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Full length article

PREDICTIVE MODEL TO MINIMIZE THE EFFECT OF EXTREME TEMPERATURE IN SKARDU AND ASTORE, GILGIT BALTISTAN

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ABSTRACT

Climate is a fundamental factor of the natural environment that has a role in both natural and human existence. Temperature is an important climatic element that influences snow melting, evaporation, and frost directly. Current study has used Mean Monthly Minimum Temperature (MMMT) of Skardu from 1972 to 2021 and of Astore from 1993 to 2021 based on the availability of data. In this work; we have used SARIMA (Seasonal Auto Regressive Integrated Moving Average Model) to forecast mean monthly minimum temperature. Skardu data is stationary at level form, which suggests SARMA model for Skardu station and Astore data is stationary at first difference so SARIMA time series is appropriate for mean monthly minimum temperature of Astore. Using Box Jenkins's approach it is found that the most appropriate model for Skardu is SARMA$(1,0)(1,0)_{12}$ and Astore is SARIMA $(0,1,1)(4,1,4)_{12}$ respectively. These models have been utilized to forecast MMMT from 2022 to 2036. Yearly mean minimum temperature forecasts show that the mean minimum temperature at Skardu and Astore stations is slightly decreasing. The yearly mean minimum temperature at Skardu station is 4.0 °C in 2022 and will decrease to 2.3 °C till 2036, while at Astore station it is 4.0 °C in 2022 and will fall to 2.6 °C in 2036. Our results will be useful for decision makers and insurance companies for better future planning to minimize the effect of lowest temperature.

Keywords: Temperature forecasting, SARIMA Model, Effect of minimum temperature, E-Views software.

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1. INTRODUCTION

The fundamental factor of the natural environment is climate that has a figuring out function to play in natural and human existence. Of the critical climatic parameters, temperature is also the one that affects snow melting; evaporation and frost directly while having effects on precipitation conditions and atmospheric stability indirectly. These changes affect the sector of tourism, water resources, agriculture and flowers directly according to the recent weather alternate effect evaluation research framework. Therefore, temperature forecasting is inevitable in order to avoid surprising hazards caused by temperature variations, including drought and frost which may additionally cause monetary and human losses [1]. Climate change is also a serious environmental hazards to food production, water availability, forest biodiversity, and livelihoods in many countries. [2]. Time series analysis is generally used to assess trends and seasonality in the data. The trends show long-term increases or decreases in time series, whereas the variation in data at regular short intervals is seasonality such as weekly, monthly, bi-annually, quarterly, and so on [3]. It's worth noting that ARIMA models serve not only as tools for analyzing and predicting climate change and assessing climate indices, but they also offer more accurate forecasts, particularly regarding intervals, and demonstrate greater consistency compared to other widely employed statistical approaches, as observed by certain researchers[4]. Various research endeavors concerning temperature fluctuation issues at both regional and global levels demonstrate that particular ARIMA models outperform other modeling methodologies in generating more accurate results. This superiority is attributed to the utilization of Root Mean Squared Error and Mean Absolute Error techniques during the model development process [5]. In this research, the ARIMA method was utilized to construct a model and predict the monthly average temperature at Karachi station spanning from January 1989 to December 2018. The most suitable model for temperature prediction was determined to be ARIMA (2, 1, 4) [6]. [7] Have explored about the use of SARIMA model in maximum temperature analysis that the level of risk is low in this model to estimate the maximum temperature of Karachi. Another research about forecast of monthly mean temperature in Nanjing China, for the period of 1951-2017, shows that SARIMA model may be used for forecasting accuracy [8]. [9] Have assessed the relationship between electricity consumption and mean monthly maximum temperatures in Pakistan by using ARIMA model. The study reveals that the increase in consumption of electricity is caused by the increase of monthly maximum temperature, due to use of cooling appliances as Ali et al, 2013 say, “Our calculation also shows that for an increase of 1°C temperature there will be an increase of 109.3 million-kWh electricity demand for Pakistan” (p. 7). Time series model forecasts about the upcoming values on the basis of the data / values observed in the past data. So, it helps understand the future values by examining the past value [10]. [11] has done a comparative analysis using ARIMA, exponential smoothing (ETS), and cubic splines approaches on daily maximum temperature and discovered that the ARIMA model is the best at forecasting one-step-ahead daily maximum temperature in Umea, with a one-year training period. To forecast the monthly mean surface temperature in the Brong Ahafo Region of Ghana, used the ARIMA model and discovered a declining trend [12].

