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Research article

Modeling and Forecasting of Sugarcane Production in South Asian Countries

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Abstract

Keywords

ARIMA;

ETS;

forecasting;

policy;

sugarcane production

Sugarcane industry is of crucial importance to the South Asian countries. These countries depend heavily on agriculture and the sugarcane industry has immense potential to contribute towards its economic development. Hence, the precise and timely forecast of sugarcane production is of concern for farmers, policy makers and other stakeholders. In this manuscript, we strived to forecast the production and growth rate of this important commodity using standard statistical approaches. The ARIMA (Auto Regressive Integrated Moving Average) and ETS (Exponential Smoothing) models were applied and compared on the basis of their forecasting efficiency for South Asia countries. This study also investigated the trends in sugarcane production in the region and studies the causes of the decline in production of sugarcane in Sri Lanka and Bangladesh. Furthermore, the expected production for following 7 years was computed using both models. In addition, we also calculated the projected growth rates of sugarcane production of South Asian countries over the years 2020-2027.

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1. Introduction

Sugarcane is a tropical grass native to Asia that has been cultivated for over 4,000 years and used to produce refined sugar. Sugarcane sugar production began in India around 400 B.C. Sugarcane juice is rich in potassium, calcium, magnesium, iron, zinc, thiamine, riboflavin, and amino acids. So, it is used in medicines to treat various illnesses. Bakers and cereal makers use refined sugar the most, followed by confectioners. Sugar is a common sweetener used in beverages and food. Sugarcane juice contains 113.43 calories, 0.20 g protein, 0.66 g fat, and 25.40 gr carbohydrate. Sugarcane is also full of antioxidants like flavonoids and polyphenols that help improve overall health and reduce oxidative stress.

Nearly 80% of the world's sugar comes from sugarcane. In 2018, sugarcane was grown on 26 million hectares worldwide. Asia produced 66.12 MMT sugar, or 40% of the global sugar market [1]. These countries also imported 60% of their sugar requirement, while India (376.9 MT), China (108.1 MT), and Pakistan (67.2 MT) produced the most. These were the major sugar producing countries in South Asia [2]. Sugarcane production in 2018 was 1.91 billion tones, with Brazil contributing 39%, India 20%, and China 6% [1]. India aims to produce 35 MT of sweeteners by 2030 and is the world's second largest producer and consumer of sugar. Presently, Pakistan ranks 9th in the sugar exporting countries in the world [3]. Twenty-nine grams/capita/day sugar are required by Bangladeshis, so they need 1.0 to 1.2 million tons of sugar every year in order to fulfil their demand for consumption as reported by FAO [4]. Another large consumer is Sri Lanka which had an expected demand of 1 MMT in 2020. Only 7% of its demand has up to recently been fulfilled by native production and more than 90% of sugar being imported currently. The largest export market for sugar is Asia; Japan, China, Thailand, Cambodia, South Korea, Indonesia (Figure 1) account for about 12% of total sugar exporter globally.

Sugarcane production increased by 52% between 2008 and 2016, reaching at least 3.2 per cent of sugarcane overall production in 2016. China's sugar consumption in 2020 was expected to rise to 1.7-18% MMT due to increased imports [5]. Sugar consumption in Asia is expected to grow by 49% by 2030. Overall, more sugar factories were needed to improve sugarcane production and future sugar demand. Sugar demand is expected to reach 260 MT by 2030 [6]. A sugarcane surplus was predicted to persist until 2025 under assumed favorable conditions through improved farm productivity and expansion of the area of plantation crops, especially in China [3, 7].

There are many constraints for South Asian nations if they are to keep pace with world international trends in sugarcane production practices, and these problems are mainly to do with manual to mechanical limitations. Other challenges which are also problematic, include abiotic stresses, biotic stresses, cost boom, excess fertigation, the use of limited numbers of cultivars, price volatility and poor prices at farm [8, 9].

Despite reasonable growth in the area of forecasting, the cane sector has faced other important problems affecting both overall sustainability and economy. Intervention by government with the imposition of subsidies and tariffs on imports, has affected the price of sugar greatly. Other factors include shift in patterns of weather, changes in methods of production (increased mechanization), and fluctuations in exports due to demands of countries like India and Brazil [10-12].

