-which is an indication of the non-stationarity of the series. The conclusions regarding the partial autocorrelation coefficients are analogous.

A third method for testing stationarity involves utilizing two statistical tests. (I) The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test evaluates whether a time series is stationary around a deterministic trend (trend-stationary) [14]. Specifically, it examines trend stationarity by testing whether the series reverts to a constant mean or to a deterministic trend over time. If the series is trend-stationary, it implies that after removing the trend, the residuals are stationary. If not, it suggests that the series contains a unit root, rendering it non-stationary. (II) The Augmented Dickey-Fuller (ADF) test statistic is tests the presence of a unit root in a time series dataset, assisting in determining whether the series is stationary or non-stationary [8,17]. A unit root indicates that the series is non-stationary, meaning that its statistical properties (mean, variance, autocorrelation) change over time.

The non-stationarity of the time series can also be confirmed using the Augmented Dickey–Fuller (ADF) test (Table 4), which is not statistically significant in this case ($t = -1.48645$, p-value = 0.128).

Augmented Dickey-Fuller Test

Null hypothesis: Data are non-stationary
Alternative hypothesis: Data are stationary

Test Statistic	P-Value	Recommendation
-1,48654	0,128	Test statistic > critical value of -1,94169. Significance level = 0,05 Fail to reject null hypothesis. **Consider differencing** to make data stationary.

Table 4: Augmented Dickey–Fuller Test for the temperature time series of Larissa.

Since the time series of the temperature is not stationary and exhibits strong seasonality, we construct the time series of the first seasonal differences (differencing):

$$D_t = y_t - y_{t-12} = \left(1 - B^{12}\right) y_t, \; t = 1, 2, \ldots$$

where B is the lag operator (the lag operator is defined by: $By_t = y_{t-1}$, $B^d y_t = y_{t-d}$). That is, we calculate the difference between the value for a given month and the corresponding value for the same month in the previous year.

The time plot of the seasonal differences series is shown in Figure 5. Although seasonality has been largely eliminated from the t.s. and its values oscillate around a mean value, they exhibit some fluctuations (outliers). Ignoring these, the series could be characterized as stationary. Consequently, taking standard 1st order differences of the seasonal differences series is not required.

Table 5: Time series of seasonal differences D_t of the temperature in Larissa.

	C1-D Date	C2 Temperature	C3 D_t
1	01/1988	7,29	*
2	02/1988	6,59	*
3	03/1988	8,91	*
4	04/1988	12,77	*
5	05/1988	20,18	*
6	06/1988	26,16	*
7	07/1988	30,29	*
8	08/1988	27,33	*
9	09/1988	22,92	*
10	10/1988	15,51	*
11	11/1988	6,66	*
12	12/1988	2,88	*
13	01/1989	3,27	-4,02
14	02/1989	7,30	0,71
15	03/1989	11,34	2,43
16	04/1989	16,04	3,27
17	05/1989	18,69	-1,49

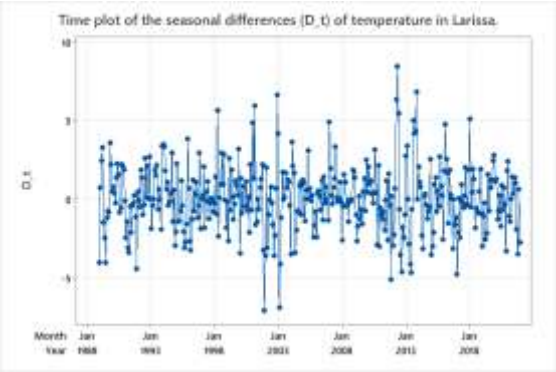
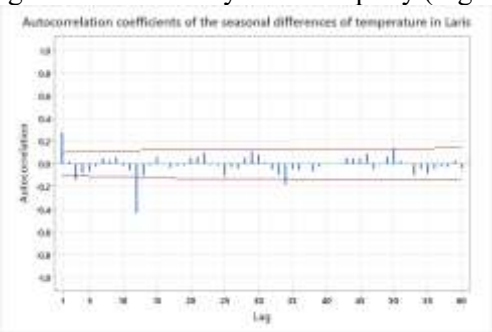


Figure 5: Time plot of the seasonal differences (D_t) of tem5perature in Larissa.

This conclusion can also be observed from the autocorrelation plot. Apart from the autocorrelation coefficient at lag 1 (and possibly lag 3) and lag 12 (seasonal), the remaining coefficients are statistically non-significant and decay to zero rapidly (Figure 6).



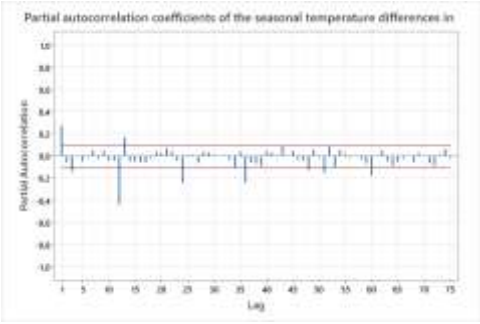


Figure 6: Autocorrelation coefficients of the seasonal differences of temperature in Larissa.
Figure 7: Partial autocorrelation coefficients of the seasonal temperature differences in Larissa.

