THE IMPACT OF SEASONALITY IN TEMPERATURE FORECAST
ON TOURIST ARRIVALS IN BANGLADESH: AN EMPIRICAL EVIDENCE

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Abstract: In the present study, we aim to investigate how seasonality influences the climate changes on the outdoor thermal comfort for traveling to visit Bangladesh. Wherein, the effect of temperature on tourist arrival is assessed using SANCOVA and SARIMA model at seven attractive sightseeing diverse places in Bangladesh. The highest temperature has appeared in Khulna and Rajshahi with 35.53 °C and 35.85 °C and the lowest temperature was appeared in Rajshahi and Rangamati with 10.40 °C and 11.72 °C, respectively. This result also revealed that the temperature for Dhaka, Chittagong, Cox's Bazar, Khulna, and Sylhet has extreme values of decreasing, in Dhaka the temperature will be 25.140 °C on January 2023, in Chittagong 260 °C on January 2027, Cox's Bazar 26.490 °C on January 2030, in Khulna 25.610 °C on January 2023, and in Sylhet 26.560 °C on January 2020. Our findings also indicate that the tourism industry of Bangladesh is more vulnerable to seasonal variation and this seasonality has a 74% effect on tourist's arrival as well as a 98% effect on overall temperature in Bangladesh.

Key words: seasonality, temperature, modeling, forecasting, SANCOVA model, SARIMA model

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INTRODUCTION

"Tourism" is associated with the stays rendered by people other than their normal environment (Pablo-Romero et al., 2017). In raising economic sector, tourism is the fastest-growing segment in the world. It plays a significant role in many national and local economies (Fyfe et al., 2020). According to the World Travel & Tourism Council's (WTTC) investigation, it is visible that this sector contributes 10.4% of collective GDP and 10% of total service, or 319 million careers, in 2018 (WTTC, 2019). Climate has a significant effect on the tourism resources, tourism zone, tourism seasons, tourism supply and demand, etc (Fang and Yin, 2015). For destination selection, they are not only influential factors but are also important in altering activities and travel plans, during the trip. Temperature is one of the most crucial factors in climatic variables for tourism in summer and bones trembled in winter tourism (Wilkins et al., 2018). Nice weather conditions encourage outdoor tourists and entertaining activities and thus play a key role in the choice of tourism destinations (Grillakis et al., 2016).

LITERATURE REVIEW

From the view of the tourism industry, it is generally assumed that the climate of places greatly influences the likings and pleasure of tourists (Kovács et al., 2016; Witchayakawin et al., 2020). Due to its seasonality, this issue determines the availability and quality of certain open-air recreational activities (Hewer et al., 2016). Climate change may affect short-term and long-term cost repercussions for the tour operators and economies reliant on tourism (Dube and Nhamo, 2018). Climate variables such as temperature compete a vital role in tourism flows worldwide. This enhances tourism at the forefront of the economic segments to be affected by climate change (Pintassilgo et al., 2016). It is identified as a motivator factor for travel, in the area of tourism research (Li et al., 2018).

Tourists want to travel to a wide diversity of environments, including urban and isolated regions (Priego et al., 2015). It is dangerous and unpleasant to hike or involve in energetic hard work during high temperatures (Hoogendoorn and Fitchett, 2018). But it has a positive impact on the tourists in large numbers and feels enjoyable environments on an outing in cool areas (Jedd et al., 2018). Therefore, climatic resources contribute significantly to tourists' decision-making processes, travel, as well as the related allocation of tourism expenditures (Scott et al., 2016). Different types of tourism, such as tourism for beaches and natural sights are vastly affected by seasonality as it is considered as an input in designing the tourism product, such as wintertime sports, and water sports (Li et al., 2017). Climatic variables have an important effect as well as a significant relationship with the tourism stakeholders to choose the destination and planning to travel in different seasons (Zhang and Kulendran, 2017). Therefore, seasonality is an essential issue that should be addressed at policy, marketing, and operation levels.

Tourist destinations have begun to identify the complexities of destination, attractiveness, climate change, and develop strategic plans (Becken et al., 2015). The feasibility of forecasting depends on the instant application of a surveillance system (Pasetto et al., 2017). So, the importance of temperature prediction is addressed in several studies. Chen et al. (2017) used the SARIMA model to analyze the monthly mean temperature in Nanjing, China. Naing and Htike (2015) carried out a study to forecast Malaysian monthly temperature using random forests. Research has also been undertaken on the impact of weather on tourist activities, tourist satisfaction, and tourist safety. Temperature and rainfall fluctuations of West Bengal and Assam, India has been analyzed and forecast by using the ARIMA model (Pratiher et al., 2016; Patowary, 2017). Historical and memorials, a lot of resorts, lovely beaches, natural picnic spots, green forest, tea plantation, and different tribal people in hill tracts are the main attractions for the visitors in Bangladesh. In the country's north, it includes the biggest and most ancient archaeological site, the Buddhist monastery, and the temple city in Rajshahi. The south-east of Bangladesh features

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natural and hilly, such as the Chittagong Hill Tracts, including a lot of natural lakes and beaches, along with the longest sea beaches in the world, at Cox's Bazar. South-west Bangladesh boasts, Sundarbans, includes the largest mangrove forest in the world, as well as royal Bengal tigers, mottled deer, and the historically important Sixty Dome Mosque in Khulna. There are green tea plantations on small hills and natural national forests with wildlife are in the Sylhet division, the north-eastern part of Bangladesh. Natural waterfalls and migratory birds in the haor (wetlands) areas are also popular attractions during winter. However, the temperature forecast potentially influences the tourist destination for touring Bangladesh's tourist attractions.