Suresh and Priya [13] predicted the yields of sugar cane using an ARIMA model. Sajid *et al*. [14] used data from time series to predict sugarcane and cotton production and yields in Pakistan. An ARIMA model was appropriate in their study. Moreover, an ARIMA model was used to predict India's sugarcane production area, production and productivity [15]. Mehmood *et al*. [16] considered an ARIMA model to be their best research device for developing and estimating time series models to forecast the production of sugar cane in Pakistan. The comparison of ARIMA and other time series models based on different types of scientific data series is now a subject of elevated research [17-24]. The ARIMA prediction equation is a linear equation that comprises the dependent variable

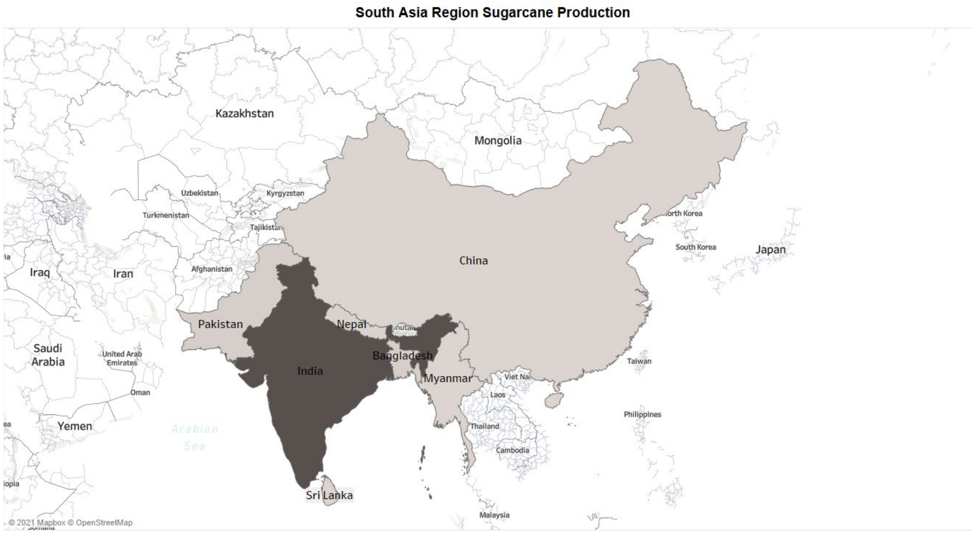

Figure 1. Sugarcane production in the counties of South Asia region

and/or prediction error lags. Most time series data, however, do not follow a linear trend. This study is unique in that a Holt's nonlinear model is used to cater for the volatility associated with sugar cane production data. Based on our objectives, we used sugarcane production data series from South Asian countries including China and Myanmar to estimate forecasting behavior with ARIMA and Holt's nonlinear models and to find out the best model for prediction purposes.

2. Materials and Methods

2.1 Data

To produce forecasts for sugarcane production in South Asia region, we used available annual data from 1961 to 2019. The data were in tons, and we modeled and predicted sugarcane production data relying on EViews programing using ARIMA and Holt's nonlinear models (ETS Exponential Smoothing) (Figure 2).

2.2 ARIMA models

ARIMA models are one of the categories of statistical models that appeared in the 1970s, and are used for analysis and forecasting of time series. These models focus on the random side of the time series. The acronym ARIMA (p,d,q) is divided into three main sections:

AR (p): Autoregressive models, where the present value is formed as a linear function in the lagged values of the variable, and is given according to the following equation:

$$y_t = c + \sum_{i=1}^{p} \beta_i \, y_{t-i} + \varepsilon_t \tag{1}$$

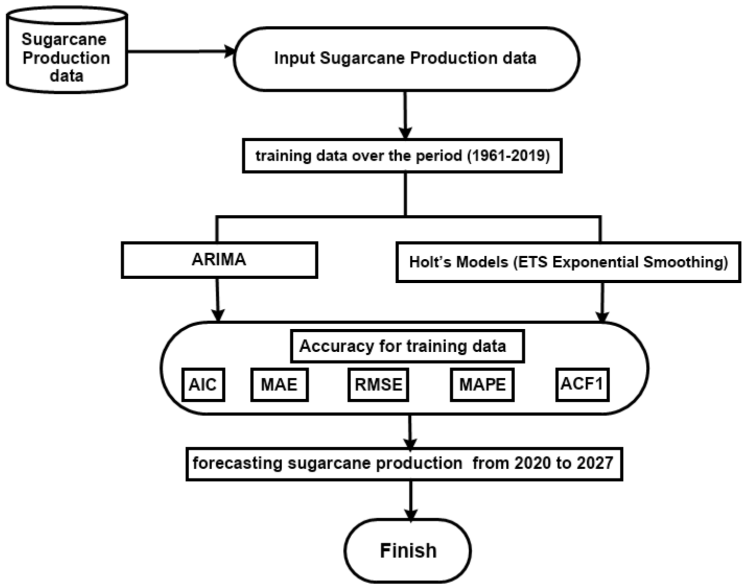

Figure 2. Total framework of our study

where β_i is the parameters of the auto regressive, p: lag operator, ε_t: error terms, c is constant.