Similar results are obtained from the partial autocorrelation coefficients (Figure 7). Here, statistically significant coefficients (besides lag 1) are those at lags 12, 24, 36, 48, and 60 (five in total)-specifically, those related to the periodicity order of the time series. The stationarity of the seasonal differences time series is supported by the Augmented Dickey-Fuller Test (Table 6).

Augmented Dickey-Fuller Test

Null hypothesis:	Data are non-stationary
Alternative hypothesis:	**Data are stationary**

Test Statistic	P-Value	Recommendation
-12,1479	0,000	Test statistic <= critical value of -2,86892. Significance level = 0,05 Reject null hypothesis. Data appears to be stationary, **not supporting differencing.**

Table 6: Augmented Dickey-Fuller Test for the seasonal differences time series.

3. RESULTS

In order to identify our stochastic $\mathrm{ARIMA}(p,d,q)(P,D,Q)_{12}$ model we follow the 4 stages below.

Stage 1: Model Identification

- We considered the time series of seasonal differences, so D = 1.
- We did not proceed with any additional differencing, therefore d = 0.
- From the table of autocorrelation coefficients of the seasonal differences, it can be observed that, among the seasonal lags of order 12, 24, 36, etc., only the coefficient at lag 12 is significant. Therefore, Q = 1, which corresponds to a seasonal moving average model SMA(1). Looking at the coefficients of the non-seasonal component, the first three (at most) coefficients are significant, indicating q = 3, corresponding to a non-seasonal moving average model MA(3). In this case, we assume that p = P = 0. [3]
- From the table of partial autocorrelation coefficients of the seasonal differences, if we examine the seasonal lags of order 12, 24, 36, 48, 60, etc., we observe that they are significant and therefore we could consider P = 5 and an AR(5) model, but this would be a relatively complex model. If we examine the coefficients of the non-seasonal component, the first three (at most) are significant, indicating p = 3, corresponding to an AR(3) model. In this case, we assume that q = Q = 0. [15]

When selecting a model, we prefer: (I) models with fewer coefficients, as they are easier to estimate; (II) MA models over AR models, since the former are stationary; (III) the model that produces the lowest

MSD; (IV) one could select models using (only) information criteria (AIC, AICc, BIC). In addition, the statistical significance of the model coefficients also plays an important role.

Therefore, the model we selected is SARIMA $(p,d,q)(P,D,Q)_{12}$ = SARIMA $(0,0,3)(0,1,1)_{12}$

Stage 2: Model Estimation

The estimation of the coefficients/parameters of a (stationary) model is achieved through one of the following approaches (computationally and mathematically intensive): (a) **Method of moments:** the coefficients are computed using the Yule-Walker equations. This method is suitable for low-order models. (b) **Least squares method:** The well-known method typically encountered in multiple regression, which in this context is appropriate only for pure AR models. (c) **Maximum likelihood method:** A complex approach because it requires solving systems of non-linear equations, making the use of appropriate software essential.

With the help of Minitab, we will attempt to determine the mathematical expression of the model, i.e., the coefficients of its defining equation. The method used for their determination is The Maximum likelihood.

Table 7: Parameters and statistics of the SARIMA $(0,0,3)(0,1,1)_{12}$ model.

Final Estimates of Parameters

Type	Coef	SE Coef	T-Value	P-Value
MA 1	-0,3740	0,0505	-7,41	0,000
MA 2	-0,1216	0,0532	-2,29	0,023
MA 3	0,0759	0,0503	1,51	**0,132**
SMA 12	0,9380	0,0252	37,25	0,000

Residual Sums of Squares

DF	SS	MS
392	858,191	2,18926

Back forecasts excluded

Modified Box-Pierce (Ljung-Box) Chi-Square Statistic

Lag	12	24	36	48
Chi-Square	12,14	15,46	34,82	44,82
DF	8	20	32	44
P-Value	0,145	0,750	0,335	0,437

From Table 7, we can see that the MA(3) coefficient is not statistically significant (p-value = 0.132 > 0.05), so it should be removed. Therefore, we will consider the following model:

SARIMA $(0,0,2)(0,1,1)_{12}$. In this case, we obtain the following results.

Table 8: Parameters and statistics of the SARIMA $(0,0,2)(0,1,1)_{12}$ model.

Final Estimates of Parameters

Type	Coef	SE Coef	T-Value	P-Value
MA 1	-0,3902	0,0499	-7,82	0,000
MA 2	-0,1467	0,0496	-2,96	0,003
SMA 12	0,9424	0,0246	38,38	0,000

Residual Sums of Squares

DF	SS	MS
393	861,254	2,19149

Back forecasts excluded

Modified Box-Pierce (Ljung-Box) Chi-Square Statistic

Lag	12	24	36	48
Chi-Square	14,79	17,88	37,10	46,54
DF	9	21	33	45
P-Value	0,097	0,656	0,285	0,409

Additionally, we will examine the SARIMA $(0,0,1)(0,1,1)_{12}$ model.

