Research & Reviews: Journal of Statistics
Volume 2, Issue 2, ISSN: 2278-2273

Seasonal ARIMA for Forecasting Sea Surface Temperature of the North Zone of the Bay of Bengal

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Abstract

The behavior of the sea surface temperature (SST) of the north zone of the Bay of Bengal plays an important role for understanding climate changes over Bangladesh. The monthly average of SST of this zone is used in this study which is obtained from January 1900 to December 2009. Box and Jenkins method is used to fit a seasonal auto regressive integrated moving average (ARIMA) model used in forecasting SST of the north zone of the Bay of Bengal. The most commonly used model selection criteria's such as the Akaike's information criterion (AIC), the Bayesian information criterion (BIC), etc. are used for model comparison. The Root Mean Squared Error, Mean Absolute Error and Mean Absolute Percent Error are also used for diagnostic checking in model selection procedure. Seasonal ARIMA (2, 0, 1) (0, 1, 1)$_{12}$ model is suggested for forecasting the SST of the north zone of the Bay of Bengal.

Keyword: *Sea surface temperature, seasonal ARIMA, Akaike's information criterion, Bayesian information criterion, forecasting value*

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BACKGROUND

Sea surface temperature (SST) plays a vital role in the behavior of the earth's climate and weather. It is constantly changing same as the atmospheric temperature. The interaction between the ocean and the atmosphere is the one that scientists are constantly researching, especially in light of climate change. Water warms up and cools down at a slower rate than air [1]. So, diurnal variations seen in the atmosphere are hard to observe in the ocean. Sea surface temperature of the Bay of Bengal is important for tropical cyclogenesis. It is also important in determining the formation of sea fogs and sea breezes. When sea surface temperature increases, the atmospheric temperature also increases and the sea level rises [2–4]. These causes heavier river flows from melting Himalayan glaciers, more rapid shifts in river channels, high water changes during storms, more intense cyclones and rainstorms. All of these are coming on top of the irreversible rise in the Bay of Bengal. Bangladesh is located by the north zone of the Bay of Bengal. Knowledge of sea surface temperature (SST) of north zone of the Bay of Bengal is essential for understanding the rainfall variability's over Bangladesh. That is why the SST of the north zone of the Bay of Bengal is very important for Bangladesh. In this study, the SST of the north zone of the Bay of Bengal is considered (Table 1).

Recent statistics show, over the past 100 years, temperature is increased by 0.5°C, but in the next 50 years, that is, by 2050, the temperature of Bangladesh is expected to rise by 1.5–2.0°C. As temperature increases on a global scale, the hydrologic cycle will intensify and the rate of evaporation is expected to increase by 12%. This, in turn, will increase the level of precipitation globally. There may be regional variations in the amount of precipitation, but Bangladesh will experience an increase in rainfall. World Bank reported in 2001 that sea level is rising about 3 mm per year in the Bay of Bengal. A sea level rise of 1 m will engulf 17.5% of the country's vast coastal areas and flood plain zones [5]. Climate models developed by Intergovernmental Panel on Climate Control (IPCC) indicate that Bangladesh may experience 10 to 15 percent more rainfall by 2030. Bangladesh is visited by devastating floods quite frequently. In the past two decades, extensive flood had occurred in 1987, 1988 and 1998 leading to colossal damages to infrastructures and the destruction of standing crops. An increase in rainfall will only worsen the situation. Hence it is very important to know the pattern of sea surface temperature which is one of the main causes of climate warming

Table 1: *The Summary of Descriptive Statistics of SST of the North Zone of the Bay of Bengal.*

Statistics	Jan	Feb	Mar	April	May	June	July	Aug	Sept	Oct	Nov	Dec
Range	3.58	2.19	2.30	1.97	3.74	2.87	2.07	1.90	1.67	2.17	2.88	4.63
Mean	25.00	25.48	27.02	28.60	29.57	29.46	28.81	28.68	28.85	28.89	27.67	25.89
Variance	0.31	0.20	0.17	0.18	0.22	0.21	0.12	0.09	0.13	0.16	0.23	0.42
Std. Deviation	0.56	0.45	0.41	0.43	0.47	0.46	0.35	0.30	0.36	0.39	0.48	0.65
Coef. of Variation	0.02	0.02	0.02	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.03
Std. Error	0.05	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.04	0.05	0.06
Skewness	0.42	0.56	0.07	0.08	-2.23	-0.39	0.65	0.82	-0.02	-0.03	0.15	-0.27
Excess Kurtosis	0.86	0.14	0.10	-0.48	12.61	0.71	1.16	2.35	-0.69	-0.07	0.66	2.25
Min	23.35	24.46	25.85	27.59	26.67	27.78	27.95	27.97	28.01	27.79	26.17	23.20
5%	24.23	24.85	26.34	27.89	28.90	28.70	28.27	28.23	28.31	28.20	26.85	24.96
10%	24.32	24.94	26.50	28.02	29.11	28.85	28.37	28.34	28.36	28.37	27.11	25.14
25% (Q1)	24.57	25.16	26.74	28.30	29.34	29.16	28.63	28.47	28.58	28.61	27.36	25.47
50% (Median)	25.00	25.43	26.99	28.58	29.57	29.47	28.80	28.65	28.87	28.89	27.69	25.88
75% (Q3)	25.34	25.74	27.31	28.92	29.90	29.82	28.97	28.84	29.16	29.13	27.94	26.35
90%	25.73	26.18	27.56	29.15	30.06	30.03	29.33	29.03	29.34	29.38	28.32	26.68
95%	25.94	26.43	27.71	29.36	30.21	30.17	29.56	29.20	29.39	29.55	28.59	26.92
Max	26.93	26.65	28.15	29.56	30.42	30.66	30.02	29.87	29.68	29.96	29.05	27.84