I (d): integration, indicates the degree to which the variable is stationary, and is given by the following equation:

$$y_t' = y_t - y_{t-1} \tag{2}$$

MA (q): moving average. Where the current value of the variable is written as a linear function in the present value of the random error term and a number of its lag values, and it is given by the following equation:

$$y_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \, \varepsilon_{t-i} \tag{3}$$

Where θ_i the parameters of the moving average, μ is the expectation of y_t (often assumed to equal 0).

The ARIMA model estimation method includes several stages before making predictions, identification stage: which the degree of stationary of the variable is determined using Augmented Dickey Fuller (ADF). After defining (d), we define (p) and (q) based on the autocorrelation function (ACF) and the partial auto correlation function (PAC) estimation stage: the model using Maximum likelihood method based on Akaike information criterion (AIC) to compare between the possible models. Forecasting stage: where the prediction is made using the model. Forecasting validation stage: the model is validated on the predictions based on several indicators that represent the deviation of the calculated values from the actual values, which are (MAE, RMSE, and MAPE). It is also ascertained that there is autocorrelation between the residual values using plot (ACF). Table 1 shows the definition of indicators used in assessing the validity of forecasts.

Table 1. The definition of indicators used in assessing the validity of forecasts

Indicators	Formula	Define terms
Autocorrelation function (ACF)	$\rho_l = \frac{Cov(\varepsilon_t, \varepsilon_{t+l})}{\sigma^2}$	: error terms $\boldsymbol{\varepsilon_t}$: number of lags $\boldsymbol{l}$
Akaike Information Criterion (AIC)	$-2logL(\hat{\theta}) + 2k$	: maximum value of the likelihood function $\hat{\boldsymbol{\theta}}$: number of estimated parameters $\boldsymbol{k}$
Mean Absolute Error (MAE)	$\frac{1}{n}\sum_{t=1}^{n}\lvert\hat{y}_t - y_t\rvert$	: the forecast value $\hat{\boldsymbol{y}}_t$: the actual value $\boldsymbol{y_t}$: number of fitted observed $\boldsymbol{n}$
Root Mean Square Error (RMSE)	$\sqrt{\frac{\sum_{t=1}^{n}(\hat{y}_t - y_t)^2}{n}}$	
Mean Absolute Percentages Error (MAPE)	$\frac{1}{n}\sum_{t=1}^{n}\left\lvert\frac{\hat{y}_t - y_t}{y_t}\right\rvert \times 100$	

Note: The assessment of the validity of the predictions is also based on the plot of (actual-forecast) value.

2.3 Holt's nonlinear models

Most time series do not follow a linear trend, and contain volatility. Thus, it may be appropriate to include items that take these attributes into account in the estimated model. Holt's nonlinear models represent a systemic development that combines exponential smoothing (ETS) models to form a nonlinear dynamic model. Analysis of these models is conducted using state-space-based probability calculations, support model selection, and prevision standard error calculation [17].

The models include three main time series components: trend (T), seasonal (S), error (E). This reflects long-term trends of time series movement, which is the unpredictable part of the time series. In our case, we did not worry about the seasonal term since the data was annual. The components we needed were combined in our model in various additive and multiplicative combinations to produce y_t. We had additive model y_t = T+E or multiplicative model likey_t = T*E, where the individual components of the model are given as follows:

$$E\ [A, M]$$
$$T\ [N, A, M, AD, MD]$$
$$S\ [N, A, M]$$

Where N = none, A = additive, M = multiplicative, AD = additive dampened, and MD = multiplicative dampened (damping uses an additional parameter to reduce the impacts of the trend over time). Accordingly, the models that we were interested in estimating can be written (after selecting S [N]) as shown in the following Table 2.

Table 2. State space equations for each of the models in the Holt's nonlinear

Trend	Additive Error Models	Trend	Multiplicative Error Models
N	$y_t = l_{t-1} + \varepsilon_t$ $l_t = l_{t-1} + \alpha\varepsilon_t$	N	$y_t = l_{t-1}(1 + \varepsilon_t)$ $l_t = l_{t-1}(1 + \alpha\varepsilon_t)$
A	$y_t = l_{t-1} + b_{t-1} + \varepsilon_t$ $l_t = l_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t$	M	$y_t = (l_{t-1} + b_{t-1})(1 + \varepsilon_t)$ $l_t = (l_{t-1} + b_{t-1})(1 + \alpha\varepsilon_t)$ $b_t = b_{t-1} + \beta(l_{t-1} + b_{t-1})\varepsilon_t$
AD	$y_t = l_{t-1} + \phi b_{t-q} + \beta\varepsilon_t$ $l_t = l_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t$ $b_t = \phi b_{t-1} + \beta\varepsilon_t$	MD	$y_t = (l_{t-1} + \phi b_{t-1})(1 + \varepsilon_t)$ $l_t = (l_{t-1} + \phi b_{t-1})(1 + \alpha\varepsilon_t)$ $b_t = \phi b_{t-1} + \beta(l_{t-1} + \phi b_{t-1})\varepsilon_t$

Where parameters: α: smoothing factor for the level, β: smoothing factor for the trend, ϕ: damping coefficient. For initial states, l: initial level components, and b: initial growth components, which is estimated as part of the optimization problem.

