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Research Paper

Modelling and Forecasting of Maize Production in South Asian Countries

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ABSTRACT

The challenges of fighting poverty and enhancing food security in South Asia have made maize a strategic crop in this region. In this study, maize production in South Asia, encompassing Afghanistan, Bangladesh, Bhutan, China, India, Nepal, Pakistan, and Sri Lanka, was analysed and projected from 1961 to 2027 using state-space and ARIMA models. The estimation outcomes demonstrated the state-space models' superior performance in predicting trends in maize output for all eight time series. Additionally, the forecast estimation revealed that we anticipated an uptick in the output of maize in these nations; this finding would be encouraging for the countries in this region as it would heighten the problem of food security. India would be leading countries in maize with production of 380438 thousand tonnes in 2027.

HIGHLIGHTS

- According to the estimation results, state-space models performed better than other models at predicting future trends in maize production for all eight time series.
- With an upswing in maize production anticipated in all eight countries, governments may be more at ease pursuing more efficient strategies.

Keywords: Maize production, Forecasting, South Asia, ARIMA, State Space Model

Economic liberalisation that took place in South Asia in early 1990s (Dev, 2000) has made the region manifest promising economic growth alongside poverty reduction (Devarajan and Nabi, 2006). Despite this, a large section of population residing in south Asia is facing the problem of undernourishment and malnutrition (Akhtar, 2016; Wali *et al.* 2019). The Indian governments have undertaken many strategies to combat the

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prevailing food insecurity, for instance, developing high yielding varieties, improved nutrition and irrigation resources, increased investments in research and development in agriculture etc. (Bishwajit *et al.* 2013). Regardless of all these technological developments in agriculture aiming to cope up with the food demands of the increasing population of the region, climate still plays a key role in determining the production and productivity of the crops (Zhai and Zhuang, 2009). Owing to the fact that climate change is inevitable and temperature is going to rise consistently in future, there's a need to focus on cultivation of heat resistant crops like maize (Prasanna, 2011; Tesfaye *et al.* 2017; Tiwari and Yadav, 2019).

In a region like South Asia, where small land holdings are accompanied with high population density, maize is cultivated widely because of its high yielding nature making it a staple crop of the region (Grote *et al.* 2021). Changing dietary pattern and income level has permuted maize from being a staple crop to a crop of industrial importance (Pasuquin *et al.* 2014). Studies suggest that one of the reasons of increased in production of maize is increase in poultry production as it serves an important ingredient of poultry ration (Shiferaw *et al.* 2011; Hellin *et al.* 2015; Lee *et al.* 2015; Tesfaye *et al.* 2017). Thus, it can be established that maize is an important crop in South Asia as it is a heat resistant crop which not only enhances food and nutritional security of the region but also serves as an important input in various other enterprises. Increasing demand of the crop in the region calls upon a need to forecast the production of the crop in major maize producing countries of South Asia so that the demand – supply is balanced, thereby, keeping a check on increase in the prices of the crop.

The present paper aims to forecast the production of maize in South Asia including the countries of Afghanistan, Bangladesh, Bhutan, China, India, Nepal, Pakistan and Sri Lanka in the study. Choudhury *et al.* (2021) forecasted yield of maize in northern and western Bangladesh using CERES maize model while Xiong *et al.* (2007) used the same model to forecast maize production in China. Matsuura *et al.* (2014) forecasted the maize production and yield in China using linear regression and artificial neural networks whereas Chen *et al.* (2021) used machine learning approaches such as Cubist, Xgboost, RF and SVM for the forecast. Models of trend analysis were used by Tahir and Habib (2013) to forecast maize area and production in Pakistan while Ahmad et al. (2018) used remote sensing and crop modelling to predict the same in Faisalabad- Punjab of Pakistan. ARIMA has been applied as tool for forecasting of maize production in India (Sahu and Mishra, 2014; Sharma, 2018; Verma, 2018). The current study also employs ARIMA model to predict maize production in South Asia.

MATERIALS AND METHODS

In this research, we aim to predict the production of maize in south Asian countries. The study period extends (1961-2019 from www.fao.org) an annual frequency. Dataset is yearly data from 1961 to 2019 about Maize production; we used training data from 1961 to 2014 and testing last 5 years from 2015 to 2019. The schema of present work has given in Fig. A.