METHODOLOGY

By using time series, this study aims to analyze the Sea Surface Temperature (SST) data on the north zone of the Bay of Bengal. The time series approach used in this study is based on Box-Jenkins model.

Box-Jenkins is referred as Autoregressive Integrated Moving Average (ARIMA) method. Until nowadays, a lot of researchers still use this model in many area of research because the result effectiveness in forecasting field [6–8].

Data Source

The data used for modeling of sea surface temperature of north zone of the Bay of Bengal in the present study have been extracted from the archives of the Bangladesh Meteorological Department (BMD). All the computations involved in this research have been performed by using Eviews 7 and SAS version 9.01.

Seasonal ARIMA

Box and Jenkins (1976) suggested the use of seasonal autoregressive (SAR) and seasonal moving average (SMA) terms for monthly or quarterly data with systematic seasonal movements. A $SAR(p)$ term can be included in model specification for a seasonal autoregressive term with lag p. The lag polynomial used in estimation is the product of the one specified by the autoregressive (AR) terms and the one specified by the SAR terms. The purpose of the SAR is to allow forming the product of lag polynomials. Similarly $SMA(q)$ can be included in model specification to specify a seasonal moving average term having lag q. The lag polynomial used in estimation is the product of the one defined by the moving average (MA) terms and the one specified by the SMA terms. As with the SAR, the SMA term allows to build up a polynomial that is the product of underlying lag polynomials [9]. To obtain the model by the Box-Jenkins methodology, there are four steps that must be considered which are tentative identification, parameter estimation, diagnostic checking and finally model is used in prediction purposes. This step is the important procedure in order to determine the best ARIMA model for time series data [10]. The Box-Jenkins approach for modeling and forecasting has the advantage in analyze the seasonal time series data. In this case the seasonal components are included and the model is called seasonal ARIMA model or SARIMA model. A seasonal ARIMA model is classified as an $\text{ARIMA}(p,d,q)\times(P,D,Q)$ model, where, P =is the number of seasonal autoregressive (SAR) terms, D =is the number of seasonal differences, Q =is the number of seasonal moving average (SMA) terms. The Seasonal ARIMA model $\text{SARIMA}(p,d,q)\times(P,D,Q)_S$ where the lowercase for non-seasonal part meanwhile the uppercase for seasonal part can be written in form of

$$\Phi_P\left(B^S\right)\phi_p\left(B\right)\nabla_S^D\nabla^d\, SST_t = \Theta_Q\left(B^S\right)\theta_q\left(B\right)u_t$$

where,

$$\Phi_P\left(B^S\right)=1-\Phi_1 B^S-\Phi_2 B^{2S}-\cdots-\Phi_P B^{PS}$$

$$\Theta_Q\left(B^S\right)=1-\Theta_1 B^S-\Theta_2 B^{2S}-\cdots-\Theta_Q B^{QS}$$

$$\phi_p\left(B\right)=1-\phi_1 B-\phi_2 B^2-\cdots\phi_p B^p$$

$$\theta_q\left(B\right)=1-\theta_1 B-\theta_2 B^2-\cdots\theta_q B^q$$

$$\nabla_S=1-B^S$$

Model Selection Criteria

For identification of the models performance, there are many methods used for measuring accuracy. Commonly used penalized model selection criteria, the Akaike's information criterion (AIC) and the Bayesian information criterion (BIC), the Mean Square Error (MSE), the coefficient of determination $\left(R^2 \text{ or } \bar{R}^2\right)$ and Log-Likelihood function are examined and compared.

The AIC is a measure of the relative goodness of fit of a forecasting model and it is grounded in the concept of entropy as well as likelihood function. In the general case, the AIC is

$$AIC = 2k - 2\ln\left(L\right)$$

where, k is the number of parameters in the forecasting model, and L is the maximized value of the likelihood function for the estimated model.

