Modelling and Forecasting of Pulses Production in South Asian Countries and its Role in Nutritional Security

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10.18805/LRF-645

ABSTRACT

Background: The goal of this study was to forecast pulse production in six countries: Afghanistan, Bangladesh, China, India, Nepal and Pakistan (2020-2027). In this study, time series forecasting was used.
Methods: The data series were divided into training set from 1961 to 2015 for model building, testing set from 2016 to 2019 for validation and finally, after selecting the best model, forecast was used from 2020 to 2027, the models were compared. The best-fit model was chosen based on the minimum ME, RMSE, MAE, MPE, MAPE, MASE, ACF1 values on the training data set and the minimum MAPE values on the testing data set.
Result: The best fitted model for India was NNAR (1,1). Similar to Afghanistan, the best fit model for forecasting was NNAR (3,2). The best fit model for forecasting in China was ARIMA (0,1,1). The best fit model for forecasting in Nepal was ARIMA (1,1,0). The best fit model for forecasting in Pakistan was ETS (A, N, N) (M, N, N). With a 15.73 per cent growth rate from 2020 to 2027, the best models predict that the production of pulses in (Afghanistan, China, India) will increase until 2027. India will continue to be the largest producer of pulses among the six countries, with production expected to reach 1088.778 thousand tons in 2027. Afghanistan and China have extreme growth rates of 25.19% and 11.95%, respectively, while the rest of the countries have relatively stable production volumes. These results may be crucial for developing an effective agriculture production policy, whether by providing forecasted production values or evaluating such policies.

Key words: ARIMA, ETS, Forecasting, Modeling, NNAR.

INTRODUCTION

Pulses are highly pretentious and are one of the major food crops globally. It is also an important crop in India, as it contributes the most to financial gains by amounting to a large part of the exports. Major pulses are grown like chickpeas, pigeon peas, moong beans, black beans, lentils, peas and various other kinds of beans. Protein forms a major part of pulses by weight (20 to 25%), as compared to the amount of protein present in wheat and rice. It is also a major source and an integral part of vegetarian protein in the Indian diet. Globally, India produces the largest amount of pulses, although nutritional and food security issues are still present because of imbalanced growth in agriculture, which is more concentrated on rice and wheat production. Pulse production in recent decades has been increased but not in response to an increased population. Furthermore, there has been a decline in consumption of pulses, which leads to malnutrition. This would be overcome by institutional and policy support, adopting high yielding varieties of pulses, low-cost technologies and proper marketing for pulses (Shalendra *et al*. 2013). Singh *et al*., 2007; Bera and Nandi, 2011). Development and research activities have received less attention from both international and private multinational corporations, along with other economic and physical factors (Reddy, 2010; Joshi and Saxena., 2002; Vani and Mishra, 2019).

Although there has been a strong demand for pulses over the past two decades, this has contributed to a positive

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trade in pulses. In countries such as the U.S., Canada and Australia, technological advances combined with good prices mean farmers are obliged to produce better yields to compete effectively in terms of returns with other important crops. This expansion of pulse production is linked to the increasing importance of the commodity in international trade. However, production fluctuations in importing

countries are significant, which can cause uncertainty for pulse exporting countries. Export countries' farmers were not sure if pulses were planted because of unstable foreign demand (Belhassen and Rawal, 2018). In a study carried out by Vishwajith *et al.* (2019) on the forecasting of mung production, ARIMA (4,1,4) was the best-fitted model over the ARIMAX and GARCH models. Contrary to it, Ray and Bhattacharyya (2020) found the ARIMAX (1,1,1) model for pulse production better suited than the ARIMA model. Price prediction serves as an important tool to forecast the market price, which is necessary for framing policies for sustained production and remunerative prices (Darekar and Reddy, 2017). The three aspects such as data trends in a certain location, amount of production and productivity of pulses in India were researched by Savadatti (2017) who applied the ARIMA type and observed stagnancy in the area while increasing pulse production and productivity. Many other studies have employed the ARIMA model for forecasting, *viz.*, cotton crop production and yield (Ali *et al.*, 2015) in Pakistan, the different crops of forecasting of area, production and productivity (Balanagammel *et al.*, 2000), pulses in South Asian counties (Mishra *et al.*, 2021) , sugarcane yield (Mishra *et al.*, 2021) in India and many more. Vishwajith *et al.* (2018) could not establish the superiority of either GARCH or ARIMA in modeling of data for arhar production in India.

