GeoJournal of Tourism and Geosites
ISSN 2065-1198, E-ISSN 2065-0817
Year XV, vol. 41, no. 2, 2022, p.606-613
DOI 10.30892/gtg.41235-869

DO TOURIST ARRIVALS IN BANGLADESH DEPEND ON SEASONALITY IN HUMIDITY? A SARIMA AND SANCOVA APPROACH

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Citation: Hossen, S.M., Ismail, M.T., Tabash, M.I., & Anagreh, S. (2022). DO TOURIST ARRIVALS IN BANGLADESH DEPEND ON SEASONALITY IN HUMIDITY? A SARIMA AND SANCOVA APPROACH. *GeoJournal of Tourism and Geosites*, 41(2), 606–613. https://doi.org/10.30892/gtg.41235-869

Abstract: Humidity is one of the most significant climate factors influencing destination decisions and the distribution pattern of vacationers during various seasons. This variable influences the benefit of day-to-day travel industry activities and keeps up the destination competitiveness. In this paper, the univariate Seasonal Autoregressive Integrated Moving Average (SARIMA) model has been applied to conjecture month-to-month humidity for Bangladesh mainstream tourist spots up to the year 2025. Later, the influence of humidity on tourist arrival that contributes to the national economy was also assessed using the Seasonal Analysis of Covariance (SANCOVA) model. Our findings indicate that the Bangladesh tourism industry is more vulnerable to seasonal variation, and this seasonality has a 72% effect on tourist arrival and a 58% effect on overall humidity. The findings suggest that if per unit humidity in seasonality increases, then the tourism industry income will increase by approximately 59.463 thousand Taka (Bangladesh currency) in every season.

Key words: seasonality, humidity, SARIMA, SANCOVA model, Bangladesh

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INTRODUCTION

The travel industry assumes an undeniably significant role in the economy. Key factors that impact touristic exercises incorporate climate, famous attractions, and policy-driven issues (Salata et al., 2017). Europe has appreciated the long haul of the travel industry development, yet its presentation concerning the end of the week the travel industry fluctuates among its member countries (Maráková et al., 2016). Tourism is a vital industry for developing countries since it promotes quite a lot to their GDP. Bangladesh is a very well industrialized country and popular as a tourist destination (Lim and Giouvris, 2017). In 2013 the number of arrivals was 277596, while in 2017 this number increased by 778143. Because of the expanding trend, it is significant to conjecture the number of visitor appearances with exactness since it will profit from the immediate and circuitous exercises that identified with the tourism industry. Along these lines, the legislature or related organization and offices could utilize the projected figure to make an improvement situation, for example, preservation of natural resources and to produce appealing open doors for foreign investors.

In Bangladesh in 2018, the travel and tourism industry grew 11.6% and contributed 4.4% of the country's total economic output. Bangladesh ranks in 11th position in the world's 20 fastest growing countries in terms of travel and tourism; by 2029 travel and tourism are forecast to constitute 6.1% of Bangladesh's GDP (WTTC, 2019).

Bangladesh has a tropical monsoon climate described by wide seasonal varieties in precipitation, high temperature, and high humidity. Three seasons are commonly perceived: a hot, muggy summer from March to June; a hot, humid, and rainy monsoon season from June to October; and a warm-hot, dry winter from November to February. These weather conditions have attracted the researcher to examine climatology data such as rainfall, maximum and minimum temperature for some Bangladesh stations using the ARIMA model. However, as far as the author's knowledge, humidity forecasts for Bangladesh tourist areas have not been done yet. Thus, in this study, we will empirically examine the impact of humidity on tourist arrival and the effect on Bangladesh's national economy to fill up the research gap.

By providing monthly humidity data on popular tourist spots the Bangladesh Agricultural Research Council (BARC) and the Bangladesh Meteorological Department (BMD) helped to conduct this study. Then this study applies the seasonal ARIMA model using the Box-Jenkins method to build a forecasting model for the month-to-month humidity data of

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popular tourist spots in Bangladesh. Furthermore, this study also proposes the SANCOVA model to evaluate the effect of seasonality on the national economy in Bangladesh. The followings are the main contribution of this study:

1. To identify the association between seasonal variation in humidity and the tourism industry in Bangladesh.
2. To construct an appropriate SARIMA model for the humidity on the seven tourist stations and examines the effect of seasonality on the national economy in Bangladesh by SANCOVA model.
3. To obtain the parameters of the required model and use diagnostic tests to determine model accuracy.

The outline of the paper is as follows. Section 2 highlight the literature review and Section 3 provides details about the Materials and Methods used in the study. Section 4 presents the results of the study with a relevant discussion. Finally, we present the conclusion with implications in Section 5.

LITERATURE REVIEW

It was discovered that a favorable climate (summer and winter) for a given product and certain assets that would attract vacationers could influence demand or appearances in traveler destinations (Akhtar et al., 2019). A study also found a correlation among climatic variables such as temperature, humidity, and wind speed with human entertaining in open places for their comfort (Dillimono, 2015). Human wellbeing depends to some extent on the physiological and mental responses of the body to local climatic conditions – the way toward adjusting to new conditions when traveling can influence these responses (Katerusha and Matzarakis, 2015; Csete and Szécsi, 2015). In the present day, the travel industry (with brisk exchanges to distant destinations with an alternate climate as for the typical local conditions) agreements with visitors to adjust the new atmosphere which their body can absorb physically and psychologically through a temporary lived time (Hanna et al., 2016; Matzarakis et al., 2010; Salata et al., 2016). For outdoor comfort during spring, higher temperatures and meteorological pressures positively correlate with entertaining (Keller et al., 2005). However, higher temperatures bring about more negative attitudes surpassing comfort during the summer.