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:

$$y_t = c + \beta_p y_{t-p} + \varepsilon_t \qquad \ldots(1)$$

Where β_p: parameters of model, P_p: lag order of the autoregressive process, y_t: error term. Integrated (d) refers to the degree of stationary of a variable that is determined using augmented Dickey–Fuller (ADF) test.

State Space Models (SSM)

State Space Models (SSM) is broadly used and, maybe is recognized under numerous names:

Structural models in Econometrics, Dynamic linear models and Bayesian forecasting models in Statistics, linear system models in engineering, Kalman filtering models in control engineering, also known as Kalman filtering, was first introduced by Kalman (Kalman 1960). The State Space Models are effective tool which opens the way for dealing with a wide range of time series models with unobserved components are commonly encountered in Economics and Finance. The Kalman filter can be used once a model has been put in state space form, it also opens up further estimation algorithms for prediction, filtering, smoothing, and forecasting. It also resolves issues linked to missing values in the time series. State Space Models (SSM) provides a united representation for a wide range of ARIMA and time varying regression models. State Space Models are flexible enough to capture diverse specifications of non-parametric and non-linear spline regression models. State space models involve 2 equations to account for 2 variation distinct sources at the same time: the state equation (latent process): which deals with the process uncertainty produced by the unobserved factors, and the observation model incorporates the effect of the error produced by the measurement of outcomes. The general form for a state space model is:

Observation equation: $Y_t = Z_t\, \alpha_t + \varepsilon_t$,

State transition equation: $\alpha_{t+1} = T_t\, \alpha_t + \eta_{t+1}$ …(2)

where n * 1 vector α_t is the state vector, denoting the state at time t; and k * 1 vector y_t is the observations at time t; and α_t and ε_t are the observation and state noises, which are respectively drawn from normal distributions with zero means, variances of R_t and Q_t, and S_t covariances. The n * n matrix T_t named the transition matrix and the k * n matrix Z_t called the output matrix in Eq. (2) are referred to as the system matrices with appropriate dimensions. It is well recognized in the time-series analysis that unobserved components models have been confirmed to be very effective (Koopman & Ooms 2006; Golpe *et al.* 2012; Mnif 2017). And a very successful and widely accepted unobserved components model includes trend, cycles, seasonal and irregular components (Mishra *et al.* 2021).

The general form of SSM model is:

$$y_t = \mu_t + \gamma_t + c_t + \varepsilon_t \quad \text{…(3)}$$

where y_t refers to the observation vector at time t, μ_t refers to the trend component, the trend component can be modeled in many ways, usually it is named level when there is no slope component. γ_t is the seasonal component, c_t is the cycle component, ε_t and is an irregular component. The modeling details for these components are defined in the following. The trend component is a Dynamic regression model extension that contains an intercept and linear time-trend and is given as (Sarder *et al.* 2021 & Pandey *et al.* 2021):

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_{t-1} \beta_t = \beta_{t-1} + \varsigma_{t-1} \quad \text{…(4)}$$

where the level is a generalization of an intercept term that can Dynamically differ across time, and the trend is a generalization of the time-trend thus the slope may Dynamically differ across time $\mu_t \sim N\left(0, \sigma_\eta^2\right)$; and $\mu_t \sim N\left(0, \sigma_\varsigma^2\right)$. The seasonal component is modeled as:

$$\mu_t = -\sum_{j=1}^{s-1} \gamma_{t+1-j} + \omega_t \quad \text{…(5)}$$

where s is the number of seasons (12 in monthly data), and $\omega_t \sim N\left(0, \sigma_\omega^2\right)$. This component results in one parameter to be selected by maximum likelihood: σ_ω^2 and one parameter to be selected, the number of seasons s. The cyclical component is intended to encapsulate the cyclical effects at time frames much longer than those captured by a seasonal component (Mishra *et al.* 2022).