MATERIALS AND METHODS

In this research, we aim to predict the production of pulses in six countries (Afghanistan - Bangladesh - China - India - Nepal - Pakistan). In present studies these countries for selected for south Asian region on the basis of higher production. The study period extends (1961-2019 from www.fao.org) an annual frequency. To forecast pulses production up to year 2027, we use three types of models Autoregressive Integrated Moving Average **(**ARIMA) - Nonlinear autoregressive neural network (NNAR) - Exponential Smoothing (ETS) first use the full forms followed by short forms) and compare their results. We will use data spanning from (1961-2015) for estimation and training by models and data from (2016 - 2019) to validate the models. Before that, our methodology goes through several stages:

DATA exploration

To visualize the data features (patterns, unusual observations, changes over time) we need to plot the data and then translate that through descriptive statistics and normal distribution of the data using the following statistic:

$$\text{Jarque - Bera} = \frac{n}{6}\left[S^2 + \frac{1}{4}(K-3)^2\right] \quad ....(1)$$

Where
n: Number of observations, S: Skewness, K: kurtosis.

DATA stationary

Time series that have a trend and volatility are not stationary, will affect the value of the time series at different time. Thus,

the series cannot be predicted in the long run. One way to determine whether a time series is stationary or not is to use a unit root. The time series in Augmented Dickey-Fuller test is described by the equation (Dickey and Fuller, 1981):

$$\Delta y_t = c + \alpha.t + \delta y_{t-1} + \beta_{p-1}\Delta y_{t-p+1} + \varepsilon_t \quad ....(2)$$

Where
c : constant, α: coefficient on a time trend, p: lag order of the autoregressive process. The ADF test is carried out under the null hypothesis $\delta = 0$ (not stationary) against the alternative of $\delta < 0$ (stationary). If the null hypothesis is not rejected, we perform the first difference to make the series stationary:

$$y_t = y_t - y_{t-1} \quad ....(3)$$

Estimation of models

To forecast pulses production up to year 2027, following three types of models are used:

ARIMA model

ARIMA models are the most widely used statistical models for time series forecasting, this is done by describing the autocorrelation in the data (Box *et al.*, 2015). These models are divided into three parts, according to their nomenclature (Auto Regressive-Integrated-Moving Average) (p, d, q).

Autoregressive (p) refers to predicting a variable using a linear set of its preceding values, the model of order p can be written as:

$$y_t = c + \beta_p y_{t-p} + \varepsilon_t \quad ....(4)$$

Where
β_p: parameters of model, p: lag order of the autoregressive process, ε_t: error term. Integrated (d) refers to the degree of stationary of a variable that is determined using ADF test.

Moving average (q): uses past forecast errors in in regression. The equation will be in the form:

$$y_t = c + \varepsilon_t + \beta_q \varepsilon_{t-q} \quad ....(5)$$

Where
β_q: Parameters of model, q: Lag order of the moving average, ε_t: Error term.

Whereas (d) is determined by ADF test, (p) and (q) are determined by the autocorrelation $\rho(p)$ function and the partial autocorrelation function R(p), which are given according to the following:

$$\rho(p) = \frac{\text{Cov}(y_t, y_{t+p})}{\sigma^2} \quad ....(6)$$

$$[\rho(p-1)\ \rho(p-2)....\rho(0)]\ (\beta q) = R\ (p) \quad ....(7)$$

NNAR model

Neural network autoregressive models are statistical models that allow complex nonlinear relationships to predict a variable using its lagged values. Where lagged values of the time series can be used as inputs to a neural network. (Hyndman *et al.*, 2012) previously suggested this method. These models are distinguished from ARIMA models by the presence of a hidden layer, in which the linear weighted input is modified by a nonlinear function before it is output:

$$N_i = \beta_i + \sum_{i=1}^{i} \omega_i y_i \qquad \dots(8)$$

In the hidden layer, this is modified using a nonlinear function:

$$f(y) = \frac{1}{1+ e^{-y}} \qquad \dots(9)$$

Where

β_i and ω_i parameter of model are learned from the data. This model can be written as *NNR(p, k)* where *p* lagged input and *k* nodes in the hidden layer. Model is neural network with observations (y_{t-p}) used as inputs for forecasting the output y_t and with *k* neurons in the hidden layer, with neglecting the effect of seasonality because the data is annual. The optimal number of lag *p* as (*p, q*) in ARIMA model is chosen using akaike information criterion (AIC), which is given as follow:

$$-2\log L\ (\hat{\theta}) + 2k \qquad \dots(10)$$

Where

$\hat{\theta}$ maximum value of the likelihood function. We remind that this model does not assume restriction about the stationary and therefore the random part is included in the predictions, Lama *et al.* (2021).

ETS Model

Whereas ARIMA model describe autocorrelation in the data, exponential smoothing model (ETS) are based on describing the trend in the data, which was suggested by (Holt, 1957), Mishra *et.al* (2021), Devi *et al.,* (2021) and (Winters, 1960).

ETS models are a systematic development in which exponential smoothing models (ETS) are combined into a nonlinear dynamic model. Analysis of these models using state-space based likelihood calculations, with support for model selection and calculation of forecast standard errors Hyndman *et al*, (2002).

Interested in the model in three main component of time series: trend (T), seasonal (S), error (E). Reflects the trend term of the long-term movement of time series and the error term is the unpredictable component of the time series. In our case, do not care about the seasonal term because the data annual. The components we need are combined in our

model, in various additive and multiplicative combinations to produce y_t. We have additive model y_t = T+E or multiplicative model like y_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). The models that we are interested in estimating can be written (after selecting S [N]) in the following Table A:

Performance indicators

To compare the prediction performance of the three models used, we first test the validity of the model by calculating mean absolute percentages error (MAPE) between the estimated data and the actual data during the period (2015-2019):

$$\frac{1}{n} \sum_{t=1}^{n} \left| \frac{\hat{y}_t - y_t}{y_t} \right| \times 100 \qquad \dots(11)$$

Then we evaluate the performance of the model by calculating root mean square error (RMSE) and (MAPE) between the estimated data and actual data during the period (1961-2015):

$$\sqrt{\frac{\sum_{t=1}^{n} (\hat{y}_t - y_t)^2}{n}} \qquad \dots(12)$$

Where

$\hat{y}_t$: the forecast value, y_t: the actual value, n: number of fitted observed. The last stage is to predict the pulses production for the countries of the study sample until 2027, the model that has the least values of (RMSE-MAPE) is the best and the uncertainty is included in the expectations 95% prediction interval is given by (Mishra *et al.,*2021):

$$\hat{y}_{T+h} \pm Z^{\alpha}/_2 \sqrt{\hat{\sigma}_h} \qquad \dots(13)$$

Where

$\hat{y}_{T+h}$ observation that will be predicted, $Z^{\alpha}/_2$=1.96, $\hat{\sigma}_h$: forecast variance.