Seasonal changes have an impact on the relationship between climatic variables and variability in attitude. Shorter hours of sunshine may lead to negative feelings during seasonal changes (Beecher et al., 2016). Bangladesh is bestowed with immense natural beauty. Its captivating historical and natural attractions have drawn many travelers from far and wide throughout the ages. The Country additionally flaunts a rich social inheritance. More than 2,000 years of its checkered history, numerous distinguished administrations of lords and sultans have administered and vanished, leaving their imprints looking like radiant urban communities and landmarks the forsaken remnants of a considerable lot of these destinations are as yet noticeable in numerous spots all through the nation. In the north of the country, such sites incorporate Puthia, the temple city in the Rajshahi division; Mahasthangarh, the most ancient archeological site, in Bogra district; Paharpur, the religious community of Buddhist in Naogaon district; and Kantaji, the ornamental, stoneware of Hindu religion, in Dinajpur district. Sandy sea beaches with natural and hilly areas, including tribal with their engaging cultural activities in the Chittagong Hill Tracts, highlight Bangladesh south-east. The Cox’s Bazar, a prominent and the longest sandy sea beach globally, is the key choice for tourists observing sunset in the southeast part.

South-west Bangladesh flaunts the world's biggest mangrove forest, Sundarbans, just as royal Bengal tigers and mottled deer in the Khulna locale. The verifiably significant Sixty Dome Mosque in the city of Bagerhat is another Famous site. In the Bangladesh north-eastern part, the land cover with a green carpet of enchanting tea gardens on little slants with glamorous water flow in the Sylhet division. Forests with natural beauty and stone bath water flow, as a transient feathered creature in the haor (wetlands) regions during winter. The Ministry of Tourism structures national approaches for the advancement and promotion of the travel industry and keeps up the Beautiful Bangladesh crusade. The Bangladesh Government has formed a Tourist Police unit to secure local and foreign tourists more readily and take care of the usual attractions and natural life in significant tourist destinations. Therefore, we aimed to ascertain the impact of humidity for the tourists to discover Bangladesh. Mainly we focus on the effect of humidity asses by using SARIMA and SANCOVA models on seven attractive tourist destinations in Bangladesh.

MATERIALS AND METHODS

Data collection

Three main seasons split the year of Bangladesh climate: a wet or monsoon season, which lasts from May to October; a cooler season between October and February; and the dry season from March to May. The cool season is the best time to travel in the country from comfort. The monsoon season typically carries hefty rainfall at that time, making travel in certain areas impossible. This study uses monthly humidity data for the following locations in Bangladesh: Dhaka (the capital city), the south-eastern zone (Chittagong, Cox’s Bazar, and Rangamati), the south-western region (Khulna), the northern part (Rajshahi), and the north-eastern area (Sylhet). The study will examine the relationship between changes in the climate and the tourism business. Figure 2 shows the framework of the study.

It is impossible to use primary data because it would take much time and sophisticated equipment support, which is lacking. Thus, secondary data are used in the study. Other covariates may be included in the model building process. Even the secondary sources could not provide the data for all the years of the last three decades for all the meteorological stations. We composed secondary humidity data from the BBS (Bangladesh Bureau of Statistics), the BARC (Bangladesh Agricultural Research Council) and the BMD (Bangladesh Meteorological Department). At the very beginning, we examined the data to sort out missing values. Stations that contain missing values of more than 2% were not considered. After finishing data screening, the above seven tourist spots with enduring data (more than 40 years) were used for the present study. Therefore, humidity data from January 1972 to December 2017 for those spots were utilized in this study.

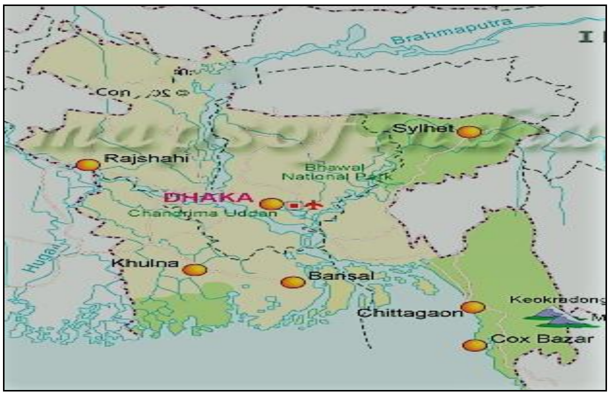


Figure 1. Map of Bangladesh with selected tourist stations (Source: www.pinterest.com)

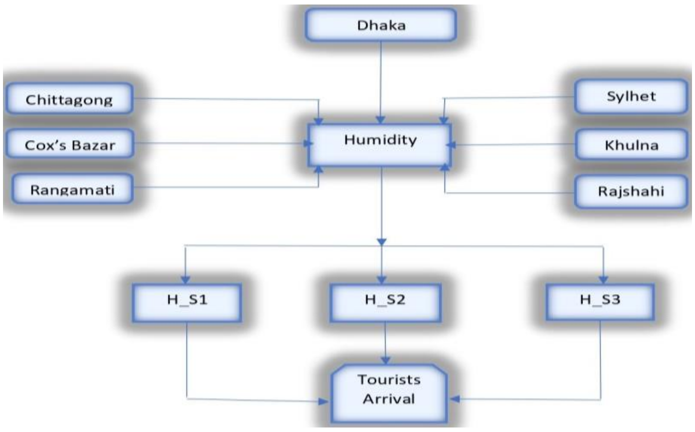


Figure 2. Framework of the study

Reasons for using SARIMA Model

Humidity is one of the most significant climate factors influencing the decision of destination and the distribution pattern of vacationers during various seasons. This variable influences not just the benefit of day-to-day travel industry activities yet additionally the arranging and structure of the travel industry facilities to keep up destination competitiveness later. Thusly, having an early sign of conceivable future humidity levels could assume a noteworthy role in planning the tourism industry. Seasonality is not a simple concept easily discussed by broad policy objectives (Connell et al., 2015). Explicitly modeling seasonality in a time series appears preferable for at least three reasons.