$$\begin{aligned} C_{t+1} &= \rho_C \left(\tilde{C}_t \cos\cos \lambda_c t + \tilde{C}_t^* \sin\sin \lambda_c \right) + \tilde{\omega}_t c_{t+1}^* \\ &= \rho_c \left(-\tilde{C}_t \sin\sin \lambda_c t + \tilde{C}_t^* \cos\cos \lambda_c \right) + \tilde{\omega}_t^* \end{aligned} \quad \text{…(6)}$$

where c_t and c_t* are independent, zero-mean, normal disturbances with variance $\sigma_\omega^2, \tilde{\omega}_t, iid\ N\left(0, \sigma_{\tilde{\omega}}^2\right)$, damping factor ϱ_c can be any value in the interval (0, 1), including 1 but without 0, and parameter λ_c (the frequency of the cycle) is another parameter to be estimated by maximum likelihood estimation (MLE).

An autoregressive component (that is frequently used as a replacement for the white noise irregular term):

$$\varepsilon_t = \rho(L)\varepsilon_{t-1} + \varepsilon_t, \varepsilon_t \sim N\left(0, \sigma_e^2\right) \quad \text{…(7)}$$

The state space model can be written as:

Observation equation: $y_t = \mu_t + \gamma_t + c_t + \varepsilon_t$,

Transition equation: $\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_{t-1}$,

$\beta_t = \beta_{t-1} + \zeta_{t-1}$

$$\gamma_t = -\sum_{j=1}^{s-1} \gamma_{t+1-j} + \omega_t$$

$$c^*_{t+1} = \rho_c \left(\tilde{c}_t \cos\cos \lambda_c t + \tilde{c}^*_t \sin\sin \lambda_c \right) + \tilde{\omega}_t$$

$$c^*_{t+1} = \rho_c \left(\tilde{c}_t \sin\sin \lambda_c t + \tilde{c}^*_t \cos\cos \lambda_c \right) + \tilde{\omega}^*_t$$

$$\varepsilon_t = \rho(L)\varepsilon_{t-1} + \varepsilon_t, \varepsilon_t \sim N\left(0, \sigma_e^2\right)$$