The comparison between these models was done using the Akaike information criterion, and then the indicators in Table 1 were estimated and compared with their counterparts in the ARIMA models.

3. Results and Discussion

As a first step, we needed an exploratory analysis of the data we wanted to predict. In Table 3, some descriptive statistics on sugarcane production were visualized. Table 3 shows that India has the largest sugarcane production, approximately 3.5 times the production of China, which comes in second. The largest change in quantity of sugarcane production during the period 1961-2019 is that of Nepal, which is indicated by the coefficient of variation. Sugarcane production developed in Nepal from 93 to 4346 tons from the study period. The difference between maximum and minimum, with positive skewness in all countries except for Bangladesh, indicates that sugarcane production increased in a stable fashion from 1961 to 2018. The kurtosis values obtained in all of the countries' data series followed a platykurtic distribution, which meant that the quantity of outliers was insignificant. This is illustrated by data visualization.

Figure 3 shows sugarcane production growth had an almost linear trend for all countries, with some volatility, except for Sri Lanka and Bangladesh, which had declines in production after year 1995. The main cause of those reductions in sugarcane production may have been pressure to produce more cereals and other short-lived crops.

Table 3. Descriptive statistics of sugarcane production data (tons)

Country	Mean	Std. Dev	Coefficient of Variation %	Maximum	Minimum	Skewness	Kurtosis
China	63360.20	36782.44	58	128735.1	9829.314	0.193699	1.694668
India	222907.9	89972.65	40	405416.2	91913.01	0.218628	1.776160
Nepal	1356.087	1158.887	85	4346.754	93.00000	0.597393	2.152341
Pakistan	39657.86	16900.43	42	83332.74	11640.00	0.450874	2.459142
Sri Lanka	636.8432	385.6216	60	1528.840	112.0000	0.207447	2.125262
Bangladesh	6240.609	1265.490	20	8200.000	3141.923	-0.700266	2.322781
Myanmar	4646.793	3491.856	75	11846.18	812.2190	0.695566	1.985059

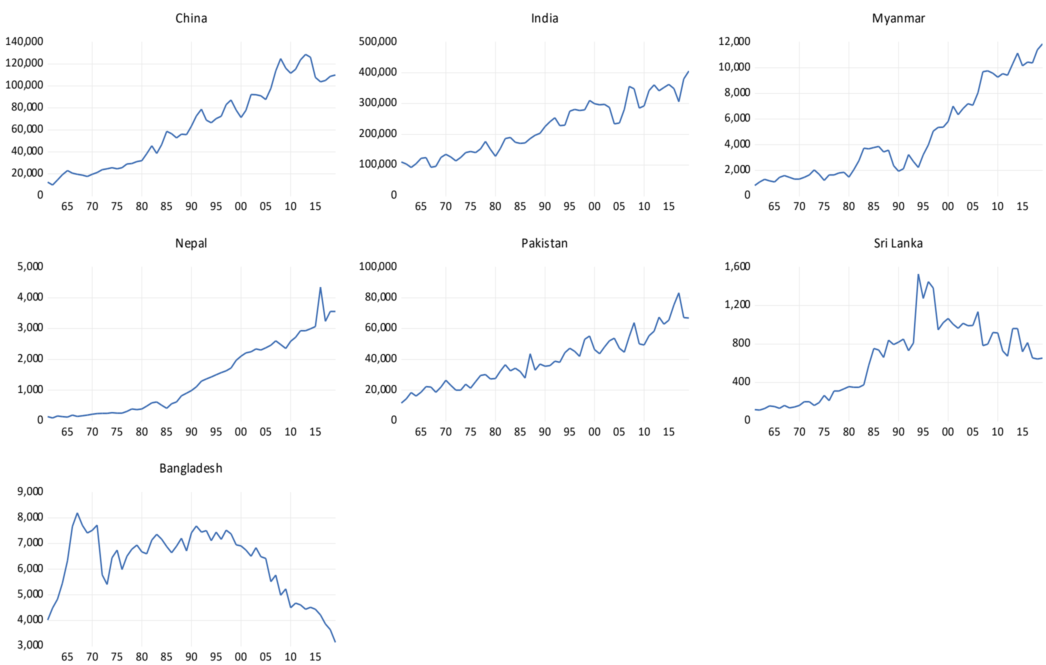

Figure 3. Evolution of sugarcane production for (China – India – Myanmar – Nepal – Pakistan – Sri Lanka – Bangladesh) during the period 1961-2019

After exploring the data through descriptive statistics and visualization, time series models used (ARIMA, Holt's nonlinear) were compared, and estimation by GARCH models was excluded due to the absence of an ARCH effect. The ARIMA and Holt's model selections for seven countries were obtained by making use of the Akaike information criterion (AIC), then comparing them using MAE, RMSE, MAPE, and Data Visualization [18]. The results are shown in Table 4.