First, in many situations, the seasonal fluctuations and forecasts thereof are of interest. For example, in marketing and tourism applications, forecasts of possible changes in seasonality can be beneficial, in addition to forecasts of the long-run trend. Similarly, information on the nature of seasonal movements in variables such as production, investment, and inventory building may be of interest, both for individual firms and policymakers (Robert et al., 1998). Second, seasonal adjustment procedures are essential to analyze the resulting seasonally adjusted series. Third, this seasonal component is overlooked and needs to be projected from the data. It has been well documented that this may distort other time series features, including trends, structural breaks, and nonlinearity. Previously, ARIMA models were not used to predict climatic variables except particularly in various scientific and engineering applications. However, this model was recently applied in the sea surface temperature (SST) data to forecast in the Baltic Sea up to the year 2050 (Baker-Austin et al., 2013). Recently, studies of climatic variables with different weather station data were also examined to compare temperature and rainfall trends in some parts of the world (Zhang et al., 2008).

The SARIMA Model

In the process of Autoregressive (AR), the present observation y_t of arranging *p* made by a weighted normal of past perceptions of *p* periods with parameters $\emptyset_1, \emptyset_2, \cdots, \emptyset_p$ and arbitrary unsettling influence in the current period. This procedure signifies as AR (*p*) and can be composed within the frame of the equation (Rahmatullah and Imon, 2017) is,

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t.$$

Similarly, in the process of Moving Average (MA), the present observation y_t of order *q* produced a weighted average previous q period of random disturbance with parameters $\theta_1, \theta_2, \cdots, \theta_q$. This procedure signifies as MA (*q*) and can be written in the form of the equation is, $y_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}$

Where c and μ are steady $\varepsilon_t$expected a typical arbitrary variable containing mean 0 and variance σ_ε^2. To indicate this MA process order, we use the system MA(*q*) analogous to the AR case. The mean of the MA (*q*) process is assumed to be 0, $E[t] = 0$. With moving average error terms, the Autoregressive (AR) structures can be written in the equation form is,

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}$$

The process mentioned above is defined by ARMA (*p*, *q*) and called an Autoregressive Moving Average (ARMA) process of order (*p*, *q*). The Autoregressive Integrated Moving Average (ARIMA) process is broadly utilized in econometric time series modeling. This model states that the data used is stationary. However, many of the econometric time series data are nonstationary and need integration to become stationary. If a time series is integrated of order one i.e.,$\mathrm{I}(1)$, its first differences are $\mathrm{I}(0)$, i.e., stationary. Similarly, if a time series is$\mathrm{I}(2)$ its second difference is $\mathrm{I}(0)$. In general, if a time series is $\mathrm{I}(d)$, then after differencing its d times, we get a $\mathrm{I}(0)$ series. Consequently, the difference of d times and applying the $\mathrm{ARIMA}(p,q)$ model in it, then the model will be $\mathrm{ARIMA}(p,d,q)$. Therefore, the $\mathrm{ARIMA}(p,d,q)$ process can be composed as

$$\Delta^d y_t = \emptyset_1 \Delta^d y_{t-1} + \cdots + \emptyset_p \Delta^d y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

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 = total autoregressive terms and q = total moving average terms; d = total differencing;

$\varepsilon_{t-1}, \varepsilon_{t-2}, \cdots, \varepsilon_{t-q}$ = errors/blunders in past 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 primary contrasts of y_t and so on.

In case the data shows up solid regular design, this demonstrates a high relationship among the values observed during the same season in progressive a long time. Therefore, for building an appropriate model for forecasting monthly humidity, we applied a seasonal ARIMA model, proposed by Box, et al. (2019). The non-seasonal part is (*p*, *d*, *q*) and the seasonal part is (*P*, *D*, *Q*) then the model can be described as SARIMA (p, d, q) * (P, D, Q)s which can be written in the equation form as,

$$\phi_p(L)\phi_p{}^S(L^S)(1-L^S)^D(1-L)^d y_t = \theta_q(L)\theta_q{}^S(L^S)\varepsilon_t$$

Where, $\phi_p(L), \theta_q(L)$ are AR and MA polynomials, s is the seasonal period,

$$\emptyset_p^S(L^S) = 1 - \emptyset_1^S L^S - \emptyset_p^S L^{SP} \qquad \theta_q^S(L^S) = 1 + \theta_q^S L^S + \cdots + \theta_q^S L^{SQ}$$

and D is the number of times the regular contrast administrator difference operator $(1 - L^S)$ is connected.

The SANCOVA model

Analysis of covariance or ANCOVA model is defined as the regression model containing the quantitative and subjective factors together. This model is the enlargement of ANOVA model. The procedure mentioned above gives measurably controlling impact of quantitative regress control factors. So, an adjusted ANCOVA model was proposed to decide the effect of diverse seasons on visitor entry, named SANCOVA model. Over other regression models, the noteworthy preference of this model is to degree the relationship and fractional impact of the autonomous variable and compare the subjective impact of the autonomous variable. To begin with, we isolated the humidity data into three successive seasons, to be specific winter/cool, summer/dry, and rainy/wet seasons.