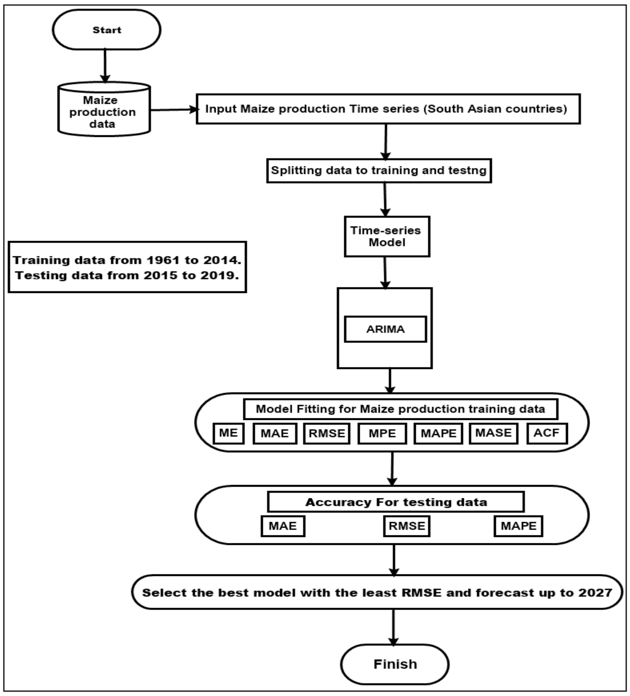


Fig. A: Schema of Maize production in south Asian countries

RESULTS AND DISCUSSION

We find that: from 1961 to 2019, the maize production in Afghanistan has increased during the period from (1066.7) thousand tonnes to (8000) thousand tonnes. Average maize production in Afghanistan was (4996.3) thousand tonnes. Ex. Kurtosis value was (-1.3936) indicating small outliers in the data. Followed by a negative value of skewness (-0.08) which is between -0.5 and 0.5, which means that the distribution is approximately symmetric. The maize production in Bangladesh has increased during the period from (9.25) thousand tonnes to (35693) thousand tonnes. The average maize production in Bangladesh was (4404.9) thousand tonnes. Ex. Kurtosis value was (3.7259) indicating big outliers in the series. Followed by a positive value of skewness (2.1736) indicating there is some possibility of growing in the maize production in Bangladesh. The maize production in Bhutan has increased during the period from (311) thousand tonnes to (940.52) thousand tonnes. Average maize production in Bhutan was (653.10) thousand tonnes. Ex. Kurtosis value was (-0.73680) indicating small outliers in the data. Followed by a negative value of skewness (-0.25585) indicating there is some possibility of decreasing in the maize production in Bhutan. The maize production in China has increased during the period from (1.6286e + 005) thousand tonnes to (2.6516e + 006) thousand tonnes. Ex. Kurtosis value was (-0.19198) indicating the distribution of the data is a mesokurtic. Followed by a positive value of skewness (0.85764) indicating there is some possibility of growing in the maize production in China. The maize production in India has increased during the period from (43120) thousand tonnes to (2.8753e + 005) thousand tonnes. Average maize production in India was (1.1472e + 005) thousand tonnes. Ex. Kurtosis value was (-0.12930) indicating the distribution of the data is a mesokurtic. Followed by a positive value of skewness (1.0657) indicating there is some possibility of growing in the maize production in India. The maize production in Nepal has increased during the period from (5759.1) thousand tonnes to (26532) thousand tonnes. In the average maize production in Nepal was (12799) thousand tonnes. Ex. Kurtosis value was (-0.54455) indicating small outliers in the data. Followed by a positive value of skewness (0.77811) indicating there is some possibility of growing in the maize production in Nepal. The maize production in Pakistan has increased during the period from (4826) thousand tones to (72363) thousand tonnes. Ex. Kurtosis value was (1.0739) indicating big outliers in the series followed by a positive value of skewness (1.4660) indicating there is some possibility of growing in the maize production in Pakistan. The maize production in Sri Lanka has increased during the period from (89.740) thousand tones to (2700.4) thousand tonnes. Average maize production in Sri Lanka was (614.59) thousand tonnes. Ex. Kurtosis value was (1.2735) indicating big outliers in the series Followed by a positive value of skewness (1.6802) indicating there is some possibility of growing in the maize production in Sri Lanka.

Table 1: Summary Statistics, using the observations 1961 – 2019

Variable	Mean	Median	Minimum	Maximum
Afghanistan	4996.3	4940	1066.7	8000
Bangladesh	4404.9	30.48	9.25	35693
Bhutan	653.1	670	311	940.52
China	1.04E+06	9.58E+05	1.63E+05	2.65E+06
India	1.15E+05	88844	43120	2.88E+05
Nepal	12799	12047	5759.1	26532
Pakistan	19892	11845	4826	72363
SriLanka	614.59	305.8	89.74	2700.4
Variable	Std. Dev.	C.V.	Skewness	Ex. kurtosis
Afghanistan	2138	0.42791	-0.088678	-1.3936
Bangladesh	8950.5	2.0319	2.1736	3.7259
Bhutan	155.72	0.23843	-0.25585	-0.7368
China	7.14E+05	0.68634	0.85764	-0.19198
India	69727	0.60779	1.0657	-0.1293
Nepal	5530.9	0.43214	0.77811	-0.54455
Pakistan	17651	0.88734	1.466	1.0739
Sri Lanka	743.35	1.2095	1.6802	1.2735

Table 2: ARIMA Model fitted for Maize production for training data set (1961 to 2014)

	MODEL	AIC	MAE	RMSE	MAPE
Afghanistan	ARIMA (1,1,0)	920	462.58	640	14.873
Bangladesh	ARIMA (1,2,1)	1002	723.86	1462.2	942.39
Bhutan	ARIMA (1,0,4)	710	58.55	84.1	10.18
China	ARIMA (1,1,0)	1506	67301	1.00E+05	7.674
India	ARIMA (1,1,2)	1262	8726.9	11682	9.2
Nepal	ARIMA (1,2,1)	928	531.97	744.17	4.5527
Pakistan	ARIMA (2,2,2)	1041	1248.4	1923	7.6376
Sri Lanka	ARIMA (4,1,2)	753	71.4	134.63	17.214