Table 9: Parameters and statistics of the SARIMA $(0,0,1)(0,1,1)_{12}$ model.

Final Estimates of Parameters

Type	Coef	SE Coef	T-Value	P-Value
MA 1	-0,3328	0,0474	-7,02	0,000
SMA 12	0,9444	0,0238	39,68	0,000

Residual Sums of Squares

DF	SS	MS
394	876,572	2,22480

Back forecasts excluded

Modified Box-Pierce (Ljung-Box) Chi-Square Statistic

Lag	12	24	36	48
Chi-Square	21,88	26,22	50,65	56,72
DF	10	22	34	46
P-Value	0,016	0,242	0,033	0,134

By comparing the two models above, we observe that:

(i) $(0,0,2)(0,1,1)_{12}$ gives MSD = 2.19149 (ii) $(0,0,1)(0,1,1)_{12}$ gives MSD = 2.22480

Therefore, we prefer the SARIMA $(0,0,2)(0,1,1)_{12}$ model because it has the lower MSD, although the errors are very close. The mathematical form of this model is given by the following equation, which is used to generate the model forecasts:

$$(1-B^{12})y_t = \left(1-\theta_1 B-\theta_2 B^2\right)\left(1-\Theta_1 B^{12}\right)\varepsilon_t$$

where B is the lag operator, θ_1, θ_2 are the coefficients of the MA(2) model, Θ_1 is the coefficient of the SMA(1) model, and ε_t is white noise. Here, using table 7 we get, $\theta_1 = -0,3902$, $\theta_2 = -0,1467$ και $\Theta_1 = 0,9424$. By analyzing the above equation, we obtain:

$$(1-B^{12})y_t = \left(1-\theta_1 B-\theta_2 B^2\right)\left(1-\Theta_1 B^{12}\right)\varepsilon_t \Rightarrow$$

$$y_t - B^{12}y_t = \left(1-\Theta_1 B^{12}-\theta_1 B+\theta_1\Theta_1 B^{13}-\theta_2 B^2+\theta_2\Theta_1 B^{14}\right)\varepsilon_t \Rightarrow$$

$$y_t = y_{t-12}+\varepsilon_t-\theta_1\varepsilon_{t-1}-\theta_2\varepsilon_{t-2}-\Theta_1\varepsilon_{t-12}+\theta_1\Theta_1\varepsilon_{t-13}+\theta_2\Theta_1\varepsilon_{t-14}$$

$$y_t = y_{t-12}+\varepsilon_t-\theta_1\varepsilon_{t-1}-\theta_2\varepsilon_{t-2}-\Theta_1\varepsilon_{t-12}+\theta_1\Theta_1\varepsilon_{t-13}+\theta_2\Theta_1\varepsilon_{t-14}$$

is the one used to make the model's predictions.

Table 10: Time series of seasonal differences D_t, residuals, and ARIMA model estimate

	Date	Temperature	D_t	Residuals	Fits
1	01/1988	7,29	*	*	*
2	02/1988	6,59	*	*	*
3	03/1988	8,91	*	*	*
4	04/1988	12,77	*	*	*
5	05/1988	20,18	*	*	*
6	06/1988	26,16	*	*	*
7	07/1988	30,29	*	*	*
8	08/1988	27,33	*	*	*
9	09/1988	22,92	*	*	*
10	10/1988	15,51	*	*	*
11	11/1988	6,66	*	*	*
12	12/1988	2,86	*	*	*
13	01/1989	3,27	-4,02	-0,70059	3,9706
14	02/1989	7,10	0,71	0,73247	6,3675
15	03/1989	11,34	2,43	1,01933	10,3290
16	04/1989	16,04	3,27	1,23012	14,8099
17	05/1989	19,69	-1,49	-2,25884	20,9488
18	06/1989	23,67	-2,49	-1,51668	25,1867
19	07/1989	26,27	-4,02	-0,83710	27,1071
20	08/1989	26,15	-1,16	-0,25069	26,3527

Minitab has saved, as shown in Table 10, the residuals of the model's estimates and the fitted values of the time series (only part of the output is presented). These data can be used to assess the adequacy of the model.

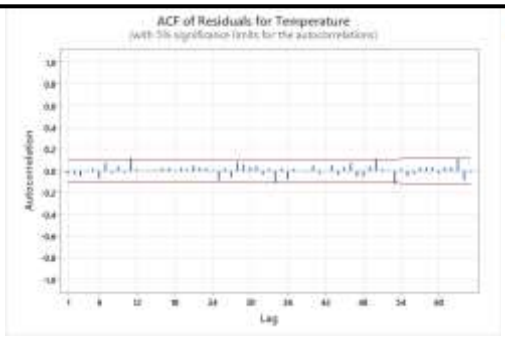
Stage 3: Model diagnostics

Following the estimation of the model parameters, it is essential to evaluate its performance via its goodness of fit. Ideally, the suitability of the model should be assessed based on outside the sample period. This requirement demands a set of (future) observations beyond those provided, which in most cases remain unknown. The standard practice is to split the available data into a "training" set, which is utilized for model identification and estimation, and a "test" set, which is reserved for evaluating the model's forecasting capability. However, the number of available observations is frequently small, necessitating that model identification, estimation, and diagnostic checking all be performed on the exact same sample. The most critical evaluation proposed by Box and Jenkins [5] is the diagnostic checking of residual randomness. The objective is to determine whether the residuals generated by the identified model constitute a white noise process.