Within the particular season, it contains the average of the normal humidity of seven visitor spots. The present research considers only four variables because of the restrictions of information accessibility. These four variables are utilized to find the relationship between tourist arrival and seasonal effect where the visitor entry is the subordinate (endogenous) variable. On the other hand, seasons are considered autonomous (exogenous) factors. We replace dummy variables for three seasons to discover the seasonal impact on visitor entry. So, SANCOVA model is considered in the present analysis. Subsequently, our considered seasonal ANCOVA model is as follows.

$$\begin{aligned} Tourists_{it} = {} & \beta_0 + \beta_1 AVG(D + C + Cox + Ran + K + Raj + S)\sum_{i=1}^{n} Wet\,(June - October) \\ & + \beta_2 AVG(D + C + Cox + Ran + K + +Raj + S)\sum_{i=1}^{n} Cool(November - February) + \beta_3 AVG(D + C \\ & + Cox + Ran + K + Raj + S)\sum_{i=1}^{n} Dry\,(March - May) + u_{it} \quad \dots(1) \end{aligned}$$

$$Y_t = \beta_0 + \beta_1 S_1 + \beta_2 S_2 + \beta_3 S_3 + u_t \quad \dots(2)$$

Where, Y_t = Tourist arrival
β_0 = Intercept,
β_1 = coefficient of Season 1/Wet humidity,
β_2 = coefficient of Season 2/Cool humidity,
β_3 = coefficient of Season 3/Dry humidity,
u_t = error terms

AVG = Average
D = Dhaka, Raj = Rajshahi,
C = Chittagong, S = Sylhet,
Cox = Cox's Bazar, S_1 = Wet season,
Ran = Rangamati, S_2 = Cool season,
K = Khulna, S_3 = Dry season,

From equation (2) our desire SANCOVA model is,

$Y_t = \beta_0 + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + u_t \quad \dots(3)$ Where, Y_t = Tourist arrival; β_0 = Intercept

$D_1 = \left.\begin{matrix} 1, When\ wet\ Season \\ 0, \quad Otherwise \end{matrix}\right\}$; $D_2 = \left.\begin{matrix} 1, \ when\ cool\ Season \\ 0, \quad otherwise \end{matrix}\right\}$; $D_3 = \left.\begin{matrix} 1, when\ dry\ Season \\ 0, \quad Otherwise \end{matrix}\right\}$; u_t = error terms

D_1, D_2, D_3 are reference categories.

RESULTS

There are four consecutive steps for developing a SARIMA model similar to an ARIMA model. They are identification, estimation, diagnostic checking, and the last step is forecasting.

Model Identification

In the beginning, we must check whether the data is stationary or not and have to confirm any seasonality that exists in the data set or not. For this checking line graph analysis, correlogram, and unit root test are utilized. The most popular and frequently used test method for testing the unit root in a parametric framework is the Dickey-Fuller (DF) test.

If the data set does not contain any trend and the disturbance terms are autocorrelated, it is not possible to apply the Dickey-Fuller test. Therefore, we can employ the Kwiatkowski-Philips-Schmidt-Shin (KPSS) and Phillips-Perron (PP) tests for stationarity. Table 1 represents the outcomes of stationarity for diverse stations. ACF and PACF were utilized to distinguish the finest Autoregressive Integrated Moving Average (ARIMA) model. The number of Moving Average (MA) and the number of Autoregressive (AR) coefficients of an ARIMA model can be assessed by autocorrelation function (ACF) and the partial autocorrelation function (PACF) respectively.

Modeling and Diagnostic Check

For the presence of seasonality, we build a Seasonal Autoregressive Integrated Moving Average (SARIMA) model for

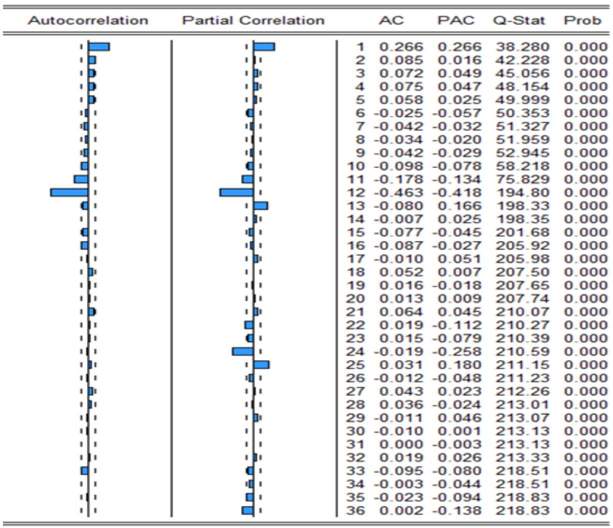
monthly humidity for Chittagong, Cox's Bazar, Rangamati, Dhaka, Sylhet, Khulna, and Rajshahi. This SARIMA model was built with the assistance of the Box-Jenkins (1976) model building strategy and the altered by Box et al. (2019). Here for model identification, we take the primary normal or seasonal distinction. Utilizing some diagnostic checking, such as residual diagnostics and stability tests we check the finest SARIMA model. The model with the lowest mean square error is selected as the leading model for forecasting. Different SARIMA models for different tourist stations have appeared in Table 2.
To illustrate the step, we consider Dhaka as an example where Figure 3 & 4 represent the ACF and PACF plots of this spot.

Table 1. Different test result for stationary

	Unit Root test							
Sampling Station	ADF	P-value	DF-GLS	Phillips-Perron test statistic	Bandwidth: using Bartlett kernel	P-value	KPSS test statistic	Bandwidth: using Bartlett kernel
Chittagong	-4.521679	0.0002	-0.876578	-6.810700	36	0.0000	0.095268	21
Cox's Bazar	-4.517176	0.0002	-0.551395	-6.755709	41	0.0000	0.101508	29
Rangamati	-4.662948	0.0001	-1.578012	-6.387226	56	0.0000	0.190154	28
Dhaka	-3.000544	0.0355	-1.055700	-6.755338	35	0.0000	1.361047	20
Sylhet	-4.516995	0.0002	-0.208896	-7.184778	37	0.0000	0.200832	27
Khulna	-4.073486	0.0012	-0.833450	-7.021207	35	0.0000	1.203526	10
Rajshahi	-3.269662	0.0168	-2.052435	-7.802133	45	0.0000	1.702987	17