Top selected ARIMA models are shown in table 2, these models were selected based on the criteria (Akaike, Root mean squared error, Mean absolute error, Mean absolute percentage error, Maximum number of significant coefficient). Table 3, show us parameters estimates for State Space Models, and the best-fitted models on training data set ("1961 to 2014"), based on, lowest values of RMSE, MAE and MAPE, is the best model for all the series. The State Space Models give better results than the ARIMA Models for Forecasting Maize production in all countries in this study. The forecasting accuracy by the State Space Models is very high and outperform the forecasting accuracy of the ARIMA models, because All values of the accuracy criteria (RMSE, MAE and MAPE) were lower than the values of the accuracy criteria of ARIMA Models (*Devi et al.* 2019) in table 4. The Actual and forecast values of Maize production given in Fig. 1 (Yadav *et al.* 2022 & Mishra *et al.* 2022).

Table 3: State Space Models for Maize production training dataset (1961-2014)

Structural time series models for Maize production										
	Component	**Value**	**Std. Err**	**t-stat**	**Prob**	**Akaike Information Criterion (AIC)**	**Bayesian Information Criterion (BIC)**	**Within-sample RMSE**	**MAE**	**MAPE**
Afghanistan	Level	3148.6519	249.55	12.6173	2.22E-16	15.5825	16.0245	150.765	98.4371	3.001
	Slope	-3.7262	185.424	-0.0201	0.9841					
	Cycle	0.0245	19.335	0.0013	0.999					
	AR2	0.004	5.506	7.20E-04	0.9994					
Bangladesh	Level	17804.4	718.952	24.764	0	17.0378	17.4061	579.2415	214.2208	84.888
	Slope	1806	351.065	5.144	4.71E-06					
	Cycle	2321.6	584.744	3.97	2.35E-04					
	AR1									
Bhutan	Level	729.068	86.423	8.4361	4.87E-11	12.0103	12.4155	2.37E-07	1.45E-07	2.43E-08
	Slope	3.124	2.756	1.1334	0.2627					
	Cycle	-10.31	50.379	-0.2048	0.8386					
	AR2	24.948	94.577	0.2638	0.7931					
China	Level	2.15E+06	1.25E+05	17.1995	0	24.8456	25.2139	7.26E-10	5.45E-10	4.98E-14
	Slope	77984.4	18977.8	4.1092	1.51E-04					
	Cycle	-31376.9	27888.4	-1.1251	0.266					
	AR1	35389.9	1.23E+05	0.2874	0.775					
India	Level	2.45E+05	5648.256	43.421	0	21.2145	21.5828	8737.2739	6479.0797	7.0655
	Slope	10399.079	2006.246	5.183	4.11E-06					
	Cycle	3.62E-04	5.573	6.50E-05	0.9999					
	AR1	0.0013	1.28E-04	7.44E-04	0.9999					
Nepal	Level	21740.1	509.865	42.6388	0	15.8433	16.2116	459.8381	332.6855	3.1243
	Slope	591.3	162.974	3.6283	6.79E-04					
	Cycle	236.9	356.9	0.6636	0.51					
	AR1	1.22E-04	1.126	1.08E-04	0.9999					
Pakistan	Level	48053.2	2096.8	22.917	0	17.5773	17.9457	3.97E-12	3.12E-12	2.42E-14
	Slope	2263.1	558.8	4.0499	1.82E-04					
	Cycle	1013.1	454.6	2.2286	0.0305					
	AR1	301.1	2076.3	0.145	0.8853					
Sri Lanka	Level	2328.0021	321.33	7.2449	3.10E-09	12.5638	12.969	3.92E-07	2.48E-07	6.47E-08
	Slope	194.3738	53.21	3.6527	6.41E-04					
	Cycle	0.0299	20.07	0.0015	0.9988					
	AR2	83.408	320.7	0.2601	0.7959					