The Bayesian information criterion (BIC) or Schwarz criterion (also SBC, SBIC) is another criterion for model selection among a finite set of models. It is also based on the likelihood function, and it is closely related to AIC. The formula for the BIC is:

$$-2.\ln p\left(x|k\right)\approx BIC = -2.\ln L + k\ln\left(n\right)$$

where, x is the observed data;
$n =$ is the number of data point in x, the number of observation, or equivalently, the sample size;
$p\left(x|k\right)$ is the probability of the observed data given the number of parameters; or the likelihood of the parameters given the dataset.

Under the assumption that the model errors or disturbances are independent and identically distributed according to a normal distribution and that the boundary condition that derivative of the log likelihood with respect to the true variance is zero, this become:

$$BIC = n.\ln\left(\hat{\sigma}_e^2\right)+k.\ln\left(n\right)$$

where, $\hat{\sigma}_e^2$ is the error variance. The error variance or mean sum square (MSE) is defined as

$$\hat{\sigma}_e^2 = \frac{1}{n}\sum_{i=1}^{n}\left(x_i-\hat{x}_i\right)^2$$

The smallest value of AIC, BIC, MSE and the value of log likelihood function are chosen as the best to be used in forecasting. And the largest value of R^2 or $\bar{R}^2$ are selected as the best forecasting model.

DATA ANALYSIS

From the graphical presentation (Figure 1), it is observed that the average sea surface temperature (SST) of the north zone of the Bay of Bengal rose dramatically from roughly 25.001°C in January until it reached a peak of 29.565°C in May. From May to June, the SST appeared to level off and remained constant at around 29.5°C. From that time onwards, the SST of north zone of the Bay of Bengal dropped minimally between June and October from nearly 29.50°C to approximately 28.885°C. The SST of this study area declined rapidly between the month October and December from about 28.885°C to nearly 25.891°C. It was observed that the SST between mid November and mid March was lower than that of overall average temperature. From this descriptive data analysis, the SST of the north zone of the Bay of Bengal was the lowest in December whereas the SST of this study area was the highest in June; the figure were 23.203 and 30.655°C, respectively. On daily average, the maximum variability occurred in the December month (Standard deviation was 0.65127°C and range was 4.6343°C) whereas, the minimum variability obtained in the August month (Standard deviation was 0.29919°C).

Time Series Plot

The monthly average of SST data used in this study is obtained from January 1900 to December 2009. The data divided into two samples data set, in sample and out sample.

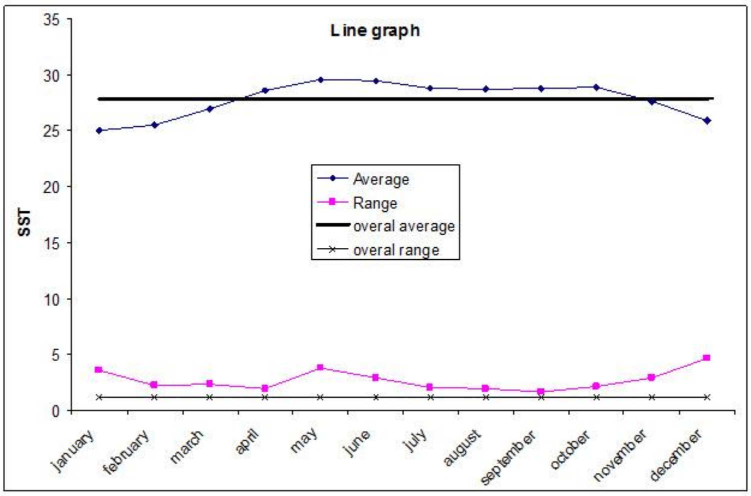


Fig. 1: *The Mean and Range Diagram of SST in each Month of the North Zone of the Bay of Bengal.*