Again, when we do forecast about any specific issue of a country such as war, flood, and pandemic, etc. then people from outside assume that the whole country is under crisis. Maybe some parts of the country are affected so we cannot say the whole situation is not in favour of traveling. Also, travellers spend their holidays for not a long period, and it is difficult to visits all the attractive tourists' spots within a short period of traveling. Besides these travellers from the different parts of the world are not the same in choice. Some like summer, some prefer rainy, and some love the winter season for traveling. Therefore, the main objective of this research is to find out the relation between seasonality in climate change and the tourism industry in Bangladesh. So far in our knowledge, there is rare studies have been applied to the SARIMA model to evaluate the temperature forecast on selecting the tourist destination in Bangladesh.

Rahman et al. (2017) have applied the ARIMA model for the future projection of climate change in Bangladesh. Wavelet-ARIMA model has been used by Nury et al., (2017) to measure the temperature of the northeastern part of Bangladesh. It is therefore our aim in this study was to determine the influences of the climatic variables on the outdoor thermal comfort for traveling to visit Bangladesh. Wherein, the effect of temperature on seven geographically diverse tourists' destinations in Bangladesh, was assessed by using SARIMA and SANCOVA model. More specifically to examine the impact of seasonality on tourist's arrival that contribute to the national economy of Bangladesh. More additionally some like beaches, some prefer archaeological sites, some want to spend in nature, and some loves adventure in hilly and forest area. So, another major aim is to model and forecasting the climatic variable of different tourists' spots of Bangladesh that might be helpful for travellers to discover Bangladesh in their convenient time and comfortable climatic variable all year-round. Which makes the wheel of the tourism industry active and profitable all year round.

METHODOLOGY
Study Area and data collection

The climate of Bangladesh splits the year usually into three seasons: between May to October is the monsoons or wet season; from October to February is called cool season; and the dry season between March to May. In a sense of comfort, it is better to visit in the cool season to discover Bangladesh. There is heavy rainfall at the time of monsoon season which makes it difficult to travel in some tourist areas. Primary data has not been used because it would take a lot of time and employs complicated mental exercise, so secondary data is used in the study. By realizing this, we collect temperature data for tourists' stations from Bangladesh Agricultural Research Council (BARC) and Bangladesh Meteorological Department (BMD). Monthly maximum and minimum temperature data of capital of Bangladesh, Dhaka, the northern part (Rajshahi), in the south-eastern part (Chittagong, Cox's Bazar & Rangamati), the south-western part (Khulna), and the north-eastern part (Sylhet) in Bangladesh are taken as study variables as shown in Figure 1.
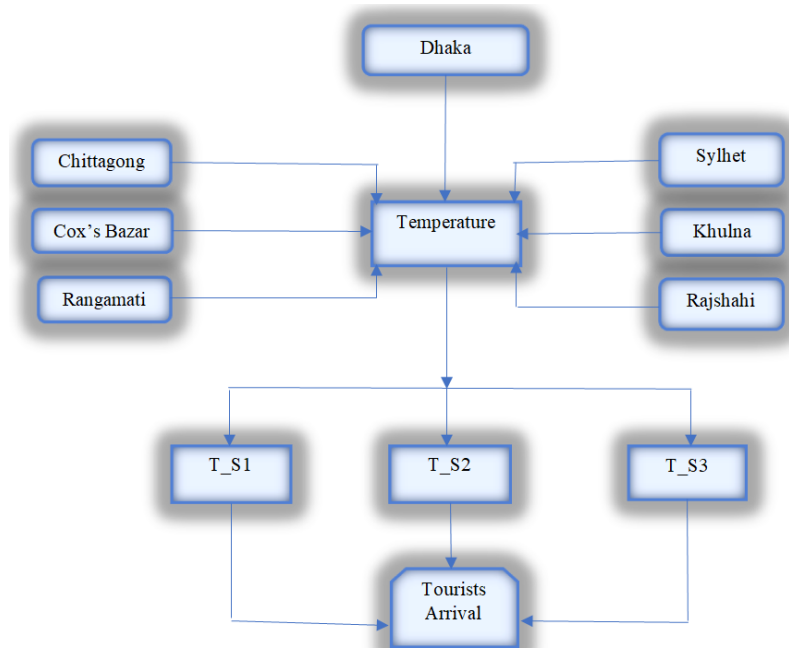

Figure 1. The Framework of the study

At first, we screen the missing values. We exclude the station from the modeling, which includes more than 2% missing value. Identification is another checking, for an equal amount of temperature along the year in the consecutive month. After checking and passing the above tests of these seven stations containing long-term data (more than 40 years) up to 2018 were used in this research. Therefore, maximum, and minimum temperature data from January 1972 to December 2018 was used for these stations.