The whole Pakistan experience that both hotness and coldness are increasing in all the regions except northern sub –Himalayan regions. 0.17-0.37℃/ decade rises in minimum temperature which is comparatively faster than rate of increase in maximum temperature i.e. 0.17 – 0.29 ℃ /decade [13]. This brings health issue in our society as research shows that mortality rate is higher due to cold than heat comparatively [14]. It has been noticed that since 19th century, cold weather has had a fatal effect on people in UK [15]. Mortality and morbidity associated with cold shows that for every 1°C fall in temperature in the coldest day’s results death percentage to 6% because of diseases in the UK [16]. Every year thousands of people expire due to the cold weather [17]. For many countries, including the UK the mortality and morbidity caused by cold is very important public health issue [18]. A reduction of 1℃ in mean temperature down to 11℃ increase the mortality rate up to 2.9% by all causes, 3.4% by cardiovascular, 4.8% by respiratory and 1.7% by the cause of non –cardiorespiratory diseases, in the major Scottish cities [19]. All causes of mortality, especially among adult, increase up to 4.5% due to the 1℃ fall of temperature during winter season, it is also observed that the cause of cardiovascular death to 3.9% and respiratory death to 11.2%, in Northern Ireland [20]. It is likely that the respiratory tract infection increases in harsh winter season, because of less humidity and the decrease of temperature [21]. Illnesses and deaths caused by cold, affect the old age people [22]. Most of the people die due to cold as compared to hot weather annually in some of countries. For instance, Netherland is one of them [23]. It is observed that research work over extreme event in northern high latitude is comparatively low [24].

The above literature review shows that the decrease of 1°C mean temperature has such an impact on people's health that it caused various cardiovascular issues. Skardu and Astore are located in Gilgit Baltistan, with an elevation of 2,228m and 2,546m respectively above sea level in Pakistan. Due to high elevation temperature drops in winter below 0°C, and the data shows that the temperature dropped up to -24.1°C in the year 1995 in Skardu. Due to the lowest temperature many problems are faced by people such as respiratory and cardiovascular diseases. The ratio of these diseases increases and even the death ratio of human beings is also increased in winter as compared to that of summer. In winter, the consumption of electricity increases due to higher usage of heating appliances. The production rate of electricity is decreased due to freezing of water resources as electricity is produced by hydro power in these areas [19], [20].

2. Study Area

The selected areas for this proposal are Skardu and Astore. Skardu is situated at latitude 35°17'24.324", longitude 75°38'43.2348" at an elevation of 2,228m above the sea level and the total area of Skardu is about 8700 km². Astore is situated at latitude 35°21'59.99", longitude 74°50'59.99" at an elevation of 2,546m above the sea level and the total area of Astore is about 5,092 km².

Figure 1. Area of Study: (png - Wikipedia)

3. Data Description and Methodology

In this study, we examine the mean monthly minimum temperature in Skardu and Astore district in Gilgit Baltistan. Mean Monthly Minimum Temperature (MMMT) data of Skardu and Astore from 1972-2021and 1993-2021 respectively have been collected from Pakistan Meteorological Department (PMD). The training set includes Skardu and Astore data from 1972 to 2019 and 2012 to 2019, respectively, while the testing set includes data from 2019 to 2021. We use Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) as goodness of fit test for the selection of appropriate SARIMA model to the data. The Mean-Square Error (MSE) is calculated to assess forecast accuracy and to compare results from different models. The below figure 2 shows the Box-Jenkin's approach.