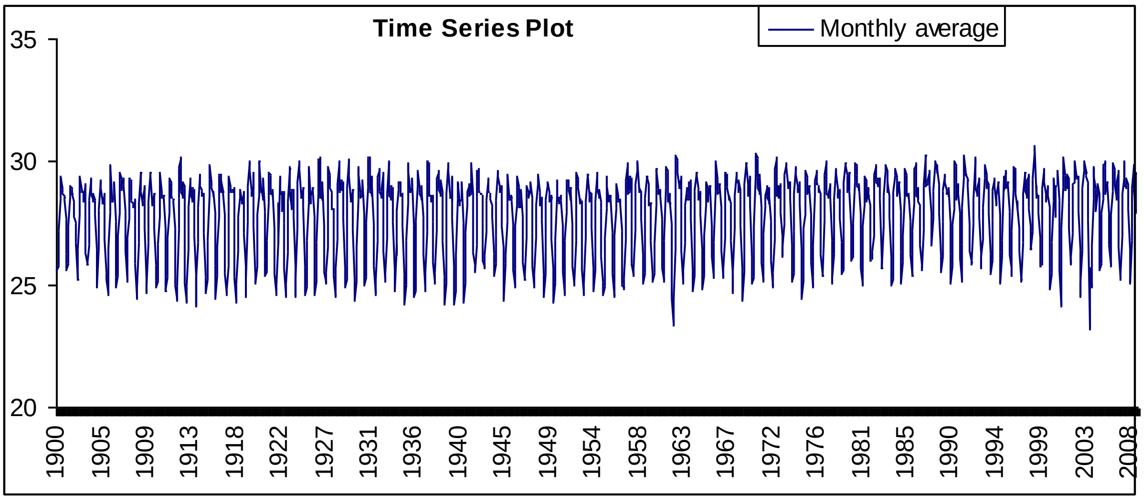


Fig. 2: *Monthly Average of SST of the North Zone of the Bay of Bengal.*

The in sample data set contain 1308 data (January 1900 until December 2008) meanwhile the last 12 data (January until December 2009) as out sample used test the model performance. The time series plot of SST of the north zone is shown in Figure 2. The time series plot illustrated that the data have seasonal pattern and the mean value this series almost constant which is roughly indicated that data are stationary. Now we need unit root test for stationary which is the initial stage in building seasonal ARIMA model before forecasting.

The Unit Root Test

The unit root test of stationarity (or non-stationarity) that has become widely popular over the past several years in the unit root test. The starting point is the unit root (stochastic) process, we start with following model

$$SST_t = \rho SST_{t-1} + u_t \qquad -1 \le \rho \le 1 \quad (3.1)$$

where, u_t is a white noise error term.

We know that if $\rho = 1$, that is in the case of the unit root, (1.1) becomes a random walk model without drift, which we know is a non-stationary stochastic process. For theoretical reasons, we manipulate (1.1) as follows:

$$SST_t - SST_{t-1} = (\rho - 1) SST_{t-1} + u_t$$

which can be alternatively written as:

$$\Delta SST_t = \delta \; SST_{t-1} + u_t \quad (3.2)$$

where, $\delta = (\rho - 1)$ and Δ is the first-difference operator.

To allow for the various possibilities, the Dickey-Fuller (DF) test is estimated in three different forms, that is, below three different null hypotheses.

SST_t is a random walk : $\Delta SST_t = \delta \; SST_{t-1} + u_t$ (3.2)

SST_t is a random walk with drift : $\Delta SST_t = \beta_1 + \delta \; SST_{t-1} + u_t$ (3.3)

SST_t is a random walk with drift around a deterministic trend : $\Delta SST_t = \beta_1 + \beta_2 t + \delta \; SST_{t-1} + u_t$ (3.4)

where, t is the time or trend variable. In each case, the *null hypothesis* is that $\delta = 0$; that is, there is a unit root–the time series is non-stationary. The alternative hypothesis is that δ is less than zero; that is time series is stationary.

The actual estimation procedure is as follows: Estimate (1.2), or (1.3), or (1.3) by OLS; divide the estimated coefficient of SST_{t-1} in each case by its standard error to compute the (τ) tau statistic; and refer to the DF tables (or any statistical package).