Table 2. Diverse SARIMA model for distinctive tourists' station

Model Fit statistics							
Station	Model	R-squared	RMSE	MAE	MAPE	Jarque -Bera	P-value
Chittagong	SARIMA(1,0,1)x(0,1,1)12	0.469278	0.471108	0.352563	74.25059	13.83105	0.000992
Cox's Bazar	SARIMA(1,0,1)x(0,1,1)12	0.475741	0.354825	0.275385	85.91686	7994.551	0.000000
Rangamati	SARIMA(2,0,2)x(0,1,1)12	0.529370	0.416703	0.305764	70.75213	135.4576	0.000000
Dhaka	SARIMA(0,1,2)x(0,1,1)12	0.646413	0.439335	0.354176	97.30819	7.80214	0.020221
Sylhet	SARIMA(2,0,2)x(2,1,2)12	0.995846	0.446867	0.350847	305.8018	22.83370	0.000011
Khulna	SARIMA(2,0,1)x(0,2,2)12 with constant	0.600524	0.447657	0.352476	107.3293	27.30440	0.000001
Rajshahi	SARIMA(1,1,1)x(0,1,1)12	0.650216	0.343145	0.272857	248.8742	215.5317	0.000000



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.266	0.266	38.280	0.000
		2	0.085	0.016	42.228	0.000
		3	0.072	0.049	45.056	0.000
		4	0.075	0.047	48.154	0.000
		5	0.058	0.025	49.999	0.000
		6	-0.025	-0.057	50.353	0.000
		7	-0.042	-0.032	51.327	0.000
		8	-0.034	-0.020	51.959	0.000
		9	-0.042	-0.029	52.945	0.000
		10	-0.098	-0.078	58.218	0.000
		11	-0.178	-0.134	75.829	0.000
		12	-0.463	-0.418	194.80	0.000
		13	-0.080	0.166	198.33	0.000
		14	-0.007	0.025	198.35	0.000
		15	-0.077	-0.045	201.68	0.000
		16	-0.087	-0.027	205.92	0.000
		17	-0.010	0.051	205.98	0.000
		18	0.052	0.007	207.50	0.000
		19	0.016	-0.018	207.65	0.000
		20	0.013	0.009	207.74	0.000
		21	0.064	0.045	210.07	0.000
		22	0.019	-0.112	210.27	0.000
		23	0.015	-0.079	210.39	0.000
		24	-0.019	-0.258	210.59	0.000
		25	0.031	0.180	211.15	0.000
		26	-0.012	-0.048	211.23	0.000
		27	0.043	0.023	212.26	0.000
		28	0.036	-0.024	213.01	0.000
		29	-0.011	0.046	213.07	0.000
		30	-0.010	0.001	213.13	0.000
		31	0.000	-0.003	213.13	0.000
		32	0.019	0.026	213.33	0.000
		33	-0.095	-0.080	218.51	0.000
		34	-0.003	-0.044	218.51	0.000
		35	-0.023	-0.094	218.83	0.000
		36	0.002	-0.138	218.83	0.000

Figure 3. The time series plot of humidity for Dhaka is shown with ACF and PACF plots before regular difference

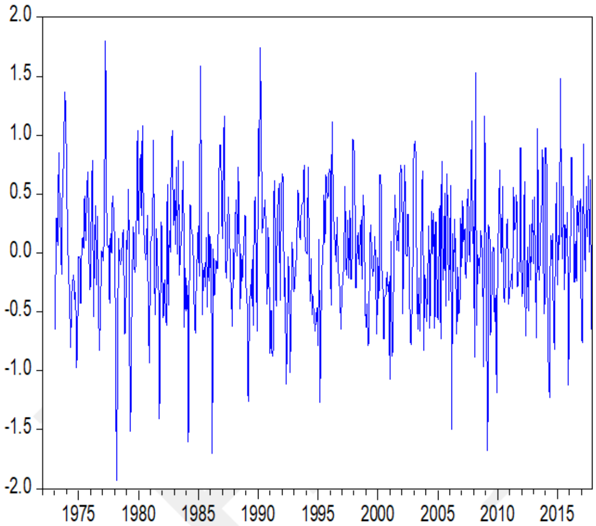
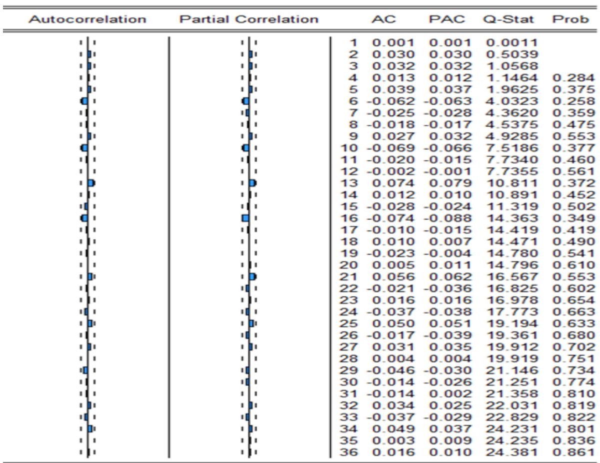


Figure 4. The seasonal difference of series after taking the seasonal difference

For model identification, consideration of seasonal differences is necessary. In time-series data, seasonal difference means the series which fluctuates from one season to another. In this study, we used the month-to-month information where in a season here are 12 periods, the regular distinction of y at period t is $y_t - y_{t-12}$, which is signified by $\nabla_{12} y_t$ where $\nabla_{12} y_t = y_t - y_{t-12}$.