Table 4. ARIMA and Holt's nonlinear model selections for sugarcane productions over the period 1961-2019

	MODEL	AR	MA	AIC	MAE	RMSE	MAPE	ACF
China	ARIMA (2,2,3)	-0.47	-0.55	20.45	9883.6	12877.58	18.96	-0.43
India	ARIMA (2,1,3)	-0.59	-0.16	22.82	130328.1	156421.7	49.32	0.02
Nepal	ARIMA (1,1,0)	-0.41	-	13.72	1292.81	1726.93	78.53	-0.17
Pakistan	ARIMA (1,0,2)	0.99	-0.29	20.31	29590.1	34133.73	67.73	-0.33
Sri Lanka	ARIMA (0,1,2)	-	-0.23	12.92	516.2	634.54	64.28	-0.23
Bangladesh	ARIMA (3,1,4)	0.06	0.27	15.33	1172.3	1305.78	20.04	0.08
Myanmar	ARIMA (3,1,3)	0.94	-0.86	15.6	3397.9	4732.40	51.44	0.07
China	Holt's (M,A,N)	-	-	1263.66	4624.6	0.105	8.5	0.23
India	Holt's (M,M,N)	-	-	1426.68	18633.8	0.105	2.07	0.40
Nepal	Holt's (M,MD,N)	-	-	805.08	107.02	0.133	10.3	-0.14
Pakistan	Holt's (M,MD,N)	-	-	1232.38	3497	0.113	9.3	0.24
Sri Lanka	Holt's (M,M,N)	-	-	787.21	117.92	0.189	16.6	0.49
Bangladesh	Holt's (M,A,N)	-	-	973.26	370.68	0.074	6.02	0.05
Myanmar	Holt's (A,A,N)	-	-	992.23	417.39	545.74	12.9	0.06

From Table 4, ARIMA models were the best models for selection. ARIMA (0, 1, 2) and ARIMA ((3, 1, 4) (for Sri Lanka, Bangladesh) had the lowest values of MAE, RMSE, MAPE, where the forecast values displayed less deviation from the actual values (Figure 4).

Figure 4 shows that China, Bangladesh, and Sri Lanka had the best forecasting for sugarcane production data using ARIMA models. In general, we find a lack of convergence between the actual values and the calculated values using the model. Thus, we were able to get forecasts of sugarcane production for seven countries until 2027.

Table 5 indicates the upward trend in sugarcane production in China, and we note that expectations in the remaining countries are less than the actual values and do not reflect the trend of clear data in Figure 2. From Table 4, we find that RMSE, MAE, MAPE values estimated using Holt's model are much lower than estimated values using ARIMA model in all countries, from which we concluded that Holt's model was the best for forecasting production in these countries as well. It is crucial to adopt a method to investigate the nonlinear characteristics of sugarcane production time series data. In our case we adjusted S {N} because the data was annual, and the rest of the options were left to the information criteria (Akaike) as shown in Table 4. Parameter estimation of both the models are given in Tables 6 and 7. Table 6 show the parameters estimates for ETS (Holt's nonlinear) model, and we find that there is a different value for α (Smoothing factor) close to one, which is a sign that the series is close to a random walk. As for the parameter β, its values are greater than zero indicating that there are changes in trend, which is what we find for both Sri Lanka and Bangladesh). Moreover, ϕ (the damping parameter) reduces the effect of the trend over time as (Nepal, Pakistan). This method gives better results than the previous one for predicting sugarcane production. From Figure 5, it can be seen that the observe and predication values are close to each other when Holt's models are used.

Figure 5 shows that the calculated values using the model are close to the actual data and go in the same trend. Thus, we find an increasing trend of sugarcane production in China, India, Nepal, Pakistan, Myanmar, and a decreasing trend estimated in Sri Lanka. The forecasting behavior is almost steady for Bangladesh data series, which is confirmed in Table 7.