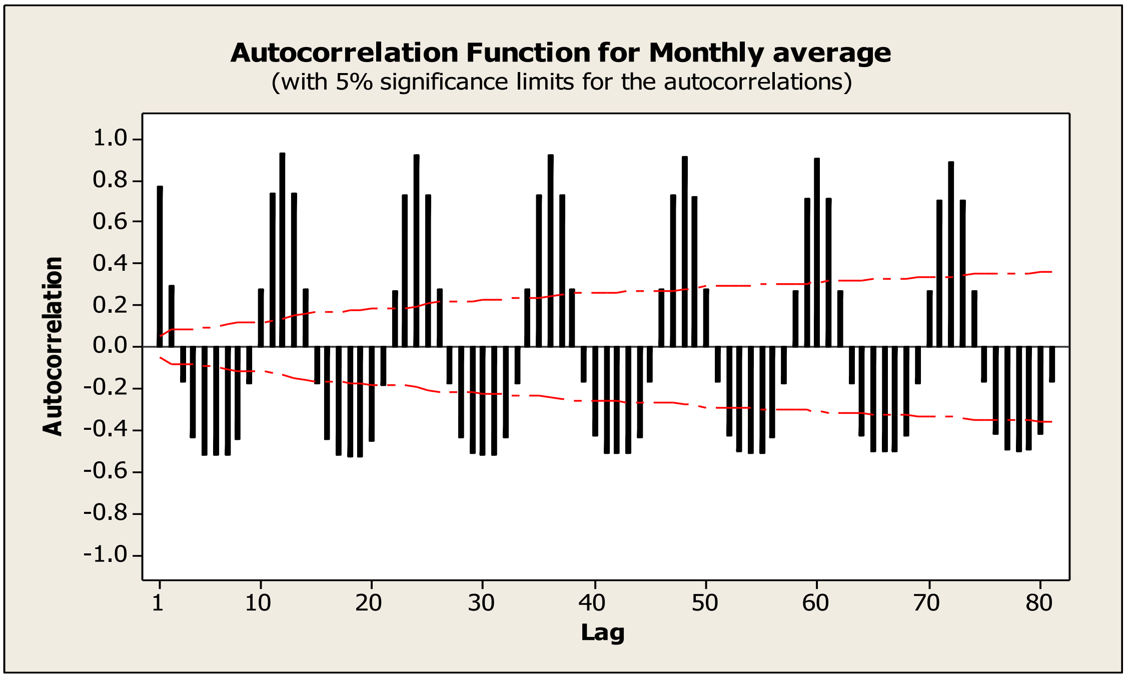
$$\Delta SST_t = \text{-}0.000727 \; SST_{t-1}$$
$$t = (\text{-}0.674024) \qquad R^2 = 0.000347 \qquad d = 0.964201 \qquad (3.5)$$

$$\Delta SST_t = 6.4766 - 0.2327 \; SST_{t-1}$$
$$t = (13.109) \quad (-13.1286) \qquad R^2 = 0.1167 \qquad d = 0.899 \qquad (3.6)$$

$$\Delta SST_t = 6.478435 + 9.02 \times 10^{-5} \, t - 0.234901 \; SST_{t-1}$$
$$t = (13.11491) \; (1.197654) \; (\text{-}13.18445) \qquad R^2 = 0.000965 \qquad d = 0.899085 \qquad (3.7)$$

Our primary interest here is in the $t\,(\text{or}\,\tau)$ value of the SST_{t-1} coefficient. The critical 1, 5, and 10 percent τ values for model (3.5) are -2.5673, -1.9396 and -1.6157, respectively, and are -3.4382, -2.8642, and -2.5682 for model (3.6) and -3.9702, -3.4157 and -3.1298 for model (3.7). As noted before, these critical values are different for the three models. In the model (3.5), the p-value of coefficient of SST_{t-1} is 0.5004 and R^2 is very low. We should rule out model (3.5). That leaves us with models (3.6) and (3.7). In both cases, the estimated τ values are -13.1286 for model (2) and -13.18445 for model (3), which in absolute value is larger even the 10 percent critical value for both model; our conclusion is then the SST time series is stationary. But we observed that the p-value of the coefficient of trend variable is 0.2313 for the model (3.7) which indicates that it is insignificant relationship. Hence our model (3.6) is appropriate of explaining unit root test.

Therefore, on the basis of graphical analysis, the correlogram (Figure 3), and the Dickey-Fuller test, the conclusion is that for the monthly periods of 1900 to 2008, the SST time series in north zone in the Bay of Bengal was stationary; i.e., it did not contain a unit root.