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

Trend	Additive rrror models	Trend	Multiplicative error models
N	$y_t = l_{t-1} + \varepsilon_t$	**N**	$y_t = l_{t-1} (1 + \varepsilon_t)$
	$l_t = l_{t-1} + \alpha\varepsilon_t$		$l_t = l_{t-1} (1 + \alpha\varepsilon_t)$
A	$y_t = l_{t-1} + b_{t-1} + \varepsilon_t$	**M**	$y_t = (l_{t-1} + b_{t-1}) (1 + \varepsilon_t)$
	$l_t = l_{t-1} + b_{t-1} + \alpha\varepsilon_t$		$l_t = (l_{t-1} + b_{t-1}) (1 + \alpha\varepsilon_t)$
	$b_t = b_{t-1} + \beta\varepsilon_t$		$b_t = b_{t-1} + \beta(l_{t-1} + b_{t-1})\ \varepsilon_t$
AD	$y_t = l_{t-1} + \Phi b_{t-q} + \beta\varepsilon_t$	**MD**	$y_t = (l_{t-1} + \Phi b_{t-1}) (1 + \varepsilon_t)$
	$l_t = l_{t-1} + \Phi b_{t-1} + \alpha\varepsilon_t$		$l_t = (l_{t-1} + \Phi b_{t-1}) (1 + \alpha\varepsilon_t)$
	$b_t = \Phi b_{t-1} + \beta\varepsilon_t$		$b_t = \Phi b_{t-1} + \beta(l_{t-1} + b_{t-1})\ \varepsilon_t$

Where parameters: α: smoothing factor for the level, β: smoothing factor for the trend, Φ : damping coefficient. And initial states: *l* : initial level components, *b*: initial growth components, which is estimated as part of the optimization problem, Devi *et al.* (2021).

Table 1: Normal distribution and descriptive statistics for pulses production in six countries during the period 1961-2019.

Countries	Normality J-B (Prob)	Mean	Standard deviation	Maximum	Minimum	Skewness	Kurtosis
Afghanistan	000	40.8	15.9	106.6	15	1.46	6.87
Bangladesh	0.13	137.7	35.4	192	71.8	-0.21	1.79
China	0.01	55.8	61.5	154.1	0	0.27	1.22
India	0.45	999.2	236.1	1506.5	535.2	0.21	2.31
Nepal	000	36.1	12.2	72.1	22.7	1.52	4.91
Pakistan	000	170.7	64.3	414.4	80.7	1.31	5.05

Empiricial study

To know the development and trends in pulses production for (Afghanistan – Bangladesh – China – India – Nepal – Pakistan) we present the following Fig 1:

The Fig1 shows that both China and Nepal achieved significant growth in the pulses production until the year 2019 almost exponentially. Afghanistan has achieved this development to 2015 and then production decreased after this year. Bangladesh and Pakistan have a similar situation they achieved a development in production until 1995 and then production decreased after this period similar to a second-order polynomial. As for India, it notices the high volatility in pulses production during the studied period and as it was shown to us that production is down trend. Descriptive statistics show the most important values of changes in data through Table 1.

The Table 1 shows us that the data for (Afghanistan-China -Nepal-Pakistan) are not distributed normally, as the probability (Jarque-Bera) is less than the level of significance 5%. Thus the estimator here (Mean and standard deviation) are useless because they are breakdown points. These countries experienced significant changes in pulses production during the studied period, as shown by the maximum-minimum values and skewnes and kurtosis coefficient that Pakistan has the greatest development, where production reached 414.4 thousand tons in 1989 before it decreased to 80.7 in 2014. We also note from the Table 1 that the data from India and Bangladeshshare distributed normally, the production of pulses in India and the largest producer among the six countries, changed from 1506 thousand tons in 1991 to 535.2 in 1992. In order to find out the effect of these volatility and trends on the stationary of the variables, we use ADF test and we get the results from Table 2.

Table 2: ADF test result.

Countries	ADF (prob)		Order of integration
	Level I(0)	First difference I(1)	
Afghanistan	0.0007	-	I(0) with trend
Bangladesh	0.675	000	I(1)
China	0.833	000	I(1)
India	0.019	-	I(0) with constant
Nepal	0.770	000	I(1)
Pakistan	0.392	000	I(1)

The Table 2 shows that (Afghanistan-India) is stationary in level with linear trend for Afghanistan and around constant for India as shown in Fig 1. For the rest of the countries, the high volatility during the studied period made it a stationary series at the first difference. With the aim of forecasting the pulses production for six countries up to 2027, we use (ARIMA-NNAR-ETS) models; we use the data during the period (1961-2015) to estimate using models (training) and (2016-2019) to verify the validity of the model (testing). The following table shows the results of estimating the ARIMA model for the six countries:

The Table 3 shows that all selected β models have better out-of-sample prediction results, as the value of (MAPE-Testing) is less then (MAPE-Training) for all models except Afghanistan, where the model failed to predict lower values after 2015. The best model is ARIMA (1,1,0) for Nepal, which achieved the lowest values of (AIC, RMSE, MAPE) among the selected models. We note from table that there is no autocorrelation problem for the residual values in all models. We estimate NNAR model for all countries and get the following results:

The Table 4 shows the prediction using NNAR models is better than the prediction using ARIMA inside the sample (Training), but the good performance decreases outside the

Table 3: Estimation of ARIMA models for six countries.

Countries	Model	Parameters ARIMA			AIC	Training period		Testing period	ACF1
		Drift	AR	MA		RMSE	MAPE	MAPE	
Afghanistan	(0,1,0)	1.6417	-	-	382.53	7.961	10.016	132.5	-0.06
Bangladesh	(0.1.0)	-	-	-	421.14	11.62	6.576	3.52	0.01
China	(0,1,1)	2.54	-	-0.24	466.01	17.27	16.77	13.81	-0.04
India	(0,0,1)	-	-	0.25	760.11	229.52	20.75	7.03	0.08
Nepal	(1,1,0)	-	-0.19	-	375.7	7.49	10.44	0.043	0.002
Pakistan	(0,1,1)	-	-	-0.55	570.4	45.33	18.24	4.67	-0.1

sample. The best model among selected models is for India NNAR (1,1), Which is better than the corresponding ARIMA model (Mishra *et.al.*,2020). We estimate ETS model for all countries and get the following results:

The Table 5 shows that the best ETS model among the estimated models is for Nepal (M,N,N), which has the lowest values of (RMSE-MAPE in – out of the sample), similar to the results of the ARIMA model. Among all selected models,

we choose the best model for forecasting pulses production to 2027 for each country:

According to these models (Table 6), a forecast of pulses production for 2027 is obtained with the inclusion of uncertainty in the forecast, as shown in the following Fig 2.