Beyond this primary check, a variety of criteria and diagnostics exist to assist in selecting the most appropriate model. Some of these include: (a) The Principle of Parsimony: choosing the simplest model that adequately explains the data (b) Stationarity and Invertibility Conditions, estimated roots lie within the appropriate bounds (c) Goodness of Fit: the fitted model must demonstrate strong explanatory power (d) Estimated Residuals Analysis: verifying the statistical properties of the model errors.

Method A: **Residuals**

We would like to determine whether the forecasts of the time-series values, calculated using our model, are good (i.e., whether the model has a good fit). One way to assess this is to check whether the residuals are a white noise stochastic process-that is, whether they have a mean of zero and are uncorrelated. Therefore, we will examine their autocorrelation coefficients.

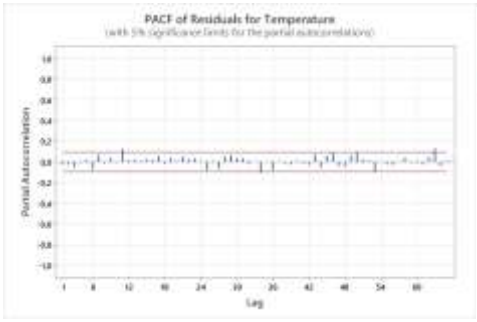


Autocorrelations

Lag	ACF	T	LBQ
1	-0,030448	-0,61	0,37
2	-0,034519	-0,69	0,85
3	-0,057114	-1,13	2,15
4	-0,005778	-0,11	2,17
5	0,019013	0,38	2,31
6	-0,072017	-1,42	4,41
7	0,081987	1,61	7,13
8	-0,012675	-0,25	7,20
9	0,036053	0,70	7,73
10	0,014496	0,28	7,81

Figure 8: Autocorrelation coefficients of ARIMA residuals, Larissa temperature.
Table 11: Autocorrelation coefficients of ARIMA residuals, Larissa temperature.

Figure 8 shows that there are no statistically significant correlation coefficients for the residuals (at any lag), which means that the residual time series is white noise (indicating our model is "good"). The results are similar for the partial autocorrelation coefficients of the residuals (Figure 9, Table 12).



Partial Autocorrelations

Lag	PACF	T
1	-0,030448	-0,61
2	-0,035479	-0,71
3	-0,059412	-1,18
4	-0,010859	-0,22
5	0,014340	0,29
6	-0,075339	-1,50
7	0,078231	1,56
8	-0,011578	-0,23
9	0,033444	0,67
10	-0,005412	-0,11

Figure 9: Partial autocorrelation coefficients of ARIMA residuals, Larissa temperature.
Table 12: Partial autocorrelation coefficients of ARIMA residuals, Larissa temperature.

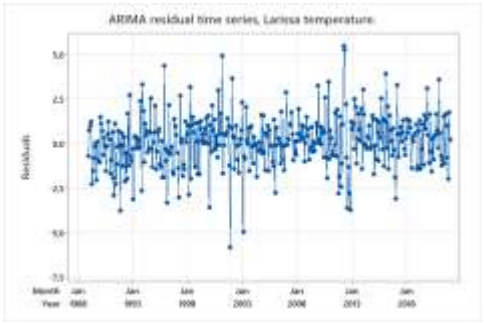


Figure 10: ARIMA residual time series, Larissa temperature.

Augmented Dickey-Fuller Test

Null hypothesis:	Data are non-stationary
Alternative hypothesis:	Data are stationary

Test Statistic	P-Value	Recommendation
-20,4452	0,000	Test statistic <= critical value of -2,86889. Significance level = 0,05 Reject null hypothesis. Data appears to be stationary, not supporting differencing.

Table 13: Augmented Dickey-Fuller Test for the residual time series.

If one constructs the residual time series (Figure 10), it becomes clear that it is a stationary time series with a zero mean and (nearly) zero correlations—meaning it behaves as white noise, although a few extreme values are present. The stationarity of the residual time series can also be confirmed using the ADF (Augmented Dickey-Fuller) test (Table 13).

Remark

For a model to be adequate, we would like the residuals to be uncorrelated (independent, if possible) and, additionally, to follow a normal distribution with a mean of zero and a constant variance. Minitab provides the following four plots

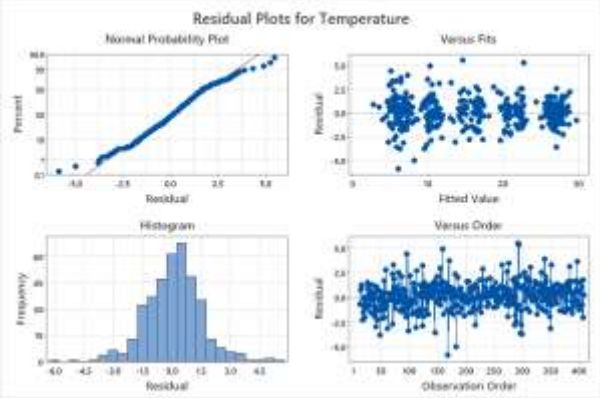


Figure 11: Model residual plots.