From the above Figure 5, we appear that the regular differenced arrangement appears to be stationary. Presently we asses Seasonal Autocorrelation (SAC) and Seasonal Partial Autocorrelation (SPAC) of $\nabla_{12} y_t$ at distinctive lags.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0011	
		2	0.030	0.030	0.5039	
		3	0.032	0.032	1.0568	
		4	0.013	0.012	1.1464	0.284
		5	0.039	0.037	1.9625	0.375
		6	-0.062	-0.063	4.0323	0.258
		7	-0.025	-0.028	4.3620	0.359
		8	-0.018	-0.017	4.5375	0.475
		9	0.027	0.032	4.9285	0.553
		10	-0.069	-0.066	7.5186	0.377
		11	-0.020	-0.015	7.7340	0.460
		12	-0.002	-0.001	7.7355	0.561
		13	0.074	0.079	10.811	0.372
		14	0.012	0.010	10.891	0.452
		15	-0.028	-0.024	11.319	0.502
		16	-0.074	-0.088	14.363	0.349
		17	-0.010	-0.015	14.419	0.419
		18	0.010	0.007	14.471	0.490
		19	-0.023	-0.004	14.780	0.541
		20	0.005	0.011	14.796	0.610
		21	0.056	0.062	16.567	0.553
		22	-0.021	-0.036	16.825	0.602
		23	0.016	0.016	16.978	0.654
		24	-0.037	-0.038	17.773	0.663
		25	0.050	0.051	19.194	0.633
		26	-0.017	-0.039	19.361	0.680
		27	0.031	0.035	19.912	0.702
		28	0.004	0.004	19.919	0.751
		29	-0.046	-0.030	21.146	0.734
		30	-0.014	-0.026	21.251	0.774
		31	-0.014	0.002	21.358	0.810
		32	0.034	0.025	22.031	0.819
		33	-0.037	-0.029	22.829	0.822
		34	0.049	0.037	24.231	0.801
		35	0.003	0.009	24.235	0.836
		36	0.016	0.010	24.381	0.861

Figure 5. The time series plot of humidity for Dhaka is shown with ACF and PACF plots after taking the first difference

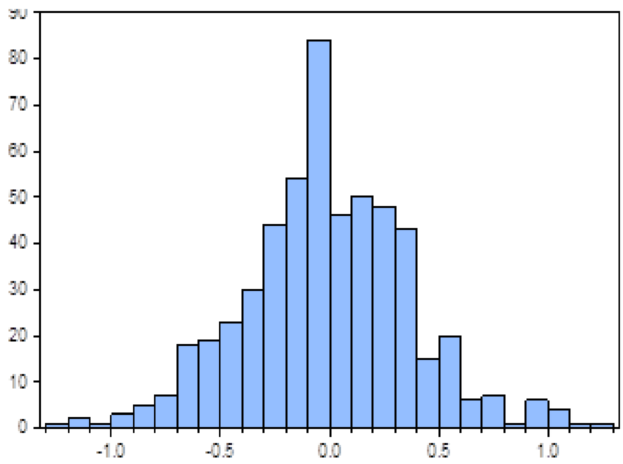


Figure 6. Histogram and Normality test for SARIMA $(0,1,2)(0,1,1)_{12}$ model

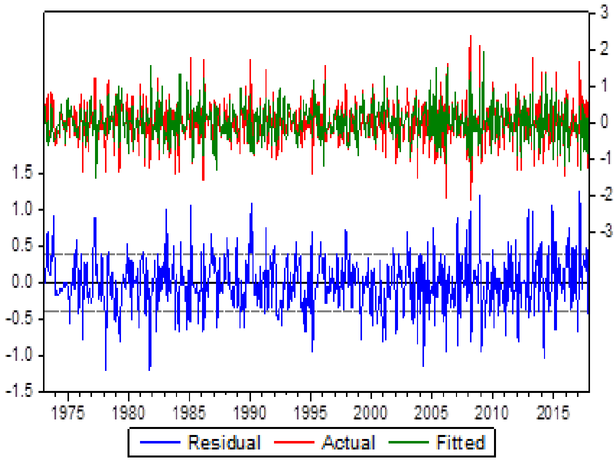


Figure 7. Actual fitted and residual plot for SARIMA $(0,1,2)(0,1,1)_{12}$ model

Figure 6 presents the results of the correlogram Q-statistics analysis. The autocorrelation and Q-test come about for distinctive lags recommend that there's no autocorrelation within the residual. Hence, we can decide that the selected model is fully specified. Now let us consider the Histogram and Normality test results presented in Figure 7 for checking the normality of the data set. From this, we can make sure that the residuals are distributed normally or not.

The Histogram and Jarque-Bera test (which appeared in Table 2) shows that the residual is distributed normally, signifying the full model specification. Figure 6 represents the actual, fitted, and residual plots that indicate the fitted model pattern. Moreover, when we examined the outline checking through a standardized residual plot for the SARIMA $(0,1,2)(0,1,1)_{12}$ model, the findings reveal that residuals are not serially correlated and distributed normally. Thus this result indicates that the above model is a good model and correctly fitted.

Estimation of Classical Linear Regression (CLRM) model

In the second empirical study of evaluating the effect of seasonal impact on visitor entry, the results of Table 3 show the sesonal effect on tourists arrival. The numerous coefficients of determination (R^2) are 0.72, which proposed that the autonomous variable explained the subordinate variable by 72% of the whole variety. This suggests that seasonality encompasses a 72% impact on traveler entry in Bangladesh.

Table 3. Seasonal effect on tourists' arrival

Model	Standardized Coefficients	t statistic	P-value	R	R^2
Wet Season	0.466	0.701	0.611	0.850	0.723
Cool Season	1.007	1.609	0.354		
Dry Season	-0.380	-0.593	0.659		

Results of SANCOVA model

Assessing the effect of regular impact on traveler entry. The results of Table 4 show the impact of seasonal effect on annualy humidity and tourists while Table 5 shows the results of Seasonal effect on annual Humidity by a log-linear model. Considering Winter season as the reference category as in equation 3, the intercept value is approximately 1315.502 thousand taka, representing the mean income in winter season from tourist arrival. β_2 indicates the mean income of summer season is lower about 107.630 thousand taka to the mean income of winter season is about 1315.502 thousand taka. β_3 suggests that the mean income within Wet/Rainy season is lower about 729.94 thousand taka, than the mean income of about 1315.502 thousand taka. Again, from equation 3, but now transform all variables to natural log, the intercept value β_0 represents the reference category mean income. Subsequently, the value of the intercept term of the regression model is about -3.344. Taking the antilog of 3.344, we find 0.035295494, which represents the mean income within the winter season from tourist arrival. β_2 represents the results of mean income in summer season. Here β_2 is higher about 0.026 to the mean income of about 6.087 thousand taka for the reference category, Winter season. Taking antilog {(-3.344+0.004)= -3.34}. we obtained 0.035436959. Thus, the income in the summer season is higher by about 0.4 % than in the Winter season. β_3 gives the results of income in Wet/Rainy season. Here β_3 is equal to the mean income -3.344 thousand taka for the reference category, Winter season. Thus, the income in the rainy season is equal to the Winter season.