Table 7 show that sugarcane production in China is expected to reach 125233.1 ton in 2022 with a growth rate of 1.51% during the period 2020-2027. In addition, in India, it is expected to reach 466265.5 ton in 2027 with a growth rate of 2.5% during the period 2020-2027. In Nepal, it should be 5034.2 ton in 2027, showing a growth rate of 3.5% during the period 2020-2027. In addition, in Pakistan, 78659.8 ton is estimated by 2027 with a growth rate of 1.16% during the period 2020-2027. In addition, in Myanmar, production should reach 13368.1 ton in 2027 with a growth rate of 1.8% during the period 2020-2027. As for Sri Lanka, we expected a decrease in sugarcane production to 612.7 in 2027, with a rate of 18.5% from 2020-2027. We expected slight changes in the expectations of the volume of sugar cane production between a rise and a decrease in Bangladesh to 13368.1 ton in 2027.

Our next objective was to estimate the best time series model for forecasting accuracy (Table 8). Therefore, goodness of fit (RMSE, MAPE) and Diebold-Mariano (DM) test [25] were introduced to assess whether the forecasting accuracy was the same or not for both models (model validation from 2010-2019). It was interesting to note that in all seven countries the ETS (Holt's nonlinear) model performed with the best forecast accuracy based on lower values of RMSE and MAPE. Furthermore, this was confirmed by the DM test. The ETS model was a better forecast model than the ARIMA model as the p value was less than 0.05, and it was possible to reject the null hypothesis. Also, it can be assumed that the poor performance of the ARIMA models may have been due to their inability to capture the complex non-linearity nature of the data series. In contrast, the ETS (Holt's nonlinear) models suited the data nature very well. The findings of the current study are consistent with the idea that linear models are inappropriate for use in many real applications [19]. A further study with more focus on applying hybrid forecasting Models and non-linear multivariate time series forecasting Models is therefore suggested.