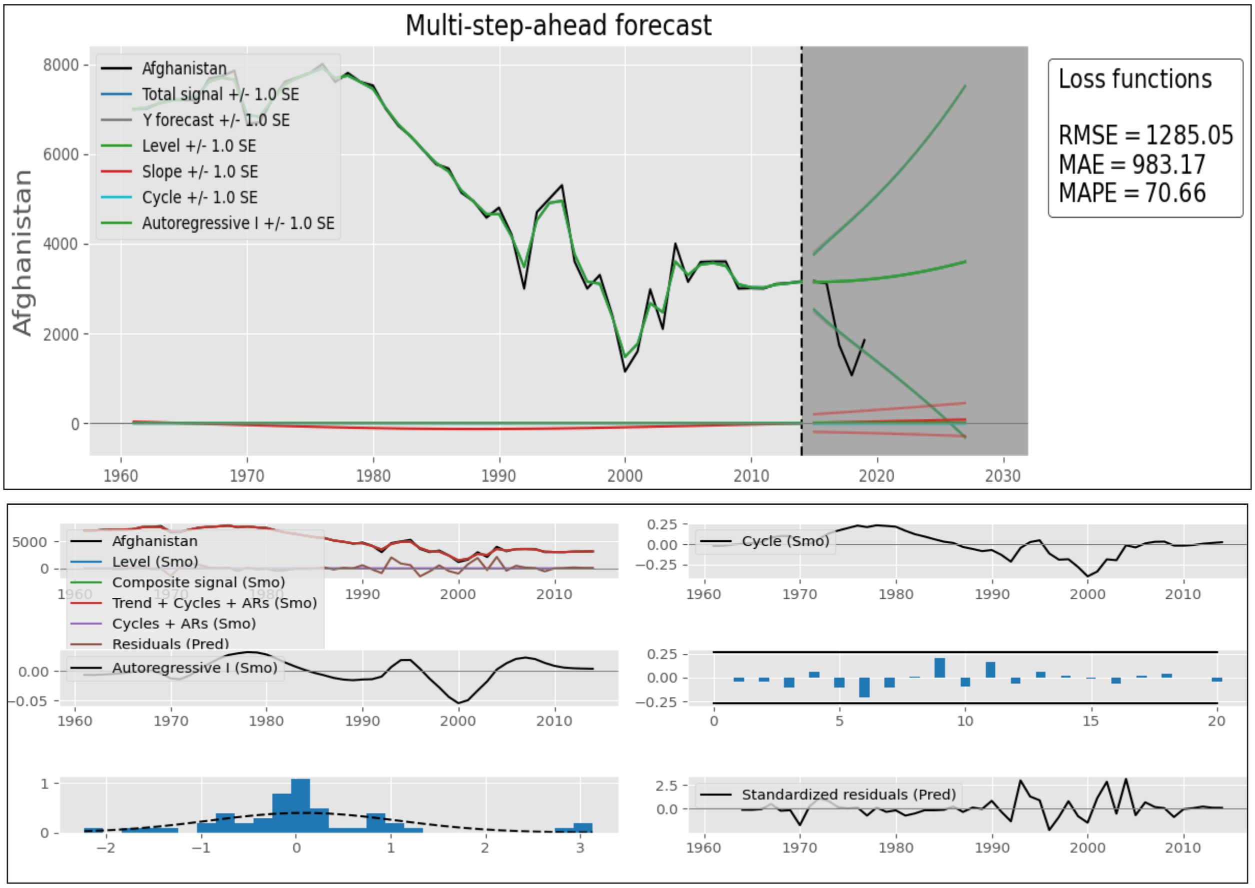
Table 4: RMSE, MAE and MAPE for testing data set (2015 to 2019)