Procedure of SARIMA Model

The present observation in the Autoregressive (AR) procedure of order p, is created by a weighted normal of past observations returning p periods together with parameters $\phi_1, \phi_2, \cdots, \phi_p$ and organized with a random disturbance in the present time frame. We indicate this procedure as AR(p) and compose the equation as,

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \varepsilon_t \quad \ldots (1)$$

Every observation in the Moving Average (MA) procedure of order q is created by a weighted average of random disturbance returning to q periods with parameters $\theta_1, \theta_2, \cdots, \theta_q$. For indicating, we write this procedure as MA (q) and compose the equation as,

$$y_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \quad \ldots (2)$$

With moving average error terms, the Autoregressive schemes of the form are denoted by-

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \ldots (3)$$

The above procedure is called ARMA (p, q) or Autoregressive Moving Average (ARMA) process of order (p, q). In general, if a time series is $I(d)$, then after differencing it d times we get an $I(0)$ i.e., stationary. Therefore, if we take difference a time series d times and then apply the ARMA (p,q) model to it, then the time series model is ARIMA (p,d,q).

Therefore, the ARIMA (p,d,q) the process can be written as:

$$\Delta^d y_t = \phi_1 \Delta^d y_{t-1} + \ldots + \phi_p \Delta^d y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} \quad \ldots (4)$$

Where, c and μ are constant ε_t is assumed to be a normal random variable with 0 mean and variance σ_ε^2

p = number of autoregressive terms and q = number of moving average terms

d = number of differencing

$\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-q}$ = errors in previous time periods

$\Delta y_t = y_t - y_{t-1}$, Δ^d indicates the d th difference of y_t and $\Delta y_{t-1} = y_{t-1} - y_{t-2}$ are the first differences of y_t and so on.

Where Δ^d indicates the d th difference of y_t. If the data shows a strong seasonal pattern, this indicates a high correlation between values observed during the same season in consecutive years. Considering (p, d, q) is the nonseasonal part and (P, D, Q)s is the seasonal part of the model then the Seasonal ARIMA model can be labeled as ARIMA (p, d, q) * (P, D, Q)s that could be written as:

$$\phi_p(L)\phi_p^S(L^S)(1-L^S)^D(1-L)^d y_t = \theta_q(L)\theta_q^S(L^S)\varepsilon_t \quad \ldots (5)$$

$$\phi_p^S(L^S) = 1 - \phi_1^S L^S - \ldots - \phi_p^S L^{SP}$$

$$\theta_q^S(L^S) = 1 + \theta_q^S L^S + \ldots + \theta_q^S L^{SQ}$$

Where $\phi_p(L), \theta_q$ are as before, s is the seasonal period and D is the number of times the seasonal difference operator (1-L^S) is applied. Building an ARIMA model consists of four systematic stages (identification, estimation, diagnostic check, and application or forecast) (Hossen S.M. et al., 2020).

The SANCOVA model

Any regression model which contains the quantitative and qualitative variables together is called analysis of covariance (ANCOVA) model. These ANCOVA models are the augmentation of ANOVA models. This technique provides a statistically controlling effect of quantitative regresses control variables. To find out the impact of different seasons on tourists' arrival, we proposed a modified ANCOVA model named seasonal analysis of covariance (SANCOVA). One of the significant advantages of this model over other regression model is with it, we can measure not only the relationship and partial effect of the independent variable but also can compare the qualitative effect of the independent variable. At first, we divided the temperature data into three consecutive seasons, namely winter/cool, summer/dry, and rainy/wet seasons. Each season contains the average of the average temperature of seven tourists' spots in the respective season. Realizing the limitations of data availability, only three variables are considered in the present research. For finding the relation between tourists' arrival and seasonal effect, in that case, the arrival of tourists is taken as the dependent (endogenous) variable and three seasons are considered as independent (exogenous) variables. In this model number of variables must be included depending on the nature of the phenomenon and the purpose of the research under consideration. In this study total tourists' arrival is quantitative variables together with three seasons the climatic variables are considered qualitative variables. To find the seasonal effect on tourists' arrival, we consider the dummy variable for three seasons. So, we consider the seasonal analysis of the covariance (SANCOVA) model in the present analysis. Therefore, our proposed seasonal dummy variable regression model is as follows.

Let us consider our desire classical linear regression model,

$$Tourists_{it} = \beta_0 + \beta_1 AVG(D + C + Cox + Ran + K + Raj + S)\sum_{i=1}^{n} Wet(June - October)$$

$$+ \beta_2 AVG(D + C + Cox + Ran + K + Raj + S)\sum_{i=1}^{n} Cool(November - February) + \beta_3 AVG(D + C + Cox + Ran$$

$$+ K + Raj + S)\sum_{i=1}^{n} Dry(March - May) + u_{it} \quad \ldots (6)$$

$$Y_t = \beta_0 + \beta_1 S_1 + \beta_2 S_2 + \beta_3 S_3 + u_t \ldots (7)$$

Where, Y_t = Tourist arrival   AVG = Average
β_0 = Intercept,   D = Dhaka,   Raj = Rajshahi,
β_1 = coefficient of Season 1/Wet temperature,   C = Chittagong,   S = Sylhet,

β_2 = coefficient of Season 2/Cool temperature,   Cox = Cox's Bazar, S_1 = Wet season,

β_3 = coefficient of Season 3/Dry temperature,   Ran = Rangamati, S_2 = Cool season,

u_t = error terms   K = Khulna, S_3 = Dry season,

From equation (7) our proposed SANCOVA model is, $Y_t = \beta_0 + D_1 S_1 + D_2 S_2 + D_3 S_3 + u_t$ ...(8)