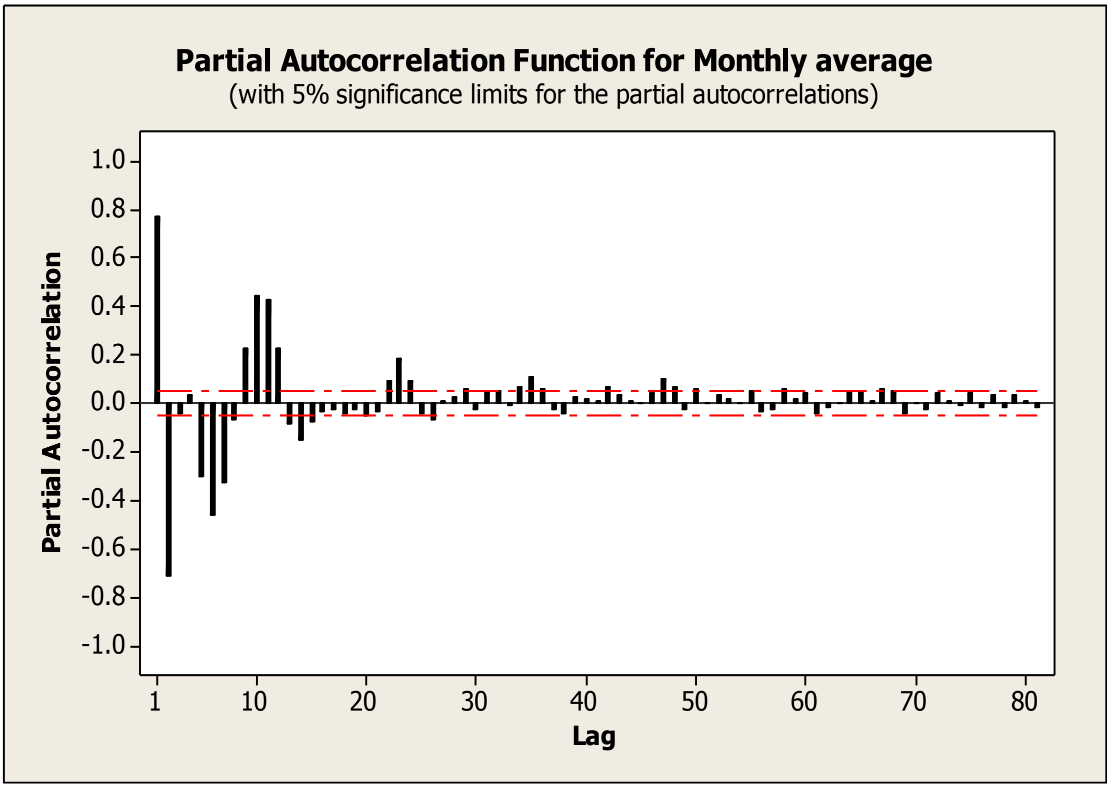


Fig. 3: *Autocorrelation and Partial Correlation Function (Correlogram).*

Model Identification

Based on Stationary series, the correlogram as well as Autocorrelation (ACF) and Partial Autocorrelation (PACF) indicated that the SARIMA model will be the best fit to explain the SST time series data and these were examined to find the best combination order of SARIMA model for the data set. The ACF and PACF of SST are shown in Figure 3. The possible models are:

Seasonal ARIMA (1, 0, 1) (1, 0, 1)12

Seasonal ARIMA (0, 0, 1) (0, 0, 1)12

Seasonal ARIMA (0, 0, 1) (1, 0, 0)12
Seasonal ARIMA (1, 0, 0) (1, 0, 0)12
Seasonal ARIMA (1, 0, 0) (0, 0, 1)12
Seasonal ARIMA (1, 0, 1) (1, 0, 1)12
Seasonal ARIMA (1, 0, 2) (1, 0, 1)12
Seasonal ARIMA (1, 0, 2) (1, 0, 1)12
Seasonal ARIMA (1, 0, 2) (1, 0, 2)12
Seasonal ARIMA (1, 0, 2) (1, 1, 2)12
Seasonal ARIMA (2, 0, 1) (0, 1, 1)12
Seasonal ARIMA (2, 0, 1) (1, 0, 1)12
Seasonal ARIMA (2, 0, 1) (2, 0, 1)12
Seasonal ARIMA (2, 0, 1) (1, 0, 2)12
Seasonal ARIMA (2, 0, 2) (1, 0, 1)12
Seasonal ARIMA (2, 0, 2) (2, 0, 1)12
Seasonal ARIMA (2, 0, 2) (2, 0, 2)12
Seasonal ARIMA (2, 0, 2) (2, 0, 1)12
Seasonal ARIMA (2, 0, 1) (2, 0, 2)12

Model Estimation

Based on tentative SARIMA models, we estimated the parameter as well as calculated the model selection indices such as AIC, BIC, MSE etc. The summary of the results are exhibited in the Table 2. It is observed that SARIMA (2, 0, 1) $(0, 1, 1)_{12}$ is the best model because it has maximum R^2 (and adjusted $R^2 = 0.9444$) and the lowest value for other model selection indices such as MSE, AIC, BIC. These estimates of the parameters are statistically significant (p-value<0.05) at 5% of significance level. The estimates of the parameters of the selected model SARIMA (2, 0, 1) $(0, 1, 1)_{12}$ are shown in Table 3.