The Fig 2 shows that (Afghanistan, China, India) are expected to increase the quantities of pulses production until 2027, with relative stability in the volume of production for
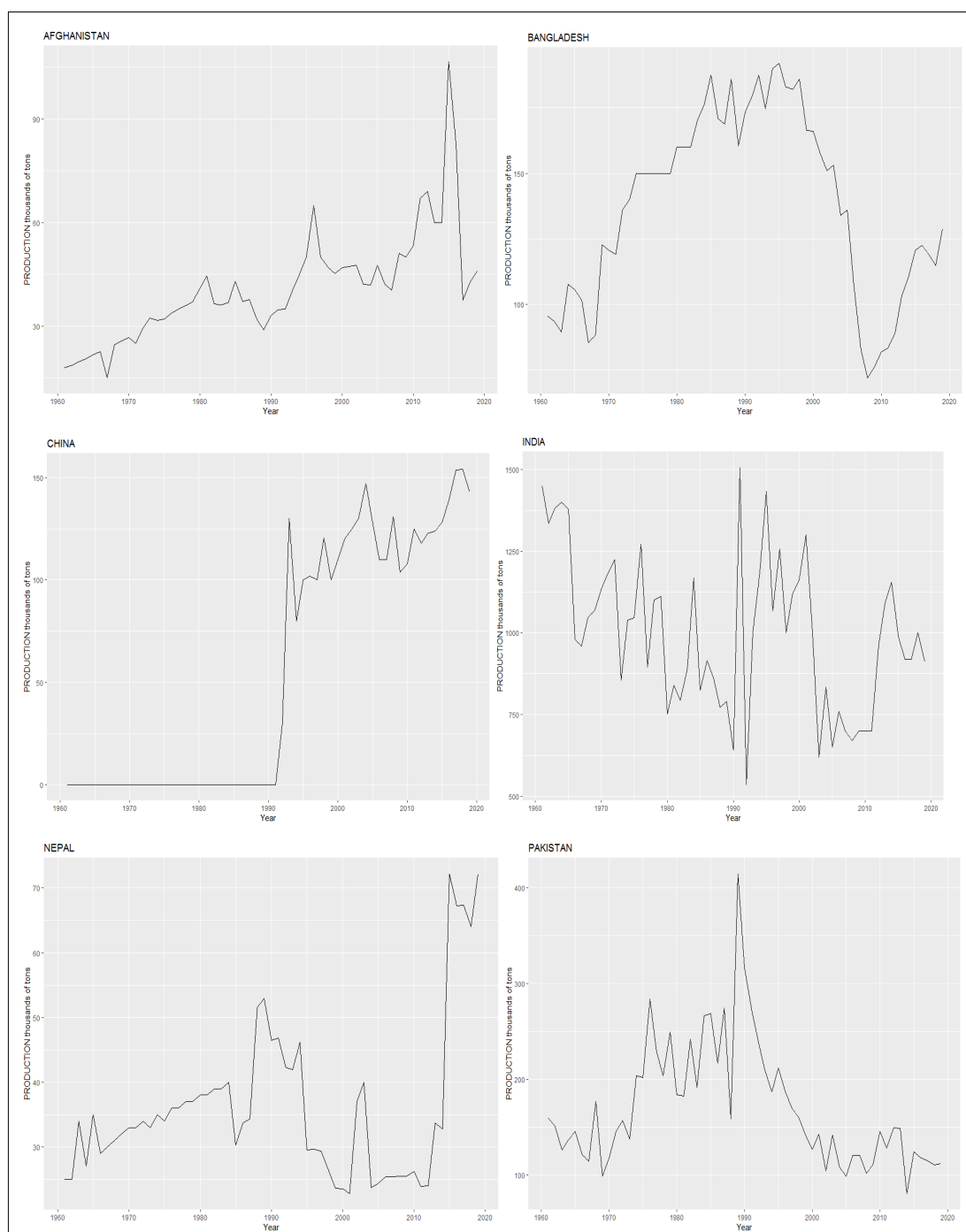

Fig 1: Development of pulses production in six countries during the period 1961-2019.

Table 4: The results of estimating NNAR models for six countries.

Countries	Model	Training		Testing	ACF1
		RMSE	MAPE	MAPE	
Afghanistan	(3,2)	6.28	9.76	16.91	0.03
Bangladesh	(0,2)	0.144	0.085	14.87	0.27
China	(1,1)	10.20	5.642	21.04	0.31
India	(1,1)	200.18	16.72	1.22	-0.18
Nepal	(0,2)	0.018	0.047	49.90	0.49
Pakistan	(0,2)	0.162	0.075	53.57	-0.02

Table 5: the results of estimating ETS models for six countries.

Countries	Model	Parameters ETS			Initial stats		AIC	Training		Testing	ACF1
		α	β	Φ	l	b		RMSE	MAPE	MAPE	
Afghanistan	(M,A,N)	0.592	0.04	-	16.7	1.08	423.3	7.82	10.1	92	0.04
Bangladesh	(A,N,N)	0.999	-	-	94.9	-	496.2	11.62	6.58	3.52	0.01
China	(A,N,N)	0.755	-	-	0.102	-	539.8	17.72	16.2	13.83	-0.03
India	(A,N,N)	0.373	-	-	1363.1	-	817.4	215.63	16.62	6.6	-0.05
Nepal	(M,N,N)	0.897	-	-	23.75	-	447.5	7.51	10.27	3.57	-0.05
Pakistan	(M,N,N)	0.431	-	-	140.07	-	633.4	45.35	18.4	4.84	-0.08

Table 6: The best model for forecasting pulses production to 2027 for each country.