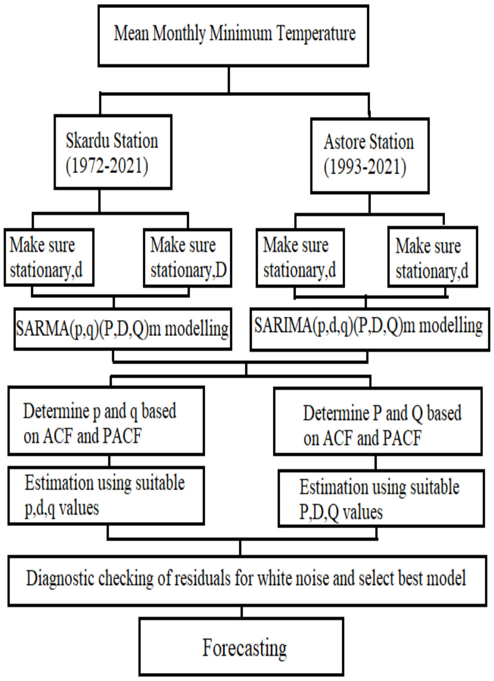

Figure 2. Methodology adopted.

When the time series shows a seasonal effect, the general ARIMA model becomes SARIMA model [25] and it is represented as SARIMA(p,d,q)(P,D,Q)12. Mathematically it can be written as:

$$\psi_{AR}(B)\ \psi_{SAR}(BS)\ (1\text{-}B)\ d\ (1\text{-}\ BS)\ D\ Y_t = \theta_{MA}(B)\ \theta_{SMA}(BS)\ \nu_t \qquad \textbf{(Eq .1)}$$

Where ψ_{AR} and θ_{MA} are non-seasonal parameters, ψ_{SAR} and θ_{SMA} are seasonal parameters and B is backward shift operator.

4. Result and discussions

Figure 3 displays the Mean Monthly Minimum Temperature (MMMT) time series fluctuations. MMMT changed from 19.2 ℃ (July 1977) to -17.9 ℃ (January 1995) at Skardu station and 16.6 ℃ (July 1994) to -12.1 ℃ (January 1995) at Astore station. Table 1 shows that the absolute t-statistic value of Augmented Dickey Fuller Test (ADFT) is greater than the critical values of temperature data at Skardu depicting that MMMT of Skardu is stationary at level form, while Table 2 shows that Astore data has been made stationary after taking first difference. After making stationary data, the next step is to determine the orders of p, d, q, P, D, and Q for SARIMA model. As the temperature data of Skardu station is Stationary at level form so the value of d and D both are equal to zero which suggests that the suitable time series model for Skardu is SARMA(p, q)(P, Q)$_{12}$. From Figure 4 the common significant lag values of ACF and PACF in the same direction suggest that the suitable orders of (p, q) and (P, Q) for Skardu station are 1,4,5,6,7,8 and 11. Since, the mean monthly minimum temperature of Astore station was not stationary at level form therefore it is made stationary by first difference technique, so the researchers have used SARIMA (p, d, q)(P, D, Q)$_{12}$ model where d = D =1 to determine the order of (p, q) and (P, Q) in SARIMA, the researchers have used first-hand information given by ACF and PACF. From Figure 5, the common significant lag values of ACF and PACF in the same direction suggest that the suitable orders of (p, q) and (P,Q) for Astore station are 1,4,5,6,7,8,9,11 and 12. From these suggested lag values, the researchers have found out all possible permutations of order p,q and P,Q and then estimated the parameters. A number of SARMA (p,q)(P,Q) and SARIMA (p,d,q)(P,D,Q) models at different orders have been excluded due to insignificant estimation of parameters. The summary of goodness of fit results of significant models at different orders of Skardu and Astore stations are given in Table 3 and Table 4 respectively. The best fitted models have been selected on the basis of R^2, AIC, BIC and RMSE as goodness of fit tests. The model is said to be the best fitted if it has less values of AIC, BIC, RMSE and highest value of R^2. The best fitted one has been made bold as shown in Table 3 and Table 4.

According to Table 3 and Table 4 SARMA(1,0)(1,0)$_{12}$ and SARIMA (0,1,1)(4,1,4)$_{12}$ show that the highest R-square and lowest AIC and BIC and RMSE. So, these models are considered the best forecasting models for mean monthly minimum temperature of Skardu and Astore respectively.