Where, Y_t = Tourist arrival; β_0 = Intercept; $D_1 = \begin{cases} 1, when\ Season1 \\ 0, otherwise \end{cases}$; $D_2 = \begin{cases} 1, when\ Season2 \\ 0, otherwise \end{cases}$; $D_3 = \begin{cases} 1, when\ Season3 \\ 0, otherwise \end{cases}$

u_t = error terms; D_1, D_2, D_3 are reference category

DISCUSSIONS
Model Identification

To check if the data is stationary and if there is any seasonality by which the data series were analyzed. Graphical analysis, Correlogram, and Unit root tests are used to test the stationarity of the time-series data. Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) test is widely used to check the stationarity. If the series has no trend and the error terms are autocorrelated, then we cannot apply the Dickey-Fuller test. Another test of stationarity is Kwiatkowski-Philips-Schmidt-Shin (KPSS) and Phillips-Perron (PP) test was used. The test results for the different stations are given in Table1. To identify the suitable Autoregressive Integrated Moving Average (ARIMA) model, we use the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). From the ACF, we can count the number of significant autocorrelations, which is a useful estimate of the number of Moving Average (MA) coefficients in the model. On the other hand, from the PACF plot, we found the number of Autoregressive (AR) coefficients in an ARIMA model.

Table 1. Different test results for stationary

| Sampling Station	Unit Root test								
	ADF	P-value	Elliott-Rothenberg-Stock DF-GLS test statistic	Phillips-Perron test statistic	P-value	Kwiatkowski-Phillips-Schmidt-Shin test			
						test statistic*	1% level	5% level	10% level
Chittagong (max)	-2.728	0.07	-0.968	-10.429	0.000	1.182	0.739	0.463	0.347
Chittagong (max)	-8.298	0.00	-0.254	-22.254	0.000	0.306	0.739	0.463	0.347
Cox's Bazar (max)	-2.272	0.182	-0.254	-16.303	0.000	3.307	0.739	0.463	0.347
Cox's Bazar (min)	-3.513	0.008	-0.030	-5.424	0.000	0.779	0.739	0.463	0.347
Rangamati (max)	-3.339	0.014	-0.846	-9.5308	0.000	1.233	0.739	0.463	0.347
Rangamati (min)	-3.672	0.005	-0.932	-4.790	0.000	0.922	0.739	0.463	0.347
Dhaka (max)	-4.544	0.0002	-0.374	-8.18	0.000	0.367	0.739	0.463	0.347
Dhaka (min)	-4.544	0.0002	-0.374	-8.180	0.000	0.367	0.739	0.463	0.347
Sylhet (max)	-3.599	0.006	-0.415	-9.78	0.000	1.804	0.739	0.463	0.347
Sylhet (min)	-3.301	0.015	0.160	-4.361	0.000	1.378	0.739	0.463	0.347
Khulna (max)	-4.871	0.000	-1.191	-7.156	0.000	0.482	0.739	0.463	0.347
Khulna (min)	-3.739	0.004	0.067	-4.633	0.000	0.406	0.739	0.463	0.347
Rajshahi (max)	-6.951	0.000	-0.369	-7.864	0.000	0.545	0.739	0.463	0.347
Rajshahi (min)	-3.804	0.003	-0.357	-4.617	0.000	0.097	0.739	0.463	0.347
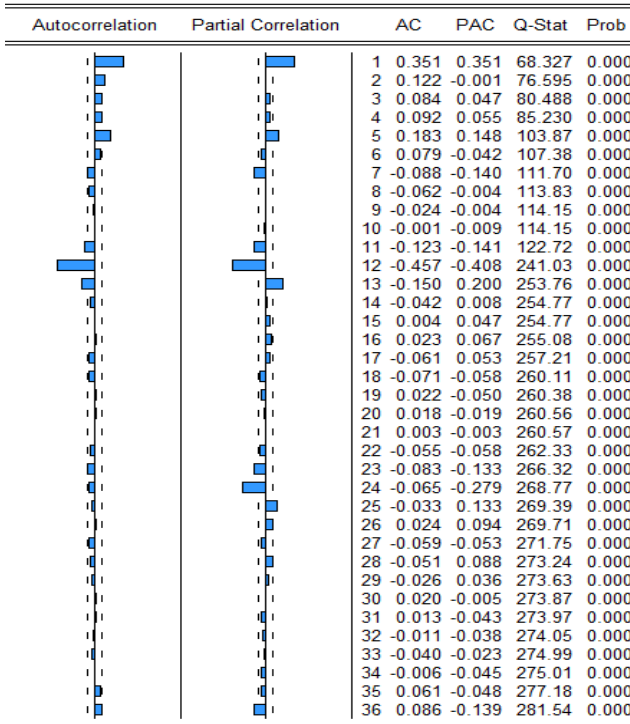
Figure 2 (a). The time series plot of temperature for Cox's Bazar is shown with ACF and PACF plots before regular difference
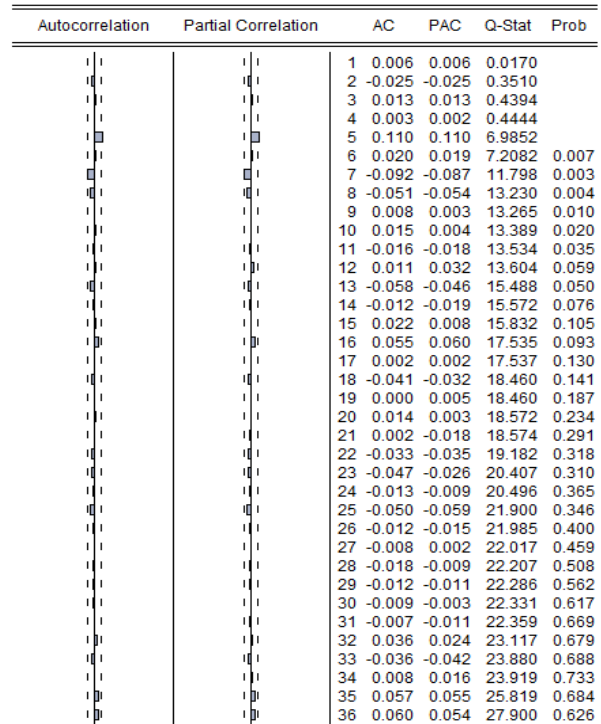
Figure 2 (b). The time series plot of temperature for Cox's Bazar is shown with ACF and PACF plots after taking the first difference