The interpretation of the plots (Figure 11) is as follows: (i) (1st plot), the points lie close to a straight line, the assumption of residual normality is satisfied (ii) (2nd plot), since the residuals are randomly distributed between -5 and 5 (without following any distinct pattern), the assumptions of normality and homoscedasticity (equal variances) are satisfied (iii) (4th plot), since there appears to be no relationship between the residuals and the order in which they were recorded, the errors/residuals are uncorrelated/independent.

Method B (expanded models)

A second method for verifying the "correct" identification of the time series model is estimating an expanded model-either by adding terms to the autoregressive (AR) component or to the moving average (MA) component (in either the non-seasonal or seasonal part).

For our estimated model to be satisfactory, the extra coefficients in the expanded models must be statistically insignificant.

We will examine the expanded model $\mathrm{SARIMA}(1,0,2)(0,1,1)_{12}$.

Table 14: Parameters and statistics of the $\mathrm{SARIMA}(1,0,2)(0,1,1)_{12}$ model.

Final Estimates of Parameters

Type	Coef	SE Coef	T-Value	P-Value
AR 1	-0,205	0,307	-0,67	**0,504**
MA 1	-0,590	0,300	-1,97	0,050
MA 2	-0,223	0,104	-2,15	0,032
SMA 12	0,9405	0,0249	37,77	0,000

The AR(1) coefficient is not statistically significant (p-value = 0.504 > 0.05), so this model is not preferred. Additionally, we will examine the $\mathrm{SARIMA}(0,0,2)(0,1,1)_{12}$ model:

Table 15: Parameters and statistics of the $\mathrm{SARIMA}(0,0,2)(0,1,1)_{12}$ model.

Final Estimates of Parameters

Type	Coef	SE Coef	T-Value	P-Value
MA 1	-0,3873	0,0502	-7,72	0,000
MA 2	-0,1458	0,0498	-2,93	0,004
SMA 12	0,9247	0,0511	18,08	0,000
SMA 24	0,0206	0,0529	0,39	**0,698**

The SMA 24 coefficient is not statistically significant (p-value > 0.05), so this model is not preferred.

Remark

(a) One could continue testing additional models. In almost all expanded models, the additional terms are not statistically significant. Consequently, our time series for temperature has been correctly identified as a $\mathrm{SARIMA}(0,0,2)(0,1,1)_{12}$ process.

(b) Alternatively, one could select models using (only) information criteria (AIC, AICc, BIC). The table below (using Minitab) displays the results for a series of models.

From Table 16, it is evident that, based on these information criteria, the most suitable model is SARIMA $(1,0,0)\ (0,1,1)_{12}$. However, upon further analysis of this model, although it outperforms our model $(0,0,2)(0,1,1)_{12}$ according to the information criteria, the residuals resulting from its use still exhibit autocorrelation (at lag 12, the p-value = 0.57, which is marginally insignificant) (Table 16); therefore, it is not preferred.

Table 16: Information criteria for SARIMA models.

Model Selection

Model (d = 0; D = 1)	LogLikelihood	AICc	AIC	BIC
p = 1; q = 0; P = 0; Q = 1*	**-738,01**	**1482,09**	**1482,03**	**1493,97**
p = 1; q = 0; P = 1; Q = 1	-737,73	1483,55	1483,45	1499,38
p = 1; q = 0; P = 0; Q = 2	-738,11	1484,31	1484,21	1500,14
p = 1; q = 0; P = 1; Q = 2	-737,68	1485,51	1485,35	1505,26
p = 1; q = 1; P = 1; Q = 2	-754,21	1520,64	1520,42	1544,31
p = 1; q = 1; P = 0; Q = 2	-756,42	1522,99	1522,84	1542,74
p = 1; q = 1; P = 1; Q = 1	-758,75	1527,65	1527,49	1547,40
p = 1; q = 1; P = 0; Q = 1	-760,75	1529,59	1529,49	1545,42
p = 0; q = 0; P = 0; Q = 2	-762,75	1531,56	1531,50	1543,44
.....	.....			
p = 0; q = 2; P = 0; Q = 2	-925,75	1861,66	1861,50	1881,41
p = 0; q = 1; P = 0; Q = 1	**-932,06**	**1870,18**	**1870,12**	**1882,06**
p = 0; q = 2; P = 1; Q = 1	-932,67	1875,50	1875,35	1895,26
p = 0; q = 2; P = 0; Q = 1	**-935,40**	**1878,90**	**1878,80**	**1894,73**
p = 0; q = 1; P = 1; Q = 2	-938,94	1888,03	1887,87	1907,78
p = 1; q = 2; P = 1; Q = 2	-943,52	1901,33	1901,04	1928,91
p = 1; q = 2; P = 0; Q = 1	-957,66	1925,48	1925,33	1945,24

** Best model with minimum AICc. Output for the best model follows.*

Moreover, although several of these models perform better according to the information criteria, some of their corresponding coefficients are not statistically significant. Additionally, the MSD of this model is slightly higher than that of our model (2.19719 compared to 2.19149).