Countries	Afghanistan	Bangladesh	China	India	Nepal	Pakistan
Model	NNAR (3,2)	ARIMA (0,1,0) ETS(A,N,N)	ARIMA (0,1,1)	NNAR (1,1)	ARIMA (1,1,0)	ETS (M,N,N)

Table 7: The expected production quantities for the six countries until 2027 with prediction interval 95%.

|	Point	Low 95%	High 95%	Point	Low 95%	High 95%
	Afghanistan			**Bangladesh**		
2020	45.489	33.359	57.213	128.563	105.856	151.270
2021	45.846	27.940	65.030	128.563	96.452	160.674
2022	46.738	23.756	69.372	128.563	89.236	167.890
2023	47.716	20.722	73.630	128.563	83.153	173.973
2024	48.922	18.480	79.347	128.563	77.793	179.333
2025	50.558	19.086	81.046	128.563	72.947	184.179
2026	52.877	18.903	86.923	128.563	68.491	188.635
2027	56.949	18.457	87.395	128.563	64.344	192.782
	China			**India**		
2020	149.295	115.828	182.762	940.778	547.976	1330.801
2021	151.842	110.503	193.181	976.560	532.082	1436.929
2022	154.389	106.453	202.324	1019.734	551.617	1398.138
2023	156.936	103.208	210.664	1058.564	484.156	1434.751
2024	159.482	100.528	218.437	1079.461	539.960	1427.360
2025	162.029	98.276	225.783	1086.471	538.585	1435.087
2026	164.576	96.360	232.792	1088.324	566.079	1427.363
2027	167.123	94.719	239.526	1088.778	583.712	1430.615
	Nepal			**Pakistan**		
2020	70.664	56.073	85.255	113.377	60.840	165.915
2021	70.894	51.927	89.861	113.377	55.854	170.901
2022	70.855	48.118	93.592	113.377	51.220	175.534
2023	70.862	44.931	96.792	113.377	46.865	179.890
2024	70.860	42.084	99.637	113.377	42.736	184.018
2025	70.861	39.495	102.226	113.377	38.796	187.959
2026	70.861	37.105	104.616	113.377	35.015	191.740
2027	70.861	34.873	106.849	113.377	31.371	195.383
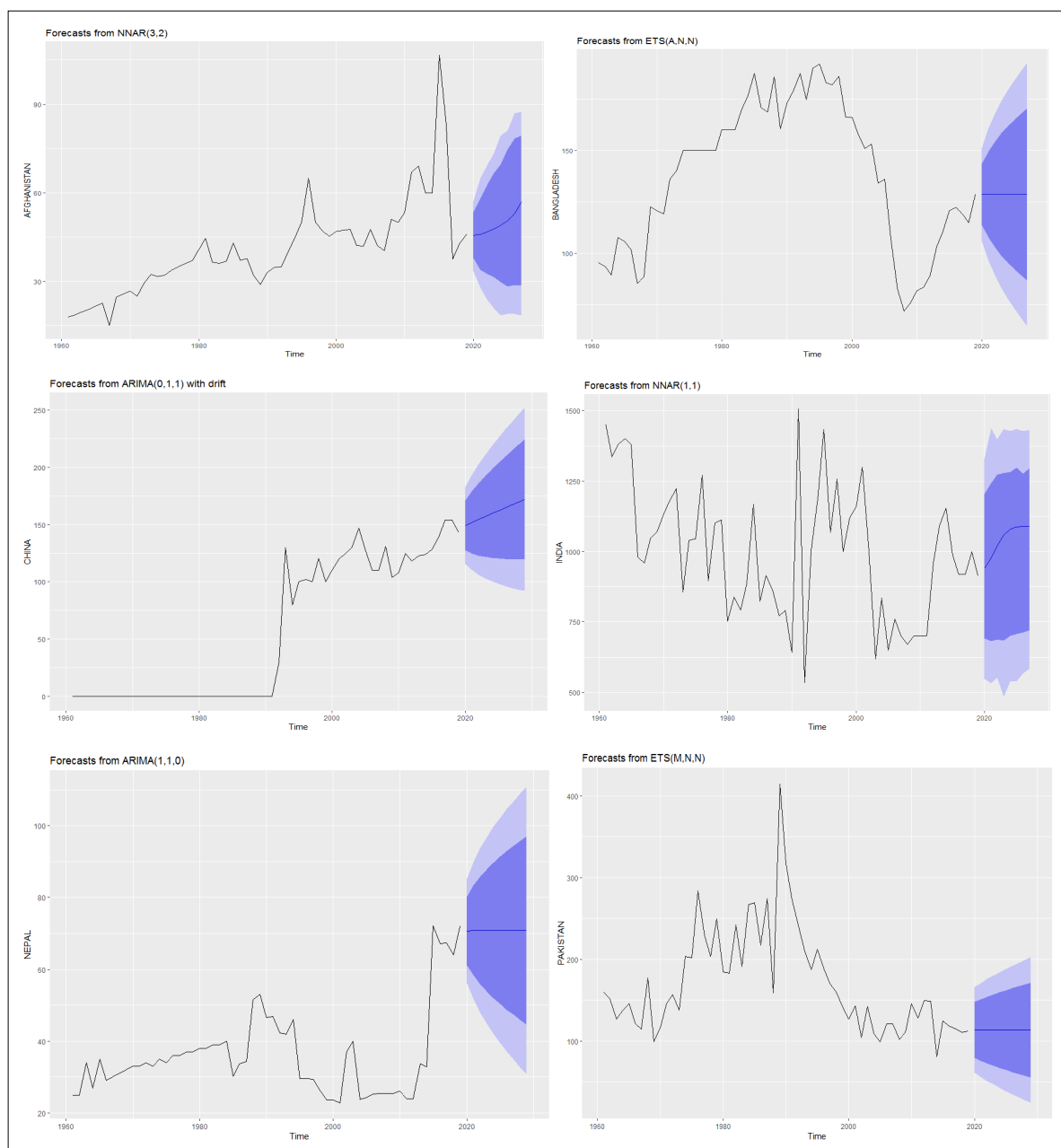
Fig 2: Pulses production forecast for six countries to 2027.