For example, the time series plot of Cox's Bazar station is shown with ACF and PACF plots in Figure 2(a). In Figure 2(b), we observed that AR and MA move in opposite directions having exponential decay. After taking the first difference, both ACF and PACF show a rapid decline and all the spikes are in standard error bounce. So, the series becomes stationary and it is an ARIMA model with the presence of seasonality in the time series data. For model identification, we take the seasonal difference. The seasonal difference of a time series is the series of changes from one season to the next. We have monthly data, in which there are 12 periods in a season, the seasonal difference of

y at period t is $y_t - y_{t-12}$. Which is denoted by $\nabla_{12} y_t$. Where $\nabla_{12} y_t = y_t - y_{t-12}$.
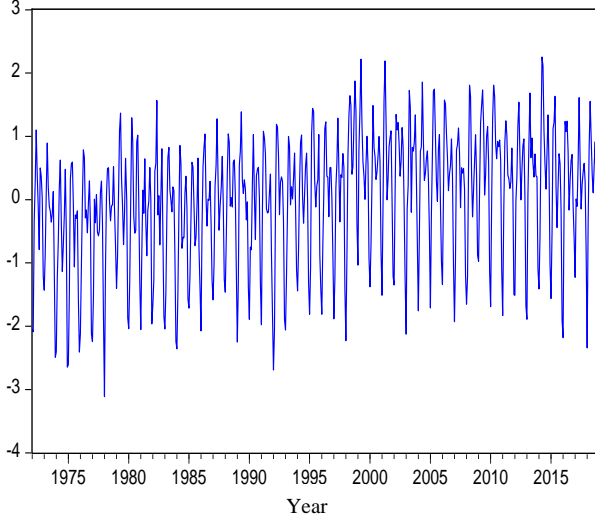

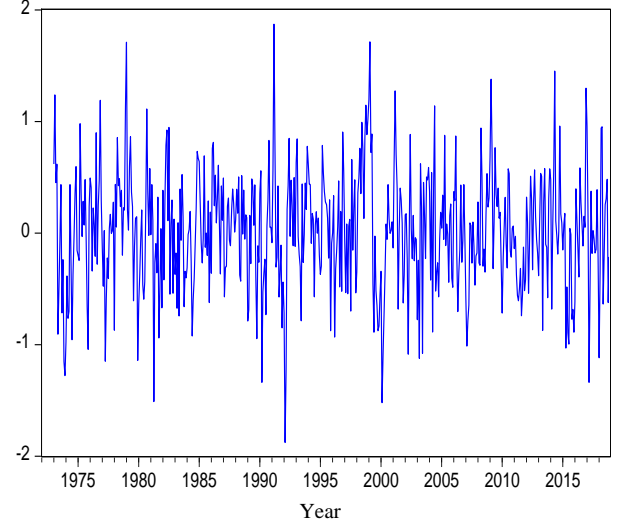Figure 3(a). The seasonal difference of series before seasonal difference

Figure 3(b). The seasonal difference of series after taking the seasonal difference

From the above Figure 3(a & b), we show that the seasonal differenced series seems to be stationary. Now we evaluate Seasonal Autocorrelation (SAC) and Seasonal Partial Autocorrelation (SPAC) of $\nabla_{12} y_t$ at different lags.

Diagnostic Checking

To know about the residuals are normally distributed or not, we will check the Histogram and Normality test. The Jarque-Bera test of normality is,

$$JB = n \left[\frac{s^2}{\sigma} + \frac{(k-3)^2}{24} \right]$$

Where, n = sample size, s= skewness, and k =kurtosis.