Table 17: Information criteria for the $(1,0,0)(0,1,1)_{12}$ model.

Model Summary (1,0,0) (0,1,1)$_{12}$

DF	SS	MS	MSD	AICc	AIC	BIC
394	870,089	2,20835	2,19719	**1482,09**	**1482,03**	**1493,97**

MS = variance of the white noise series

Modified Box-Pierce (Ljung-Box) Chi-Square Statistic

Lag	12	24	36	48
Chi-Square	17,86	21,08	41,46	50,02
DF	10	22	34	46
P-Value	**0,057**	0,516	0,177	0,317

(c) Comparing the information criteria for the two final models (Tables 17, 18) we have selected, $(1,0,0)(0,1,1)_{12}$ and $(0,0,2)(0,1,1)_{12}$, we observe that although the first model performs better according to the information criteria, its residuals still exhibit autocorrelations; therefore, it is not preferred.

Table 18: Information criteria for the $(0,0,2)(0,1,1)_{12}$ model.

Model Summary (0,0,2) (0,1,1)$_{12}$

DF	SS	MS	MSD	AICc	AIC	BIC
393	861,254	2,19149	2,17488	1878,90	1878,80	1894,73

MS = variance of the white noise series

Modified Box-Pierce (Ljung-Box) Chi-Square Statistic

Lag	12	24	36	48
Chi-Square	21,88	26,22	50,65	56,72
DF	10	22	34	46
P-Value	**0,016**	0,242	0,033	0,134

The graphical plot of the time series, the estimates, and the residuals obtained using the $\mathrm{SARIMA}(0,0,2)(0,1,1)_{12}$ model is shown in Figure 12.

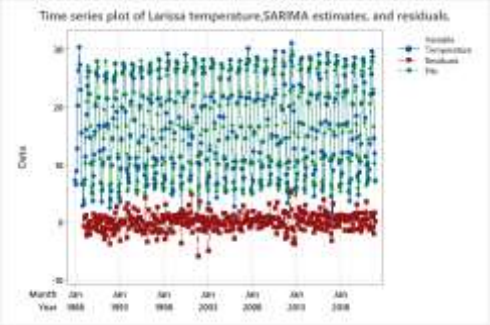


Figure 12: Time series plot of Larissa temperature,SARIMA estimates, and residuals.

4th Stage: FORECASTS

The model's forecasts for the period 1/2022–4/2024 are shown in table 19. The forecasts are also depicted in Figure 13.

Table 19: model's forecasts for the period 1/2022–4/2024

Time series forecast			
date	***Temperature (°C)***	***date***	***Temperature (°C)***
01/2022	5,68	03/2023	10,49
02/2022	7,53	04/2023	14,95
03/2022	10,49	05/2023	21,12
04/2022	14,95	06/2023	26,28
05/2022	21,12	07/2023	28,32
06/2022	26,28	08/2023	27,32
07/2022	28,32	09/2023	22,43
08/2022	27,32	10/2023	16,57
09/2022	22,43	11/2023	11,16
10/2022	16,57	12/2023	6,66
11/2022	11,16	01/2024	5,37
12/2022	6,66	02/2024	7,50
01/2023	5,37	03/2024	10,49
02/2023	7,50	04/2024	14,95

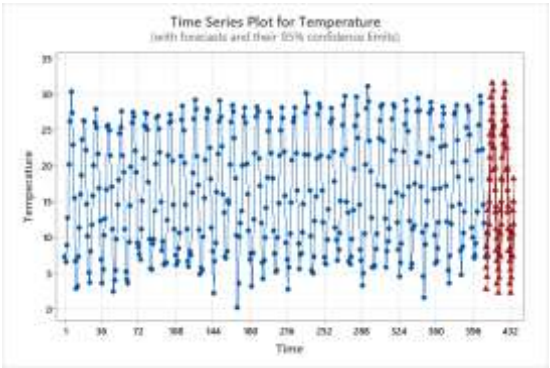


Figure 13: Time series plot of Larissa temperature and ARIMA forecasts (1/2022–4/2024).

Remark 1.

If one considers, looking at Figure 5, that the seasonal differenced time series is not stationary, or even that the residuals in Figure 10 show correlations, needs to calculate the first differences of the seasonal differenced time series-that is, the time series:

$$dD_t = D_t - D_{t-1}$$

Using this new time series, one can determine the $\mathrm{ARIMA}(p,d,q)(P,D,Q)_{12}$ model that describes the data by following a procedure like the one shown above. It is briefly outlined below.

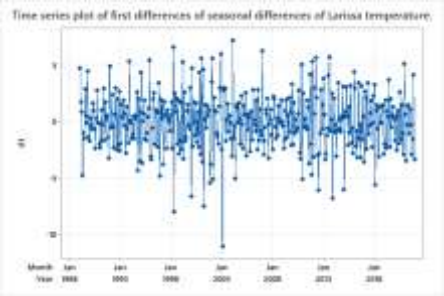


Figure 14: Time series plot of first differences of seasonal differences of Larissa temperature.