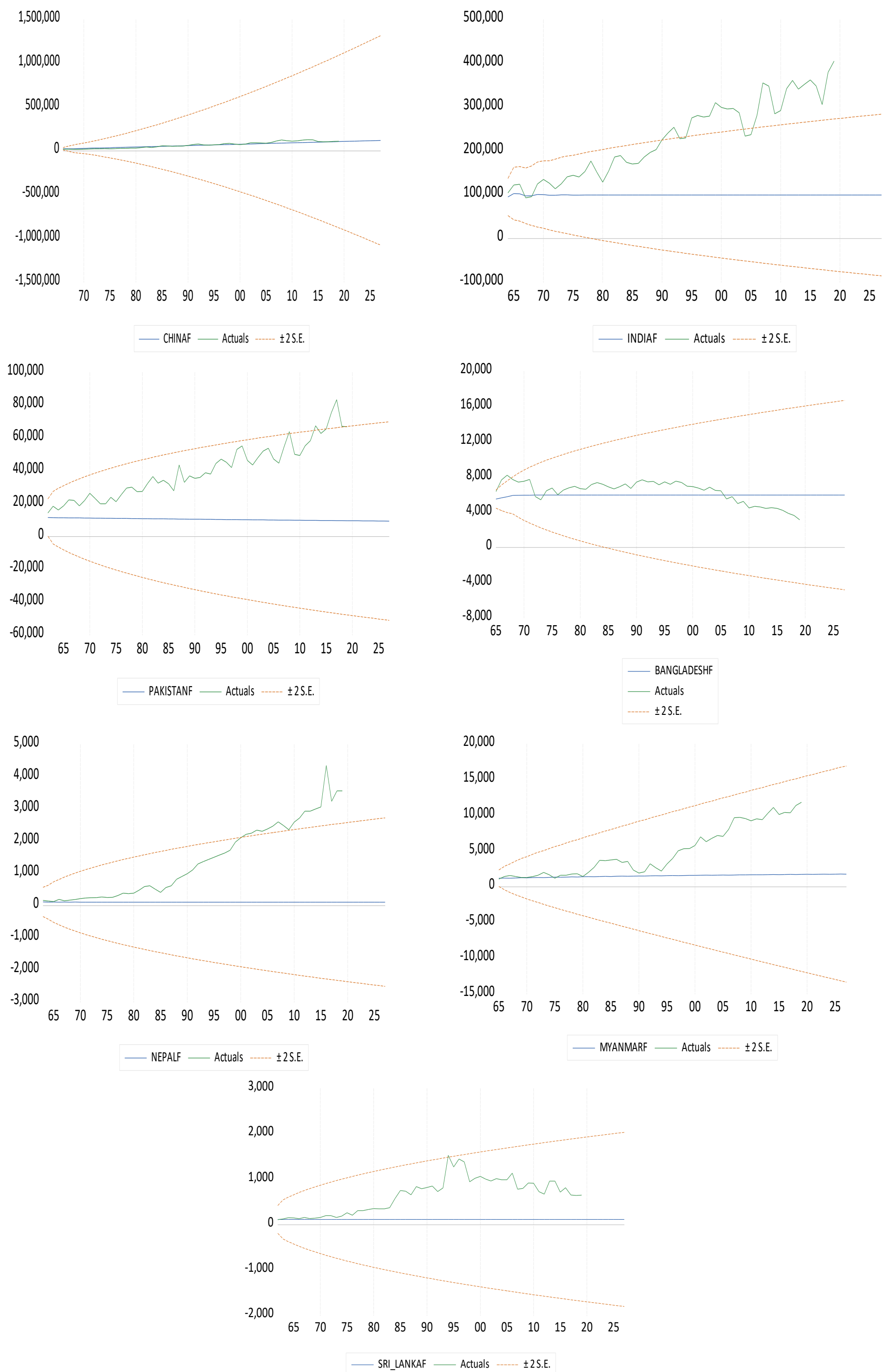

Figure 4. Actual and forecast values of sugarcane production with (±2SE) in seven countries during the period 1961-2027 using ARIMA models

Table 5. Sugarcane production forecasting using ARIMA models

Year	China	India	Nepal	Pakistan	Sri Lanka	Bangladesh	Myanmar
2020	108398.9	98338.3	85.5	9605.9	120.1	5939.5	1759.5
2021	109983.5	97652.1	106.2	9575.9	119.6	5939.5	1753.3
2022	111568.1	97674.9	92.8	9545.9	116.1	5939.5	1766.8
2023	113152.6	99290.8	105.7	9516.1	115.7	5939.5	1776.6
2024	114737.1	99525.9	96.9	9486.4	125.8	5939.5	1770.7
2025	116321.7	98058.2	99.7	9456.7	121.4	5939.5	1783.5
2026	117906.2	98313.4	99.4	9427.1	112.1	5939.5	1792.8
2027	119490.8	99611.6	91.6	9397.7	117.4	5939.5	1787.3

Table 6. Holt's models fitted for sugarcane production time series over the period (1961-2019)

	Parameters			Initial States	
Country	α	β	ϕ	l	b
China	1	0	-	10372.12	1908.698
India	0.211830	0	-	98559.07	1.023695
Nepal	0.474187	0	0.987127	118.7306	1.091086
Pakistan	0	0	0.986322	15094.70	1.038686
Sri Lanka	0.095180	0.095180	-	120.0726	1.016387
Bangladesh	0.903234	0.091682	-	3566.363	430.1913
Myanmar	1	0	-	621.9784	190.2406