Histogram and Jarque-Bera test results (shown in Table 2) indicate that the residual is normally distributed. Therefore, the test results suggest that the model is fully specified.
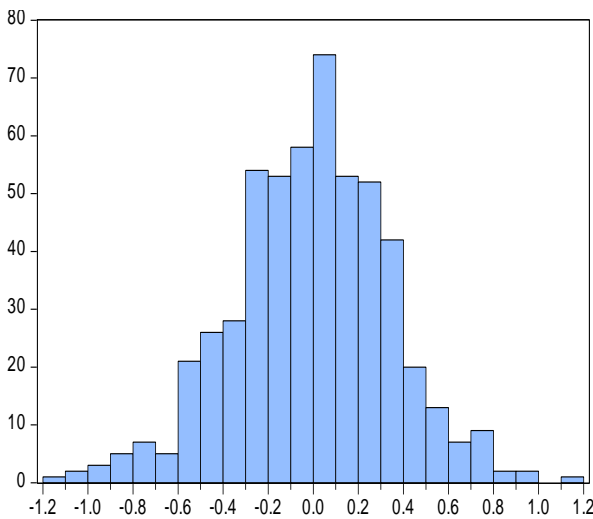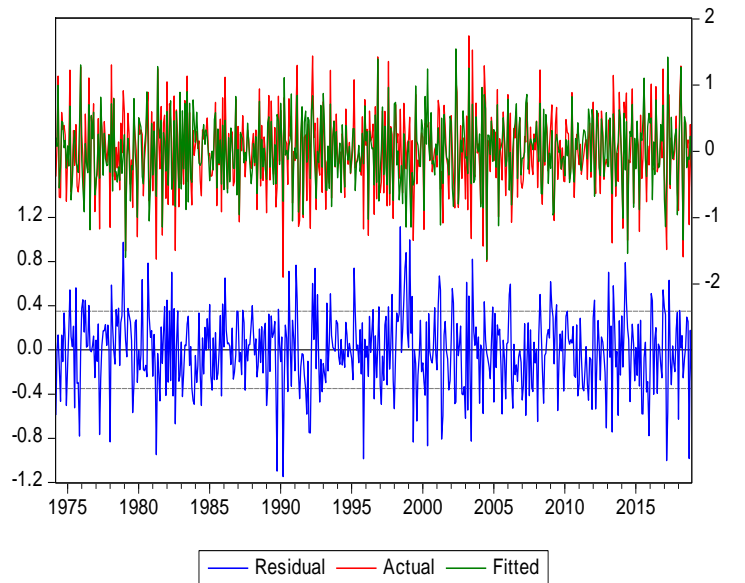

Figure 4. Histogram and Normality checking

Figure 5. Actual fitted and residual plot for SARIMA SARIMA $(1,1,1) \times (1,1,2)_{12}$

From Figure 4 and 5, it is observed that autocorrelation and Q-test for different lags support the hypothesis that there is no autocorrelation in the residual. Thus, the model is fully specified.

Modelling

For the presence of seasonality, with the help of Box-Jenkins (1976) and modified by Box et al. (2019) model building process, we have built the SARIMA model for the monthly temperature of seven geographically diverse locations in Bangladesh. There are a variety of statistical measures of forecasting error, mostly based on an average of the errors between the actual and forecast values at time t. They are:

Mean Absolute Error (MAE):

$$MAE = \frac{1}{T} \sum_{1}^{T} \left| Y_{actual} - Y_{forecast} \right|$$

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{1}^{T} (Y_{actual} - Y_{forecast})^2}{\sum_{1}^{T} (Y_{actual} - \bar{Y})^2}}$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{T} \sum_{1}^{T} \left| \frac{Y_{actual} - Y_{forecast}}{Y_{actual}} \right| \times 100\%$$

For which model we get the lowest mean square error, we take the model as the best model. We use the best model for forecasting those are shown in Table 2.

Table 2. Different SARIMA models for different tourists' stations

Station	Model	Model Fit statistics					
		R-squared	RMSE	MAE	MAPE	Jarque -Bera	P-value
Chittagong (Max)	SARIMA $(1,1,1) \times (0,1,1)_{12}$	0.602	0.503	0.407	164.563	224.806	0.000
Chittagong (Min)	SARIMA $(1,1,1) \times (0,1,1)_{12}$	0.679	0.184	0.126	31.063	441.577	0.000
Cox's Bazar (Max)	SARIMA $(1,1,1) \times (1,1,2)_{12}$	0.672	0.471	0.314	71.491	5.983	0.050
Cox's Bazar (Min)	SARIMA $(1,0,0) \times (0,1,1)_{12}$	0.536	0.199	0.138	23.895	59.924	0.000
Rangamati (Max)	SARIMA $(1,1,1) \times (0,1,1)_{12}$	0.677	0.349	0. 258	260.301	45.225	0.000
Rangamati (Min)	SARIMA $(1,0,1) \times (0,1,1)_{12}$	0.534	0.199	0.146	26.259	21.441	0.000
Dhaka (Max)	SARIMA $(2,0,1) \times (0,1,1)_{12}$	0.546	0.319	0.249	394.467	39.465	0.000
Dhaka (Min)	SARIMA $(1,0,1) \times (0,1,1)_{12}$	0.548	0.320	0.251	39.753	25.915	0.000
Sylhet (Max)	SARIMA $(1,0,0) \times (2,1,1)_{12}$	0.579	0.468	0.371	75.682	14.487	0.001
Sylhet (Min)	SARIMA $(2,1,2) \times (0,1,1)_{12}$	0.685	0.165	0.128	65.052	34.035	0.000
Khulna (Max)	SARIMA $(1,0,0) \times (0,1,1)_{12}$	0.510	0.289	0.230	48.586	73.913	0.000
Khulna (Min)	SARIMA $(2,0,0) \times (0,1,1)_{12}$	0.519	0.171	0.124	27.822	36.319	0.000
Rajshahi (Max)	SARIMA $(0,0,1) \times (1,1,2)_{12}$	0.314	0.263	0.369	90.721	54.701	0.000
Rajshahi (Min)	SARIMA $(2,0,1) \times (0,1,1)_{12}$	0.433	0.156	0.122	20.166	19.475	0.000

Estimation of SANCOVA model

Estimating the impact of seasonal effect on tourist's arrival we get the following Table 3.