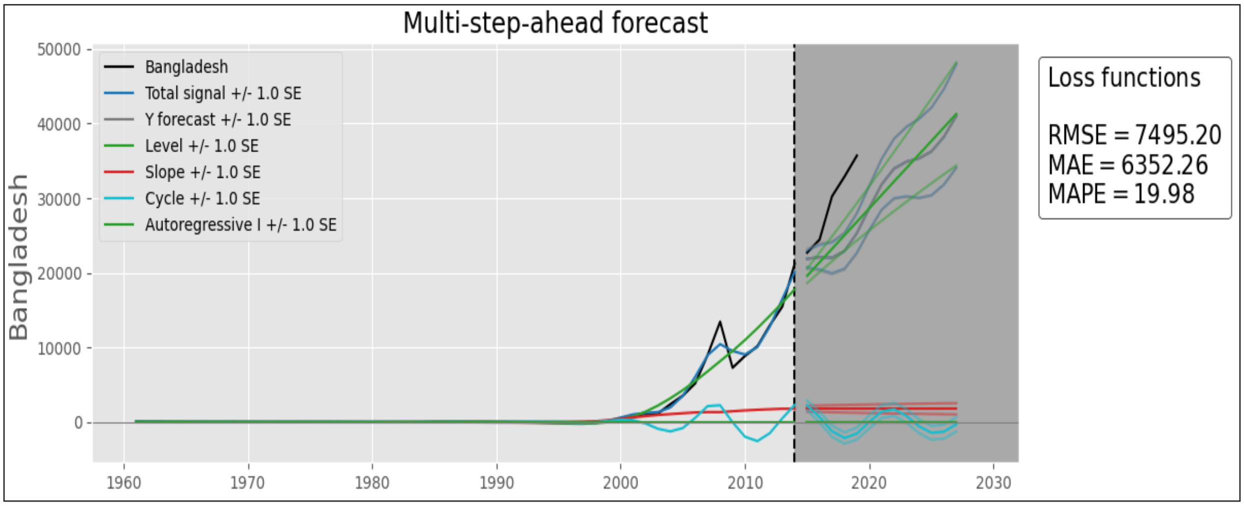
	RMSE	MAE	MAPE
Afghanistan	1285.05	983.17	70.66
Bangladesh	7495.2	6352.26	19.98
Bhutan	187.8	153.8	26.95
China	232671.13	193880.49	7.38
India	18195.29	15044.6	6.04
Nepal	1230.56	1112.64	4.5828
Pakistan	8978.72	7984.05	12.22
Sri Lanka	598.36	534.04	23.39

Table 5: Forecasting from 2020 to 2027 for Maize production using best models

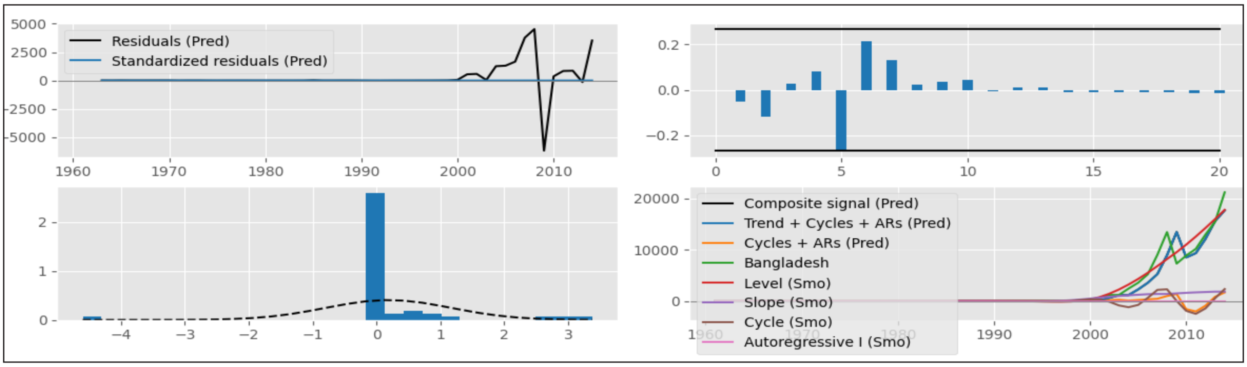
Year	Afghanistan	Bangladesh	Bhutan	China	India	Nepal	Pakistan	Sri Lanka
2020	3221.73	28681	750.504	2635957	307645	25080	62882.1	3539.51
2021	3256.17	31872.2	732.066	2721215	318044	25644.2	62519.5	3648.3
2022	3296.97	33976.2	722.486	2801423	328443	26232.2	66387.6	3919.93
2023	3344.12	34893.8	724.393	2869280	338842	26843.2	69663.3	4044.57
2024	3397.64	35332.6	736.906	2950586	349241	27473.9	69456.6	4301.89
2025	3457.51	36255.9	756.124	3029118	359640	28119.5	72963.8	4439.44
2026	3523.75	38211.9	776.51	3101611	370039	28773.9	76435	4685.1
2027	3596.35	41003.8	792.666	3180958	380438	29430.8	76409.3	4833.18