Parameters of the model are determined by using the Ordinary Least Square (OLS) method after getting p,d,q P,D and Q values. The SARMA $(1,0)(1,0)_{12}$ model for Skardu station can be represented mathematically as;

$$(1-\Psi_1\mathrm{B})(1-\psi_1B^{12})(1-\mathrm{B})^0(1-B^{12})^0Y_t = ((\theta_0B)((\theta_0B^{12})V_t \qquad \textbf{(Eq.2)}$$

We have calculated the parameters by using statistical package E-Views inserting the calculated parameters in Eq.2 and we got the specific model for Skardu station as;

$$(1-0.294435\mathrm{B})(1-0.961993B^{12})(1-\mathrm{B})^0\,(1-B^{12})^0Y_t = V_t \qquad \textbf{(Eq.3)}$$

The general equation of SARIMA$(0,1,1)(4,1,4)_{12}$ model for Astore station can be written as;

$$(\Psi_0B)(1-\psi_1B^{12}-\psi_2B^{24}-\psi_3B^{36}-\psi_4B^{48})(1-\mathrm{B})^1(1-B^{12})^1Y_t = (1-\theta_1\mathrm{B})(1-\theta_1B^{12}-\theta_2B^{24}-\theta_3B^{36}-\theta_4B^{48})V_t \qquad \textbf{(Eq.4)}$$

We have got the estimated model by putting the coefficient values into Eq.4 and here we have calculated by using E-Views software.

$$(1-0.5219B^{12}-0.6199B^{24}-0.1941B^{36}-0.3336B^{48})(1-\mathrm{B})^1(1-B^{12})^1Y_t = (1-0.840\mathrm{B})(1-0.6017B^{12}-0.7199B^{24}-0.1018B^{36}-0.5465B^{48})V_t \qquad \textbf{(Eq.5)}$$

Table 3 and table 4 are lists of SARMA and SARIMA model taken from the MMMT at Skardu and Astore stations respectively. According to table 3 and table 4, SARMA (1,0) (1,0)12 and SARIMA (0,1,1) (4,1,4)12 show the highest R-square and lowest AIC and BIC. Thus, these models are considered the best forecasting models. A diagnostic check is used to validate the forecast accuracy of the chosen model. According to table 5 and table 6, the absolute t-statistic value is greater than critical values. This shows that the residual is white noise. January 2019 to December 2021 is used as a testing set. Table 3 and table 4 show that the RMSE of SARMA (1,0)(1,0)12 and SARIMA (0,1,1)(4,1,4)12 models are 2.027128 and 1.396398 respectively which are the lowest among the others showing it to be the best fitted model. Thus SARMA (1,0)(1,0)12 will be used to predict the MMMT of Skardu, while SARIMA (0,1,1)(4,1,4)12 will be used to predict MMMT of Astore station.

Figure 6 and figure 7 firstly depict that the predicted values (red line) show the same trend with the actual values (blue line) that proves the validity of the selected models. Similarly, results have also been shown by figure 8a and figure 9a. From figure 8b and figure 9b, the forecast result of yearly mean minimum temperature shows decreasing trend at both Skardu and Astore stations. The yearly mean minimum temperature at Skardu station is 4.0 °C in 2022 and will decrease to 2.3 °C till 2036, while at Astore station it is 4.0 °C in 2022 and will fall to 2.6 °C in 2036. Table 7 and table 8 show forecast data for 15 years from 2022 to 2036 of MMMT at Skardu station and Astore station respectively.