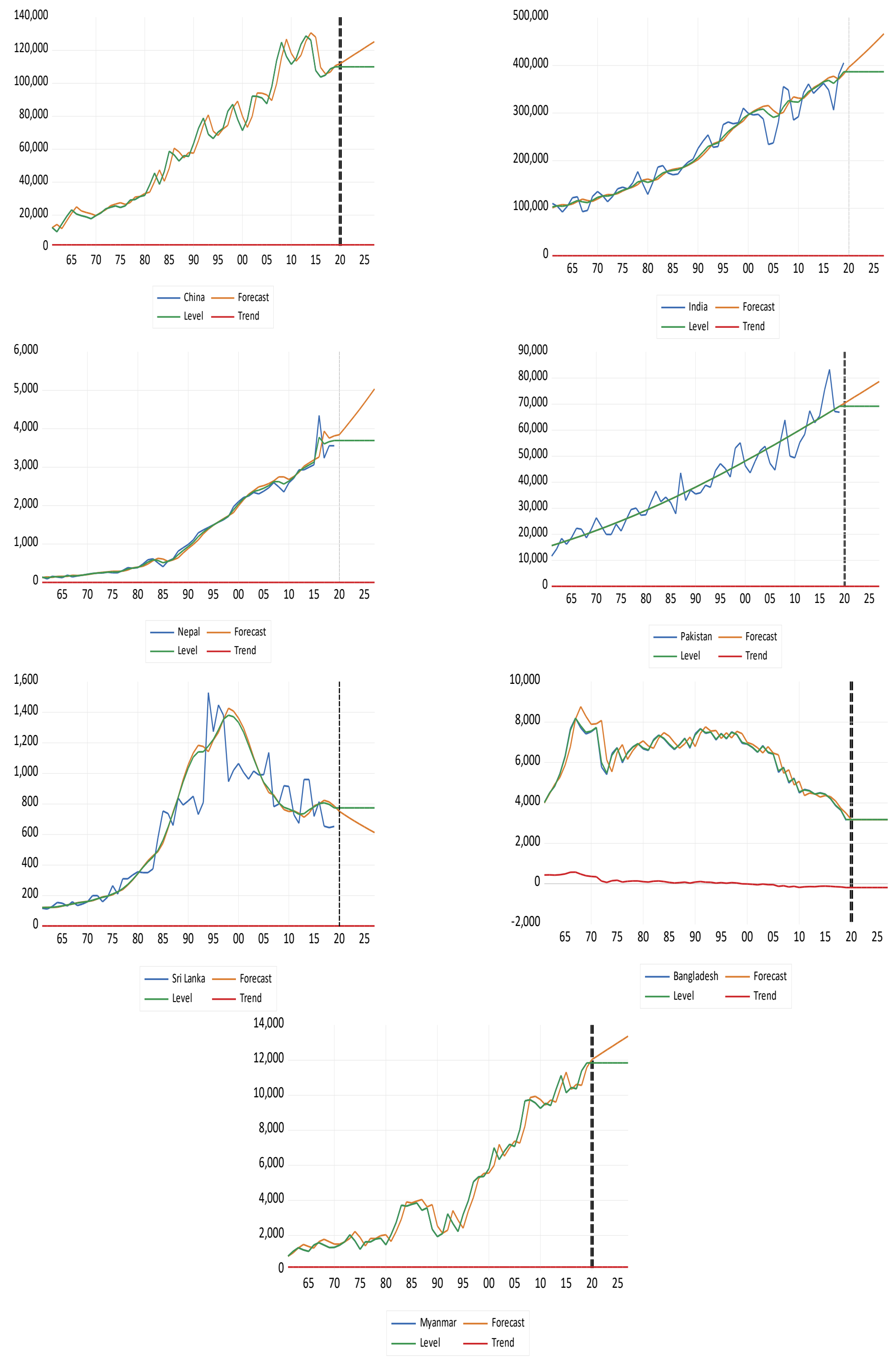

Figure 5. Actual and forecast values of sugarcane production with (Level-Trend) in seven countries during the period 1961-2027 using Holt's models

Table 7. Sugarcane production forecasting using Holt's models

Year	China	India	Nepal	Pakistan	Sri Lanka	Bangladesh	Myanmar
2020	111872.1	395767.7	3843.6	70352.4	752	2986.6	12036.4
2021	113780.8	405145.3	4000.7	71530.8	730.3	2797.4	12226.7
2022	115689.5	414745.1	4162.1	72712.4	709.3	2608.3	12416.9
2023	117598.2	424572.3	4327.8	73897.1	688.8	2419.2	12607.1
2024	119506.9	434632.4	4497.8	75084.3	668.9	2230.1	12797.4
2025	121415.6	444930.8	4672.2	76274.1	649.6	2040.9	12987.6
2026	123324.3	455473.3	4851.1	77465.9	630.9	3175.7	13177.8
2027	125233.1	466265.5	5034.2	78659.8	612.7	3175.8	13368.1

Table 8. Accuracy prediction using goodness of fit and DM test (model validation from 2010-19).

Countries	Model	Goodness of Fit		DM Test	
		RMSE	MAPE	Statistic	P Value
Bangladesh	ARIMA	1802.578	43.5294	9.945	<0.01
	ETS	262.507	5.0827		
China	ARIMA	28636.1165	23.072	4.347	<0.01
	ETS	7576.012	4.6458		
India	ARIMA	252973.3231	71.676	15.9509	<0.01
	ETS	29392.5749	6.778		
Myanmar	ARIMA	8700.7579	83.35069	31.481	<0.01
	ETS	590.149	4.6905		
Nepal	ARIMA	3142.6707	97.1376	30.165	<0.01
	ETS	426.888	7.7859		
Pakistan	ARIMA	57761.7833	86.7637	18.7826	<0.01
	ETS	7219.8213	8.0145		
Sri Lanka	ARIMA	659.9038	83.5306	14.6248	<0.01
	ETS	148.539	16.1607		

4. Conclusions

This empirical investigation has in depth studied the sugarcane production status of the South Asian region and revealed a number of interesting and promising findings. To begin with, we found the sugarcane production of these nations was showing an increasing trend, with the exception of Sri Lanka and Bangladesh. Further, we estimated the future growth rate of sugar production for these countries over the coming years (2020-2027). The growth rates varied between 1.16%-3.5%, with Nepal expected to expand its production at the highest rate of 3.5% and Pakistan with the lowest rate of 1.16%. The biggest production countries like India and China are projected to have growth rates of 2.5% and 1.51%, respectively, for the period of 2020-2027. Along with these findings, we also identified ETS to be a better model than ARIMA for forecasting the future total sugar production of these countries. Finally, using ETS models, we also obtained the predicted production of sugar for each country for the period 2020-2027. We strongly believe our study will help the national policy making bodies in the region to prepare themselves accordingly for efficient planning and management of their sugarcane industries.

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