Here, the multiple coefficients of determination (R^2) is 0.74. This result suggests that the independent variable explained the dependent variable by 74% of the total variation. That is seasonality has a 74% effect on tourist's arrival in Bangladesh. In Table 4, the multiple coefficients of determination (R^2) for all reference category is 0.98. This result suggests that the independent variable explained the dependent variable by 98% of the total variation. That is seasonality has a 98% effect on overall temperature in Bangladesh.

Table 3. Seasonal effect on tourists' arrival

Model	Standardized Coefficients	t statistic	P-value	R	R^2
Season 1	-0.042	-0.077	0.951		
Season 2	-1.174	-1.610	0.354	0.860	0.740
Season 3	0.898	1.224	0.436		

Table 4. Seasonal effect on annual Temperature

Reference category	R	R^2	β_0	D_1	D_2	D_3
Winter	0.992	0.983	22.14		0.918	1.052
Dry	0.992	0.983	29.02	-0.918		0.134
Wet	0.992	0.983	28.15	-1.052	-0.134	

Findings from the SARIMA model

Time series analysis and forecasting have become a major tool in numerous applications in meteorology and other environmental areas to understand phenomena, like temperature, humidity, and rainfall. To show the forecasting behavior of the Climate change of **Cox's Bazar** in Bangladesh, we mainly study the time series data and fit the appropriate time series model and then the forecast is based on the fitted model. After getting the series stationary, then we take the seasonal differences for the presence of seasonality in the time series data. Observing ACF and PACF we have fitted as SARIMA model.

For the monthly rainfall of **Cox's Bazar**, we have fitted SARIMA $(1,1,1) \times (1,1,2)_{12}$ model and then estimate the parameters of the model. After getting the appropriate model we check the validity of the model using Residual diagnostics and stability tests. Normal probability plot and Jarque-Bera tests are used to check the normality of the residuals. Then we forecast up-to 2030.

Similarly, Observing ACF and PACF have fitted as SARIMA model for monthly temperature of Chittagong (max. & min.), Sylhet (max. & min.), Dhaka (max. & min.), Khulna (max. & min.), Rajshahi (max. & min.) and Rangamati (max. & min.) we have fitted SARIMA(1,1,1)×(0,1,1)12, SARIMA(1,1,1)×(0,1,1)12, SARIMA(1,0,0)×(2,1,1)12, SARIMA(2,1,2)×(0,1,1)12, SARIMA(2,0,1)×(0,1,1)12, SARIMA(1,0,1)×(0,1,1)12, SARIMA(1,0,0)×(0,1,1)12, SARIMA(2,0,0)×(0,1,1)12,SARIMA(0,0,1)×(1,1,2)12, SARIMA(2,0,1)×(0,1,1)12, SARIMA(1,1,1)×(0,1,1)12 and SARIMA(1,0,1)×(0,1,1)12 model consecutively and then estimate the parameters of these model. After getting appropriate model we check the validity of the model using Residual diagnostics and stability test. Normal probability plot and Jarque-Bera test are used to check the normality of the residuals. Then we forecast up to 2030.

From the above Figure 6, we found that the maximum temperature is slightly increasing approximately 1 ^{0}C but decreasing approximately 2 ^{0}C. The highest temperature will have appeared Khulna and Rajshahi with 35.53 ^{0}C and 35.85 ^{0}C respectively. It also shows that for Dhaka, Chittagong, Cox's Bazar, Khulna, and Sylhet have extreme values for decreasing temperature. This indicates that in Dhaka, the maximum temperature will be 25.14 ^{0}C on January 2023, in Chittagong 26 ^{0}C on January 2027, Cox's Bazar 26.49 ^{0}C on January 2030, in Khulna 25.61 ^{0}C on January 2023, and in Sylhet 26.56 ^{0}C on January 2020.