DISCUSSIONS

For SARIMA model, forecasting in time series analysis has gotten to be fundamental devices in various applications in meteorology and other natural ranges to get it marvels such as humidity, temperature, and rainfall. To appear the forecasting behavior of Dhaka humidity change in Bangladesh, we fit an, appropriate model and then produced forecasts based on the fitted model. From Figure 3 it is observed that with exponential decay the AR and MA move in inverse. Both ACF and PACF appear a quick decay belonging all the spikes are in standard blunder bounce, after taking the primary contrast. Therefore, with seasonality the series gets to be stationary representing an ARIMA model. For the monthly humidity data of Dhaka, the SARIMA (0,1,2) (0,1,1) model was

Table 4. Seasonal effect on annual Humidity

Reference category	R	R^2	β_0	β_1	β_2	β_3	Humidity	Tourists
Winter Season	0.764	0.584	1315.502		-107.630	-729.94	59.463	0.008
Summer Season	0.764	0.584	1207.872	107.630		-622.31	59.463	0.008
Wet Season	0.764	0.584	585.565	729.94	622.31		59.463	0.008

fitted, and we appraise the parameters of this model. Then utilizing residual diagnostics and a stability test, we check the legitimacy of the model. To identify the type of residuals a typical likelihood plot and the Jarque-Bera test was utilized. At that point, we forecast up to the year 2025 as shown in Table 6.

Table 5. Seasonal effect on annual Humidity by a log-linear model

Reference category	R	R^2	β_0	β_1	β_2	β_3	Humidity	Tourists	Season
Winter Season	0.963	0.93	-3.344		0.004	0.000	2.336	0.141	0.035
Summer Season	0.963	0.93	-3.350	-0.003		-0.004	2.341	0.144	0.032
Wet Season	0.963	0.93	-3.343	0.000	0.004		2.336	0.141	0.035

Table 6. Forecasted values up to the year 2025 for Dhaka

Forecasting of monthly humidity for Dhaka area from 2019 to 2025							
		2020:01	-0.727011	**2022:01**	-0.739779	**2024:01**	-0.752548
		2020:02	-1.738249	**2022:02**	-1.751017	**2024:02**	-1.763786
		2020:03	-1.919477	**2022:03**	-1.932246	**2024:03**	-1.945014
		2020:04	-0.830389	**2022:04**	-0.843158	**2024:04**	-0.855927
		2020:05	-0.142563	**2022:05**	-0.155331	**2024:05**	-0.168100
		2020:06	0.553254	**2022:06**	0.540486	**2024:06**	0.527717
		2020:07	0.768589	**2022:07**	0.755820	**2024:07**	0.743051
		2020:08	0.713121	**2022:08**	0.700352	**2024:08**	0.687583
		2020:09	0.699614	**2022:09**	0.686845	**2024:09**	0.674076
		2020:10	0.168331	**2022:10**	0.155563	**2024:10**	0.142794
Year	**Standardized value (Z_i)**	**2020:11**	-0.563242	**2022:11**	-0.576011	**2024:11**	-0.588779
		2020:12	-0.327412	**2022:12**	-0.340181	**2024:12**	-0.352949
2019:01	-0.720626	**2021:01**	-0.733395	**2023:01**	-0.746164	**2025:01**	-0.758932
2019:02	-1.731864	**2021:02**	-1.744633	**2023:02**	-1.757402	**2025:02**	-1.770170
2019:03	-1.913093	**2021:03**	-1.925861	**2023:03**	-1.938630	**2025:03**	-1.951399
2019:04	-0.824005	**2021:04**	-0.836774	**2023:04**	-0.849542	**2025:04**	-0.862311
2019:05	-0.136178	**2021:05**	-0.148947	**2023:05**	-0.161716	**2025:05**	-0.174484
2019:06	0.559638	**2021:06**	0.546870	**2023:06**	0.534101	**2025:06**	0.521333
2019:07	0.774973	**2021:07**	0.762204	**2023:07**	0.749436	**2025:07**	0.736667
2019:08	0.719505	**2021:08**	0.706736	**2023:08**	0.693968	**2025:08**	0.681199
2019:09	0.705998	**2021:09**	0.693229	**2023:09**	0.680461	**2025:09**	0.667692
2019:10	0.174716	**2021:10**	0.161947	**2023:10**	0.149178	**2025:10**	0.136410
2019:11	-0.556858	**2021:11**	-0.569626	**2023:11**	-0.582395	**2025:11**	-0.595164
2019:12	-0.321028	**2021:12**	-0.333796	**2023:12**	-0.346565	**2025:12**	-0.359334