the rest of the countries. The following table shows the expected production quantities for the six countries until 2027 with prediction interval 95% (Table 7):

The Table 7 shows that India is the largest producer of pulses among all six countries, where production is expected to reach 1088.778 thousand tons in 2027, with a growth rate 15.73% during the period 2020-2027. In addition, Afghanistan and China have an extreme growth rate of 25.19%, 11.95% respectively.

CONCLUSION

Pulses have long been considered the available source of protein for the poor. Compared to ARIMA–NNAR–ETS models, this study shows that no single model is suitable for all countries. Based on the minimum values of ME, RMSE, MAE, MPE, MAPE, MASE and ACF1 among the chosen models on the training data set and the minimum value of MAPE among the chosen models on the testing data set, the best-fitted model was selected. The NNAR(1,1) model was considered the best fitted model for India. Similarly, NNAR (3,2) was the best fit model for forecasting in Afghanistan. There were two equally best models for Bangladesh: ARIMA (0,1,0) and ETS (A, N, N). The best fit model for forecasting in China was ARIMA (0,1,1). The best fit model for forecasting in Nepal was ARIMA (1,1,0). The best fit model for forecasting in Pakistan was ETS (M, N,

N). According to the best models, pulse production quantities in Afghanistan, China and India will be increased until 2027, with India remaining the largest producer of pulses among all six countries, with production expected to reach 1088.778 thousand tons in 2027, with a growth rate of 15.73% between 2020 and 2027.In addition, Afghanistan and China have an extremely high growth rate of 25.19% and 11.95%, respectively, with relative stability in the volume of production for the rest of the countries. These results may be vital for building an effective agriculture production policy, whether by providing an awareness of the forecasted production values or evaluating such policies and forecasting the food gap for pulse crops. There are a number of important changes which need to be made by policy makers, especially in Pakistan, Nepal and Bangladesh, to increase the production of pulses. Further research regarding the determinants of pulse production in these countries would be worthwhile.

Conflict of interest: None.

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