From the time series plot of the first differences of the seasonal differences (Figure 14) , we observe that the values of this time series can be considered to fluctuate around a constant mean, although they exhibit some volatility (extreme values). If these extreme values are ignored, this series could also be characterized as stationary.

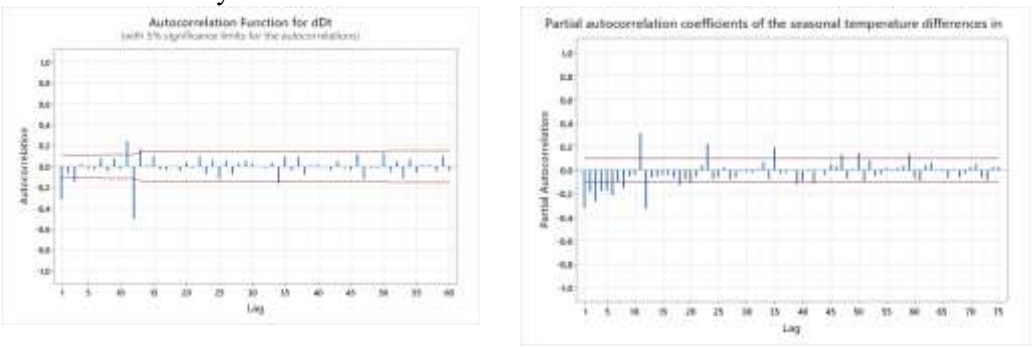


Figure 15: Autocorrelation coefficients of first differences of seasonal differences, Larissa temperature.
Figure 16: Partial autocorrelation coefficients of first differences of seasonal differences, Larissa temperature.

This can also be seen from its autocorrelation coefficient plot (Figure 15). Apart from the lag-1 autocorrelation coefficient (and perhaps lag-3) as well as lag-12, the others are statistically insignificant (falling within the significance bounds, ignoring the lag-11 coefficient) and decay to zero quite rapidly.
Similar results are obtained from the partial autocorrelation coefficients (Figure 16). Here, the statistically significant coefficients are those at lags 12, 24, 36, 48, and 60 (five in total)—namely, those associated with the period order of the time series.
Therefore, following the procedure outlined in Part 1 leads to the $\mathrm{SARIMA}(0,1,2)(0,1,1)_{12}$ model (which differs from the previously examined model in having $d = 1$). This yields an $\mathrm{MSD} = 2.20$, making the $\mathrm{SARIMA}(0,0,2)(0,1,1)_{12}$ model preferable.

Table 20: Parameters and statistics of the $\mathrm{SARIMA}(0,1,2)(0,1,1)_{12}$ model.

Final Estimates of Parameters

Type	Coef	SE Coef	T-Value	P-Value
MA 1	0,6391	0,0111	57,62	0,000
MA 2	0,3323	0,0251	13,26	0,000
SMA 12	0,9401	0,0284	33,06	0,000

Residual Sums of Squares

DF	SS	MS
392	864,099	**2,20433**

Back forecasts excluded

Modified Box-Pierce (Ljung-Box) Chi-Square Statistic

Lag	12	24	36	48
Chi-Square	22,47	23,94	53,25	59,78
DF	9	21	33	45
P-Value	0,008	0,296	0,014	0,069

Remark 2. (Comparison of analysis methods for Larissa meteorological parameters)

(A) To evaluate the goodness-of-fit (to the data) of other methods such us decomposition, Holt-Winters' smoothing, as well as their evaluation as forecasting models (predictive capacity) for the period 01/2022–04/2024, the following procedure will be followed:

- **(a)** The three methods (decomposition, Winters, SARIMA) will be evaluated regarding the fit of the models they provide for the data spanning 01/1988–12/2021.
- **(b)** The predictive capability of the models (decomposition, Winters, SARIMA) will be evaluated for the period 01/2022–04/2024.
- **(c)** The Mean Squared Deviation (MSD) will be used as the model evaluation metric. Thus, the method exhibiting the smallest MSD will be considered the most suitable in each case.

Comparing the fit of the time series decomposition method for temperature, the Holt-Winters' method with parameters $\alpha = 0.1$ (level), $\beta = 0.1$ (trend), and $\gamma = 0.8$ (seasonal), optimal parameters obtained through Excell's solver process w.r.t MSD and the $\mathrm{SARIMA}(0,0,2)(0,1,1)_{12}$ model (for the data from 01/1988 to 12/2021), we conclude that the most suitable method in this case appears to be the SARIMA method with $\mathrm{PMSD}\ 1{,}47$, compared to $1{,}72$ for Winters' and $1{,}51$ obtained from the decomposition method.

Next, to compare the forecasting performance of the three models for predictions over the 01/2022–04/2024 period (Figure 17), we compute the MSD of the forecasts. Although it is the simplest method in time series analysis, time series decomposition provides the best forecasts on average, yielding a Root Mean Squared Error (RMSE) of 1,5, compared to 1,72 for SARIMA and 1,73 for Winters (errors closed enough).