Table 2: *The Value of Model Section Criteria/Index for Model Comparisons*

Model	DF	MSE	AIC	BIC/SBC	R-Square	-2LogLH
ARIMA(1, 0, 0)	1306	1.0443252	58.72767	69.080179	0.589	55.618375
ARIMA(2, 0, 0)	1305	1.0451255	60.72767	76.256433	0.589	55.618375
ARIMA(3, 0, 0)	1304	0.5078673	-882.222	-861.517	0.801	-887.8859
ARIMA(1, 0, 1)	1305	0.7041726	-455.7607	-440.2319	0.723	-460.1731
ARIMA(1, 0, 2)	1304	0.5881288	-690.3047	-669.5997	0.769	-696.2814
ARIMA(2, 0, 1)	1304	0.7047126	-453.7607	-433.0557	0.723	-460.1731
ARIMA(2, 0, 2)	1303	0.5885802	-688.3047	-662.4234	0.769	-696.2814
Seasonal ARIMA(1, 0, 1)(1, 0, 1)12	1303	0.1574169	-2413.316	-2387.434	0.932	-2350.575
Seasonal ARIMA(0, 0, 1)(0, 0, 1)12	1305	1.6814542	682.71058	698.23934	0.323	733.35208
Seasonal ARIMA(0, 0, 1)(1, 0, 0)12	1305	0.265989	-1729.188	-1713.66	0.893	-1496.887
Seasonal ARIMA(1, 0, 0)(1, 0, 0)12	1305	0.2426559	-1849.277	-1833.748	0.903	-1835.231
Seasonal ARIMA(1, 0, 0)(0, 0, 1)12	1305	0.5708275	-730.3575	-714.8287	0.775	-729.7971
Seasonal ARIMA(1, 0, 1)(1, 0, 1)12	1303	0.157417	-2413.32	-2387.43	0.931964	-2350.58
Seasonal ARIMA(1, 0, 2)(1, 0, 1)12	1302	0.1460505	-2510.348	-2479.29	0.938	-2454.855
Seasonal ARIMA(1, 0, 2)(1, 0, 1)12	1302	0.1460505	-2510.348	-2479.29	0.938	-2454.855
Seasonal ARIMA(1, 0, 2)(1, 0, 2)12	1301	0.154374	-2436.86	-2400.63	0.937589	-2410.13
Seasonal ARIMA(1, 0, 0)(0, 1, 1)12	1293	0.139946	-2545.59	-2530.09	0.944203	-2522.35
Seasonal ARIMA(1, 0, 2)(1, 0, 2)12	1301	0.154374	-2436.86	-2400.63	0.937589	-2410.13
Seasonal ARIMA(1, 0, 2)(1, 1, 2)12	1289	0.139317	-2547.43	-2511.26	0.942	-2531.35
Seasonal ARIMA(2, 0, 1)(0, 1, 1)12	1291	0.139092	-2551.52	-2525.69	0.944613	-2532.1
Seasonal ARIMA(1, 0, 2)(2, 0, 2)12	1300	0.156651	-2416.71	-2375.3	0.942	-2390.33
Seasonal ARIMA(2, 0, 1)(1, 0, 1)12	1302	0.1411777	-2554.732	-2523.675	0.942	-2517.32
Seasonal ARIMA(2, 0, 1)(2, 0, 1)12	1301	0.1428001	-2538.791	-2502.557	0.942	-2504.316
Seasonal ARIMA(2, 0, 1)(1, 0, 2)12	1301	0.1410813	-2554.631	-2518.397	0.942	-2518.846
Seasonal ARIMA(2, 0, 2)(1, 0, 1)12	1301	0.1412115	-2553.425	-2517.191	0.942	-2517.508
Seasonal ARIMA(2, 0, 2)(2, 0, 1)12	1300	0.1428612	-2537.238	-2495.828	0.942	-2504.423
Seasonal ARIMA(2, 0, 2)(2, 0, 2)12	1299	0.1477105	-2492.582	-2445.996	0.94	-2468.107
Seasonal ARIMA(2, 0, 2)(2, 0, 1)12	1300	0.1428612	-2537.238	-2495.828	0.942	-2504.423
Seasonal ARIMA(2, 0, 1)(2, 0, 2)12	1300	0.1411741	-2552.776	-2511.366	0.942	-2519.008

Table 3: Parameters Estimate of the Seasonal ARIMA (2, 0, 1) (0, 1, 1)12.

Components	Lag	Estimate	Std Error	t Ratio	Prob>|t|
AR1,1	1	1.211191	0.000988	1225.909	0000
AR1,2	2	-0.30523	0.00025	-1220.23	0000
MA1,1	1	0.772704	0.000633	1220.647	0000
MA2,12	12	0.955754	0.000782	1221.423	0000
Intercept	0	0.00471	0.001416	3.326865	0.0009

Diagnostic Evaluation

The Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percent Error (MAPE) are used for diagnostic checking of the selected model SARIMA (2, 0, 1) (0, 1, 1)$_{12}$. The values of RMSE, MEA and MAPE (Table 4) are compared with other possible models and it is observed that the selected model SARIMA (2, 0, 1) (0, 1, 1)$_{12}$ is obtained the lowest value in all criteria indicated SARIMA (2, 0, 1) (0, 1, 1)$_{12}$ is the best model for forecasting the SST of the north zone of the Bay of Bengal. The graphical presentation of actual values and fitted values are shown in Figure 4.

Table 4: Out-sample Forecasting Performance for SST of the North Zone of the Bay of Bengal.