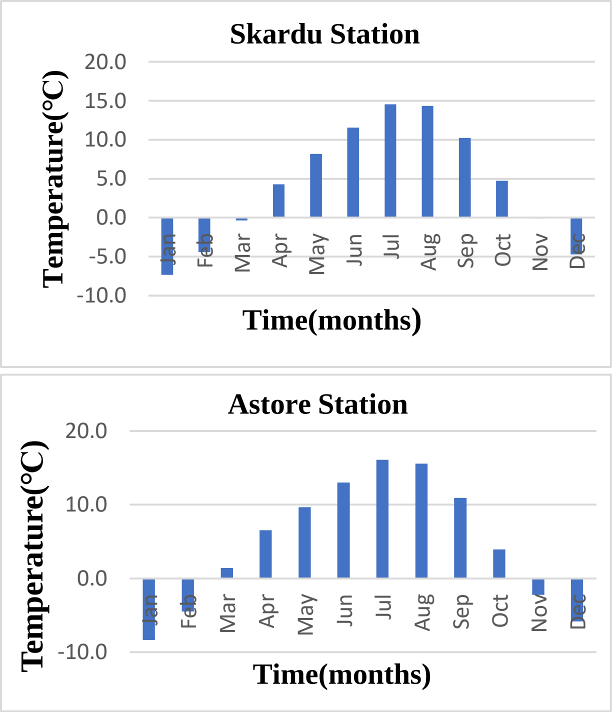

Figure 3. Mean monthly minimum temperature variation from the year (1972–2021) at Skardu station and (1993–2021) at Astore station.

Table 1. At level for intercept form.
Null Hypothesis: Skardu has a unit root.

Augmented Dickey-Fuller Test Statistic	t-Statistics	Prob.
	-4.122591	0.0010
Test Critical Values		
1% level	-3.441242	
5% level	-2.866237	
10% level	-2.569330	

Table 2. First difference for intercept form.
Null Hypothesis: Astore has a unit root.

Augmented Dickey-Fuller Test Statistic	t-Statistics	Prob.
	-19.73221	0.0000
Test Critical Values		
1% level	-3.449620	
5% level	-2.869927	
10% level	-2.571307	

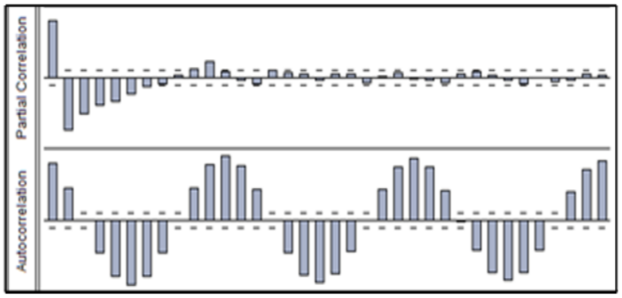

Figure 4. Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) of Skardu data at level form.

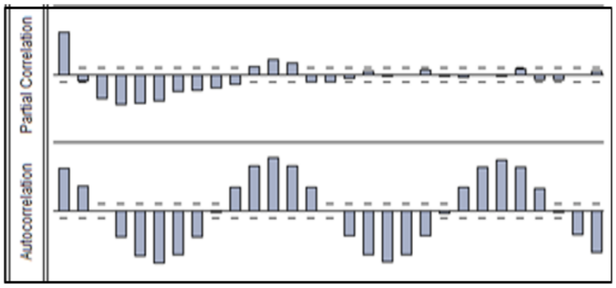

Figure 5. Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) of Astore data at 1st difference form.

Table 3. Goodness of fit tests for the best fitted SARMA model at Skardu station.

Models	R-square	AIC	BIC	RMSE
SARMA (1,0)(1,0)$_{12}$	**0.942587**	**4.229835**	**4.245229**	**2.027128**
SARMA (0,1)(1,0)$_{12}$	0.941795	4.246004	4.261376	2.050523
SARMA (0,4)(0,1)$_{12}$	0.877353	4.997535	5.035349	8.473527
SARMA (0,5)(0,1)$_{12}$	0.886351	4.924812	4.970188	8.629734
SARMA (0,6)(0,1)$_{12}$	0.888829	4.906237	4.959176	8.817009
SARMA (5,0)(0,1)$_{12}$	0.896620	4.834268	4.879950	7.889534
SARMA (0,1)(1,0)$_{12}$	0.894951	4.845419	4.883436	7.861645

Table 4. Goodness of Fit tests for the best fitted model at Astore station.