From the above Figure 7, we found that the minimum temperature is slightly increasing approximately by 1 ^{0}C but decreasing approximately by 2 ^{0}C. The lowest temperature appeared in Rajshahi and Rangamati with 10.40 ^{0}C and 11.72 ^{0}C respectively. It also shows that Dhaka has extreme values for decreasing temperature. This indicates that in Dhaka the minimum temperature will be 12.48 ^{0}C in January 2023 whereas the lowest temperature in Dhaka is 13.08 ^{0}C.
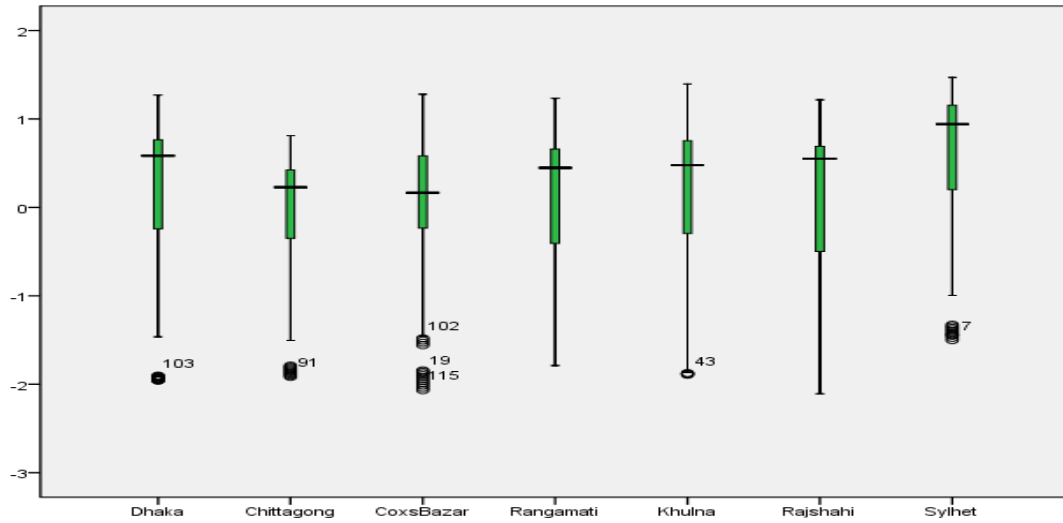

Figure 6. Comparison of forecasted maximum temperature between different tourists' stations
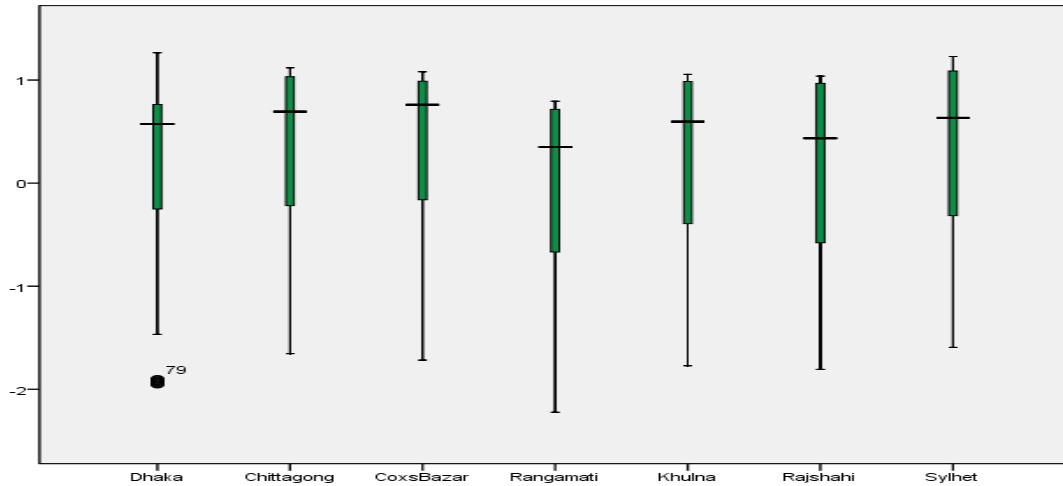

Figure 7. Comparison of forecasted minimum temperature between different tourists' stations

Findings from SANCOVA model

Here in the analysis, we found that the multiple coefficients of determination (R^2) for seasonal effect on tourists' arrival. is 0.74 and for seasonal effect on annual temperature is 0.98. This result suggests that the total seasonality has a 74% effect on tourist's arrival in Bangladesh. This result also reveals that seasonality has a 98% effect on overall temperature in Bangladesh.

Considering Winter season as the reference category

The mean value of the reference category is representing by β_0 called intercept term i.e., winter season. The intercept value β_0 represents the mean value of the reference category, i.e.; winter season. Hence, in the present analysis, the intercept value of the regression model is about 22.14^{0}C, represents the mean temperature in the winter season.

β_2 tells us the mean temperature in the summer season is greater about 0.918 ^{0}C than the mean temperature of the reference category, winter season. β_3 provides the result that the mean temperature in the wet season is higher about 1.052 ^{0}C than the mean temperature of the reference category, winter season.

CONCLUSIONS

The temperature forecast is critical in Bangladesh because of its spatiotemporal variation and non-linear pattern in size. However, the estimation of temperature is urgency in Bangladesh for harvesting rainwater, flood management, water resource management, urban planning, and maximizing the irrigation system operation. In the present study, the SARIMA model was utilized to predict the temperature forecast in seven tourisms attraction in Bangladesh. The highest and the lowest R^2 values were determined to be 0.685 and 0.314 in Sylhet and Rajshahi, respectively. This indicates that the developed SARIMA models accurately describe the temperature forecast in Bangladesh. This finding reveals that the developed SARIMA models could be utilized as a reliable mathematical tool to determine the temperate forecasting. The finding of this present study suggests that the SARIMA model can be used to carry out having more climatic parameters like wind speed and direction, wind pressure, drought, sea-level rise, solar radiation, and their impacts on human activity. Our findings also indicate that the tourism industry of Bangladesh is more vulnerable to seasonal variation and this seasonality has a 74% effect on tourist's arrival in Bangladesh. So, we can conclude that our proposed modified ANCOVA modeling named SANCOVA is better than any other regression model in the case of evaluating the seasonal effect on the national economy. It would be applicable and also possible to study climatic variables of a specific region of the country or in a specific season. The study also can carry out to estimate the effect of the climatic variable on tourist arrival, crop productions, and food security.

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