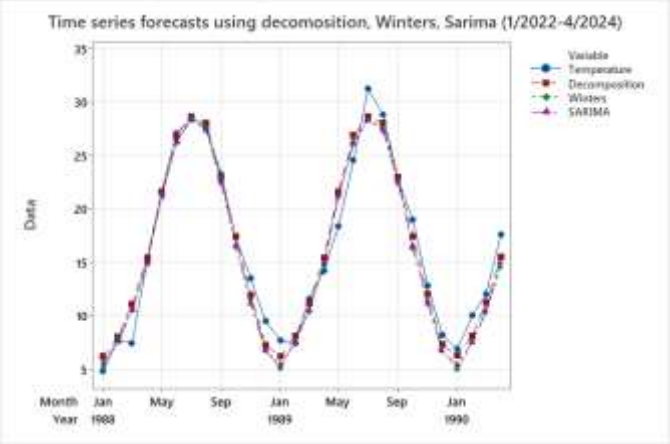
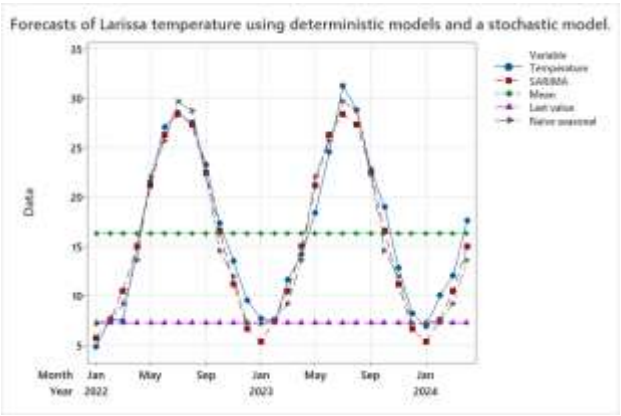


Figure 17: Comparison of time series plots for actual temperature, temperature from decomposition, Winters' method, and SARIMA.

In Figure 16 above, one can observe the actual temperature alongside the values calculated via time series decomposition, Winters' method, and the SARIMA model from 01/2022 to 04/2024. Here again, we observe that the results from time series decomposition are closer to the actual temperature values compared to those from Winters' method and the SARIMA model.

(B) If one wishes to compare the forecasting performance of the SARIMA model against other basic benchmark models, such as:

- **(i) Mean value model:** A model where all future values are equal to the mean value of the historical data.
- **(ii) Last value (Naive) model:** A model where all future values are set equal to the very last observed value of the time series.
- **(iii) Seasonal naive model:** A model where all future values are set equal to the observed values of the corresponding period from the final year.



Statistics

Variable	Variance
Sa-actu	2,48996
Naiv-actual	3,49337

Figure 18: Forecasts of Larissa temperature using deterministic models and a stochastic model.

It is evident that the stochastic model outperforms the deterministic ones (see the diagram above and the table that follows).

4. DISCUSSION

The temperature data collected from the meteorological station of the Hellenic National Meteorological Service in Larisa, Greece, were used to develop and fit a SARIMA model for the area's monthly temperature series. Temperature dynamics are influenced by several environmental factors, including geographical location, altitude, climate variability and change, and local microclimatic conditions. These factors contribute to the complexity of temperature patterns and make accurate forecasting challenging.

The fitted model had a standard deviation of 1.47, indicating relatively low variability in the forecast errors. This suggests that the model provides a satisfactory level of forecasting accuracy. Furthermore, the forecasted values were generally close to the corresponding temperatures observed, with the actual values falling largely within the forecast intervals defined by the forecasts plus or minus their associated standard errors. Overall, the results indicate that the selected SARIMA model provides an adequate representation of the observed temperature patterns and can therefore be considered a useful model for forecasting monthly temperatures in Larisa, Greece.

5. CONCLUSION

In this study, Seasonal Autoregressive Integrated Moving Average (SARIMA) models, which account for the seasonal patterns present in time-series data, were employed to model a meteorological time series. Following the Box–Jenkins model-building methodology, several candidate models were developed, and their Mean Squared Deviation (MSD), Root Mean Squared Error (RMSE), and corrected Akaike Information Criterion (AICc) values were calculated and compared. Based on these evaluation criteria, the SARIMA$(0, 0, 2)(0, 1, 1)_{12}$ model was selected as the optimal model, as it achieved the lowest MSD/RMSE values.

The selected model was subsequently used to forecast monthly temperatures in Larisa, Greece. Diagnostic analysis of the residuals indicated that they were uncorrelated and exhibited a pattern consistent with random white noise. Furthermore, the residuals approximately followed a normal distribution, suggesting that the model adequately captured the underlying structure and seasonal characteristics of the temperature series.

The performance of the optimized SARIMA model was evaluated against several basic benchmark models, and it demonstrated superior forecasting performance. Consequently, the selected model was used to generate temperature forecasts for the test period from January 2022 to April 2024. The results indicated that the model provided an adequate fit to the observed data and produced reliable forecasts. Based on the model projections, temperatures in Larisa are expected to exhibit an increasing trend over the subsequent two-year forecasting horizon.

6. ACKNOWLEDGEMENT

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7. REFERENCES

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