Model	R-square	AIC	BIC	RMSE
SARIMA (0,1,1)(1,1,1)$_{12}$	0.904761	3.358726	3.394801	1.484813
SARIMA (1,1,1)(1,1,1)$_{12}$	0.906129	3.353836	3.402050	1.504331
SARIMA (0,1,1)(4,1,4)$_{12}$	**0.914404**	**3.276852**	**3.395219**	**1.396398**
SARIMA (0,1,1)(4,1,0)$_{12}$	0.878699	3.596396	3.662155	1.729963
SARIMA (1,1,1)(4,1,0)$_{12}$	0.881672	3.582600	3.661720	1.831545
SARIMA (5,1,0)(1,1,1)$_{12}$	0.901658	3.419394	3.504574	1.531984
SARIMA (6,1,0)(1,1,1)$_{12}$	0.903872	3.400964	3.498545	1.462010

Table 5. Diagnostic test for SARMA (1,0)(1,0)12 model for Skardu station.
Null Hypothesis: ERROR has a unit root.

	t-Statistics	Prob.
Augmented Dickey-Fuller Test Statistic	-11.69991	0.0000
Test Critical Values		
1% level	-3.441715	
5% level	-2.866446	
10% level	-2.569442	

Table 6. Diagnostic test for SARIMA (0,1,1) (4,1,4)12 model for Astore station.
Null Hypothesis: ERROR has a unit root.

	t-Statistics	Prob.
Augmented Dickey-Fuller Test Statistic	-14.53341	0.0000
Test Critical Values		
1% level	-3.454085	
5% level	-2.871883	
10% level	-2.572354	

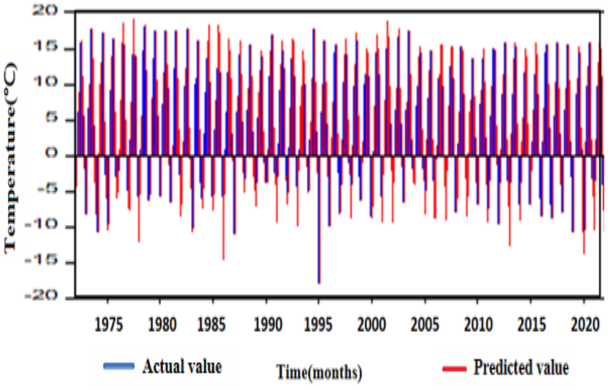

Figure 6. MMMT of Skardu station by using SARMA (1,0) (1,0)12 model from the year (1972-2021).

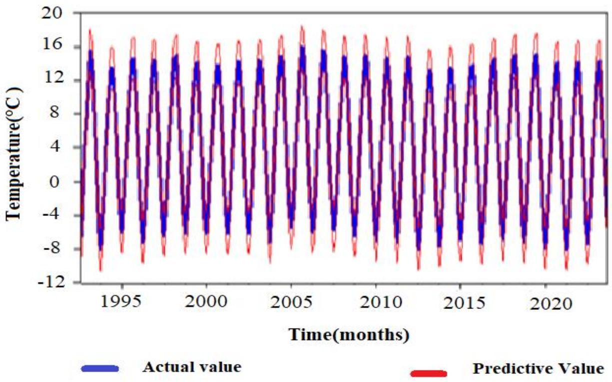

Figure 7. MMMT of Astore station by using SARIMA (0,1,1) (4,1,4)12 model from the year (1993-2021).

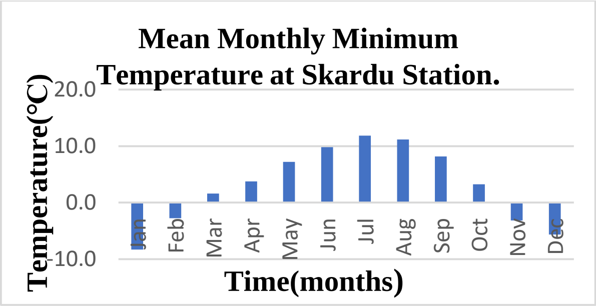

Figure8a.

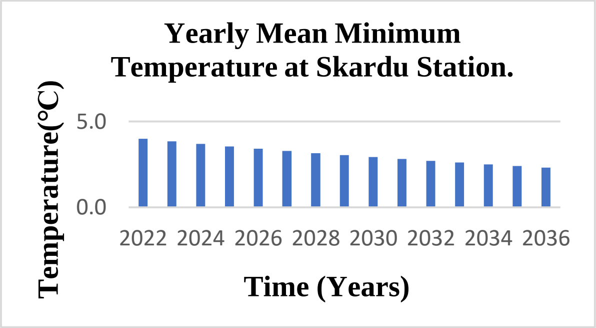

Figure 8b.