Model	RMSE	MAE	MAPE
SARIMA (2, 0, 1) (0, 1, 1)12	0.551083	0.427895	1.5830
SARIMA(2, 0, 2)(1, 0, 2)12	0.556387	0.432363	1.6004
SARIMA(2, 0, 1)(1, 0, 1)12	0.566995	0.442440	1.6385
SARIMA(2, 0, 1)(2, 0, 2)12	0.570970	0.44524	1.6118
SARIMA(2, 0, 2)(1, 0, 1)12	0.567394	0.441699	1.6274

If the forecasting SARIMA model is correctly specified, the residuals from the model should be nearly white noise. This means that there should be no serial correlation left in the residuals. The Durbin-Watson statistic reported in the regression output is a test for AR(1) in the absence of lagged dependent variables on the right-hand side. The more general test for serial correlation in the residuals named Breusch Godfrey Serial Correlation LM Test is carried out and is observed that the residuals are white noise $(nR^2 = 7.19, \quad p - value = 0.026098)$.

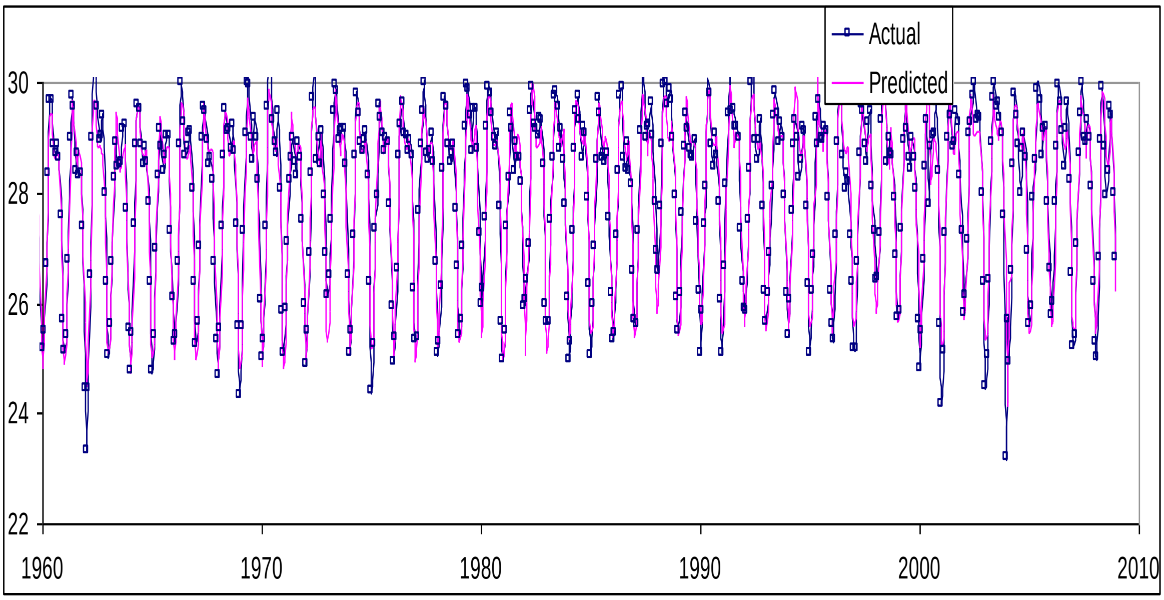


Fig. 4: Graphical Presentation of Actual Value and Predicted Value of SST (last 50 Years are Presented for Clarity of the Graph).

CONCLUSIONS

In this study, the SARIMA model is used to analyze and forecast the SST of the north zone of the Bay of Bengal which is very essential for Bangladesh. The overall average SST of the north zone of the Bay of Bengal in the study period was 27.82667°C whereas the highest monthly average temperature was around 30.655°C (in June) and the lowest monthly average temperature was about 23.203°C (in January). This temperature was fluctuating from 22 to 32°C. The time series plot and unit root test indicated that, the SST time series in north zone in the Bay of Bengal was stationary. The time series plot and correlogram exhibited that the SARIMA data will be best fit for the SST time series. The model SARIMA (2, 0, 1) $(0, 1, 1)_{12}$ is fitted for forecasting SST of the north zone of the Bay of Bengal using Box and Jenkins method. The RMSE, MAE and MAPE are used for a diagnostic checking of the fitted model. It is hoped that we can understand and describe the pattern of the SST of the north zone of the Bay of Bengal by using SARIMA (2, 0, 1) $(0, 1, 1)_{12}$ model. As the sea surface temperature is highly related with sea level and the atmospheric temperature, it would be useful to take some preventive measures before the situations worsen in the long run.

ACKNOWLEDGEMENT

The author is extremely thankful to Md. Bazlur Rashid, the Meteorologist, Bangladesh Meteorologist Department, Bangladesh, for providing him the necessary data of Sea Surface Temperature (SST) of the Bay of Bengal.

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