$X_i = Z_i \sigma + \mu$

Where, μ=74.58983, σ = 8.207461

Similarly, observing ACF and PACF for monthly humidity of Chittagong, Cox's Bazar, Khulna, Rajshahi, Rangamati, and Sylhet we have fitted SARIMA $(1, 0, 1)(0, 1, 1)_{12}$, SARIMA$(1, 0, 1)(0, 1, 1)_{12}$, SARIMA $(2, 0, 1)(0, 2)_{12}$ with a constant parameter, SARIMA $(1, 1, 1)(0, 1, 2)_{12}$, SARIMA$(2, 0, 2)(0, 1, 1)_{12}$, and SARIMA $(2, 0, 2)(2,1, 2)_{12}$ model sequentially and after that estimate the parameters of these models. After distinguishing the foremost appropriate model, the legitimacy of these models was checked by utilizing residual diagnostics and a stability test. After that normal probability plot and Jarque-Bera test were utilized for checking the typicality of residuals. At this point, we forecast humidity for the tourist stations of Bangladesh to 2025. From the above Figure 8, there is a seasonal effect on humidity. From June, humidity starts increasing, and from November, it starts decreasing. July (wet season) has the highest humidity and March (dry season) has the lowest humidity. The highest increase in Cox's Bazar and decrease of humidity in Dhaka and Rangamati district. The capital Dhaka consists of the lowest increase of humidity and the lowest decrease in the Khulna and Rajshahi district. The above results indicate that winter and dry seasons are better to visit Bangladesh under low humidity. However, travelers who love the rainy season can visit Bangladesh under high humidity, which does not affect traveling. These results also suggest that visitors belonging to high humidity countries can discover Bangladesh all year round, and visitors from low humidity countries can discover it in the rainy season. This forecast will help travelers from all around the world to plan a suitable time to visit Bangladesh. For SANCOVA model, for all reference categories, the numerous coefficients of determination (R^2) are 0.584. This result proposes the autonomous variable clarified the subordinate variable by 58% of the full variety. That represents the regularity in humidity incorporate a 58% impact on tourist's arrival. The outcome of this analysis also suggests that if per unit humidity in seasonality increases, tourism industry income will increase by approximately 59.463 thousand taka in every season. For Log-linear SANCOVA model, for all reference categories, the multiple coefficients of determination (R^2) are 0.93. Which illuminate that the dependent variable explained by an independent variable about 93% of the total variation. Subsequently, seasonality in humidity has a 93% effect on Income from visitor entry in Bangladesh. This result also suggests that if per unit humidity in seasonality increases, then tourism

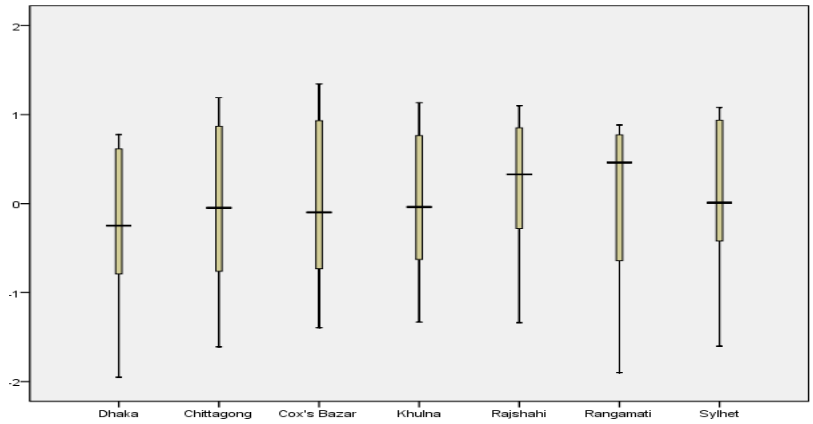


Figure 8. Forecasted humidity comparison between different tourist stations

industry income will increase approximately antilog (2.336) = 10.3397943 thousand taka in every season. This result also suggests that tourist arrival in Bangladesh is influenced by approximate antilog (0.141) =1.15 % of humidity in seasonality.

CONCLUSION AND IMPLICATIONS

Forecasting humidity is troublesome in Bangladesh because of its nonlinear trend and the spatial-temporal variety of the information. Nevertheless, the humidity forecast is vital for effective urban-like developing countries. In this paper, humidity forecasting is utilizing the SARIMA modeling method. The significant R-squared value is 0.995846, and the minimum value is 0.469278 were noticeable for Sylhet and Chittagong station, respectively. Two stations show an R-squared value below 0.60, and the rest three stations containing an R-squared value of more than 0.60, which suggests the SARIMA models developed for popular tourist spots in the current investigation are sensibly well fitted. Subsequently, for the nationwide humidity forecasting, these SARIMA models can play an important role in decision making. Findings of this analysis indicate that seasonality has a 72% effect on tourists' arrival that contains 58% impact on Bangladesh's national economy which signifies tourism industry of Bangladesh is more susceptible to regular variety. Findings also revealed that the tourist arrival in Bangladesh was influenced by approximately 1.15 % of humidity in seasonality. Therefore, we can attain a decision that in the situation of assessing the regular impact on the national economy, our proposed SANCOVA model is superior to any other regression model. Finally, we have concluded that the tourist's arrival in Bangladesh is increasing day by day. The weather and climatic condition of our country are good for tourism. As the no. of tourist's arrival is increasing so the income from tourism is also increasing which contributes to our GDP. From this analysis, the tourism demand is responsive to climate change as well as seasonality in humidity. Since tourist's arrival are depends on seasonality then we can also decide that the GDP of our country is positively related to seasonality. In conclusion, the findings suggest that further intensive studies can be carried out using more climatic parameters such as temperature, rainfall, wind speed and direction, wind pressure, solar radiation of specific regions of a country, and their impacts on the national economy. Studies could also examine the impact of these climatic variables on tourist arrivals, crop production, and food security. Therefore, tourism stakeholders can apply our proposed modified ANCOVA modeling named SANCOVA model, in exponents for policymaking, recommend adaptation and justification, and be inventors of any subsequent policy arrangements. Furthermore, in developing different tourism industries, the finding has a significant role that may add to economic recovery for overall economic growth.

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Article history: Received: 23.12.2021 Revised: 19.04.2022 Accepted: 17.05.2022 Available online: 14.06.2022