Figure 8. SARMA (1,,0) (1,0)12 (with constant) model forecast result for minimum temperature at Skardu station from the year (2022-2036).

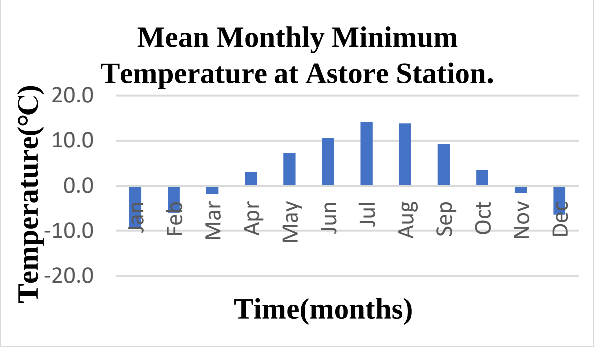

Figure9a.

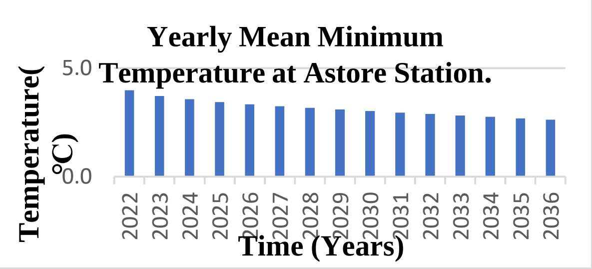

Figure 9b.

Figure 9. SARIMA (0,1,1) (4,1,4)12 (with constant) model forecast result for minimum temperature at Astore station from the year (2022-2036).

Table 7. 15-years forecast values of MMMT of Skardu station using SARMA (1,0) $(1,0)_{12}$ model.

Years	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2022	-10.7	-3.6	2.1	4.9	9.3	12.7	15.3	14.4	10.6	4.2	-4.0	-7.3
2023	-10.3	-3.4	2.0	4.7	9.0	12.2	14.7	13.9	10.2	4.1	-3.9	-7.0
2024	-9.9	-3.3	1.9	4.5	8.6	11.8	14.2	13.4	9.8	3.9	-3.7	-6.8
2025	-9.5	-3.2	1.8	4.4	8.3	11.3	13.6	12.8	9.4	3.8	-3.6	-6.5
2026	-9.2	-3.0	1.8	4.2	8.0	10.9	13.1	12.4	9.1	3.6	-3.5	-6.3
2027	-8.8	-2.9	1.7	4.0	7.7	10.5	12.6	11.9	8.7	3.5	-3.3	-6.0
2028	-8.5	-2.8	1.6	3.9	7.4	10.1	12.1	11.4	8.4	3.4	-3.2	-5.8
2029	-8.2	-2.7	1.6	3.7	7.1	9.7	11.7	11.0	8.1	3.2	-3.1	-5.6
2030	-7.9	-2.6	1.5	3.6	6.8	9.3	11.2	10.6	7.8	3.1	-3.0	-5.4
2031	-7.6	-2.5	1.5	3.5	6.6	9.0	10.8	10.2	7.5	3.0	-2.9	-5.2
2032	-7.3	-2.4	1.4	3.3	6.3	8.6	10.4	9.8	7.2	2.9	-2.7	-5.0
2033	-7.0	-2.3	1.3	3.2	6.1	8.3	10.0	9.4	6.9	2.8	-2.6	-4.8
2034	-6.7	-2.2	1.3	3.1	5.9	8.0	9.6	9.1	6.6	2.7	-2.5	-4.6
2035	-6.5	-2.1	1.2	3.0	5.6	7.7	9.2	8.7	6.4	2.6	-2.4	-4.4
2036	-6.2	-2.1	1.2	2.8	5.4	7.4	8.9	8.4	6.2	2.5	-2.3	-4.3

Table 8. 15-years forecast values of MMMT of Astore station by SARIMA (0,1,1) $(4,1,4)_{12}$ model.

Years	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2022	-7.0	-4.4	-0.8	3.9	8.0	11.7	14.5	14.2	8.8	3.9	-0.2	-5.0
2023	-7.2	-5.1	-1.4	3.8	7.9	11.1	14.4	14.2	9.0	3.9	-0.5	-5.4
2024	-7.9	-5.3	-1.1	3.6	7.7	11.2	14.3	14.2	9.0	3.7	-1.0	-5.6
2025	-8.5	-5.3	-1.4	3.4	7.6	10.9	14.4	13.9	9.5	3.8	-1.0	-5.9
2026	-8.4	-5.7	-1.5	3.4	7.5	10.8	14.2	14.0	9.3	3.7	-1.2	-6.0
2027	-8.9	-5.6	-1.5	3.2	7.4	10.8	14.2	13.9	9.4	3.6	-1.4	-6.2
2028	-8.9	-5.8	-1.7	3.1	7.4	10.7	14.2	13.8	9.4	3.6	-1.4	-6.3
2029	-9.0	-5.9	-1.7	3.1	7.3	10.6	14.1	13.9	9.3	3.5	-1.6	-6.4
2030	-9.2	-6.0	-1.8	3.0	7.2	10.6	14.1	13.8	9.4	3.5	-1.6	-6.5
2031	-9.3	-6.1	-1.9	2.9	7.2	10.5	14.1	13.7	9.3	3.4	-1.7	-6.6
2032	-9.4	-6.2	-1.9	2.8	7.1	10.5	14.0	13.7	9.2	3.3	-1.8	-6.7
2033	-9.5	-6.3	-2.0	2.8	7.1	10.4	14.0	13.6	9.2	3.3	-1.9	-6.8
2034	-9.6	-6.4	-2.1	2.7	7.0	10.4	13.9	13.6	9.1	3.2	-1.9	-6.9
2035	-9.7	-6.4	-2.2	2.6	6.9	10.3	13.9	13.6	9.1	3.1	-2.0	-7.0
2036	-9.8	-6.5	-2.3	2.6	6.9	10.3	13.9	13.5	9.1	3.1	-2.1	-7.0

Conclusion

Climate is a vital aspect of the natural environment that has a role in both natural and human existence. Temperature is a key climatic characteristic. Since, it directly impacts snow melting, evaporation, and frost, while indirectly affecting precipitation conditions and atmospheric stability. The minimum temperature in Gilgit-Baltistan in winter season drops very low up to -24 ℃ due to high elevation and creates a lot of problems for the citizens. The minimum temperature imposes its negative impacts on the sector of tourism, water resources, agriculture, power sector and health sector etc. The time series model used in this research paper is highly effective and in currency these days. Various researchers have used this model in their research works to solve issues of different areas of the world to forecast the temperature. For instance [27] has predicted temperature in the region of Ashanti using the same model to analyze historical data from 1980 – 2013 and found this an optimal model for forecasting

$(2,1,1)(1,1,2)_{12}$. Change et al have also use the same model to forecast the monthly rainfall in Yantai China and found SARIMA $(1, 0, 1)(0, 1, 1)_{12}$ a good tool for prediction [28]. Srivastava et al also have used SARIMA model to forecast weekly maximum and minimum temperature in Jabalpur district of Madhya Pradesh and from the year 1980 to 2021 and found it to be the best fitted model SARIMA (0,0,1)(2,1,0)52 for weekly maximum and SARIMA(4,0,0)(1,1,0)52 for minimum temperature [29].

Current study is to minimize the negative impacts of minimum temperature in Skardu and Astore through time series model and it is found that it is the most appropriate model for Skardu is SARMA(1,0)(1,0)12 and Astore is SARIMA (0,1,1)(4,1,4)12 respectively. By using the best fitted model the MMMT from 2022 to 2036 have been forecasted in this study. Our results reveal that the yearly mean temperature at both Skardu and Astore stations are slightly decreasing, which may increase the patients, especially cardiac patients in hospitals. It may also rapidly increase the demand of electricity that may cause the growth of the shortfall of electricity in the city. So, our results may be useful for decision makers to overcome these highlighted issues in this research.

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