Fig. 1: Actual and forecast values of Maize production with (Level -Total Signal-Slope-Cycle-Autoregressive- Trend-Residuals) in eight countries during the period 1961-2027 using State Space Models

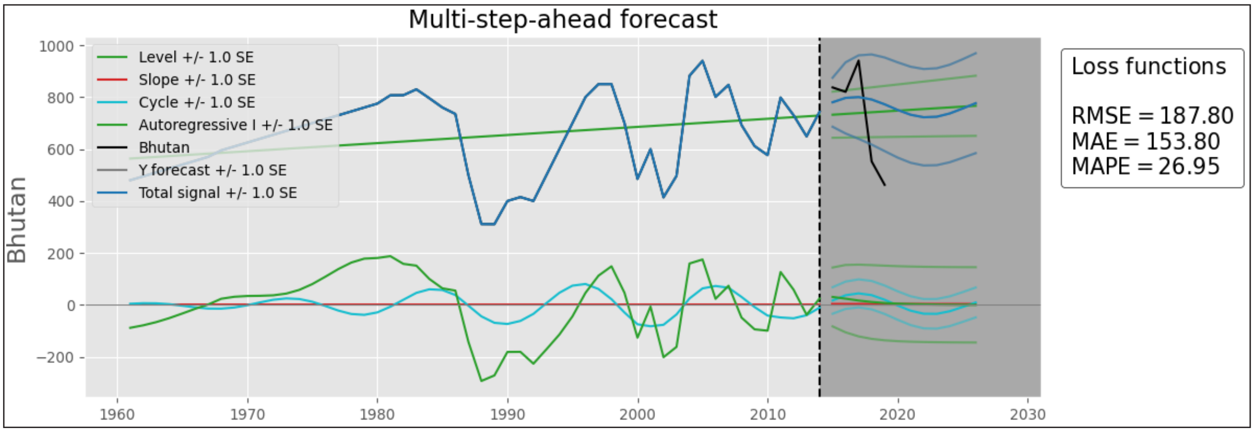




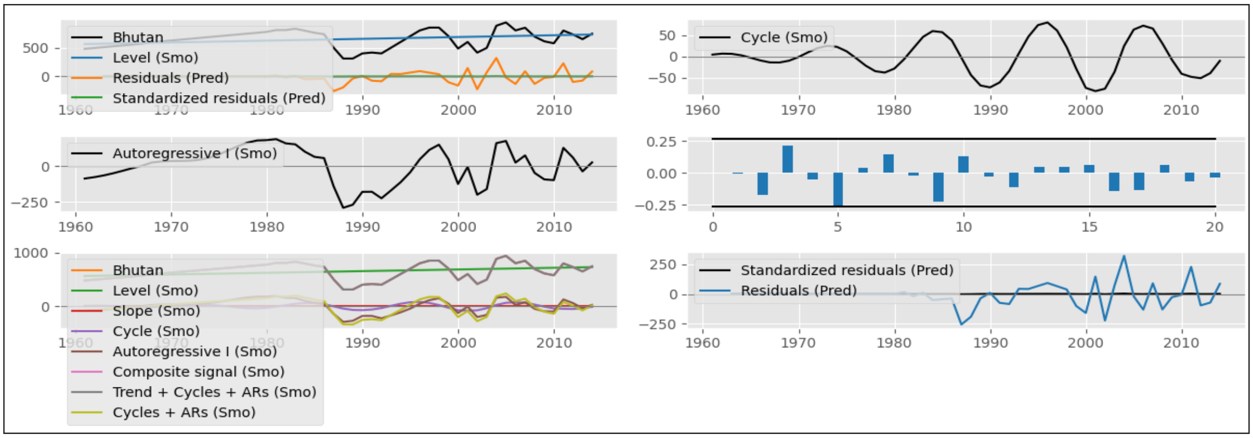
Multi-step-ahead forecast
Bangladesh
Total signal +/- 1.0 SE
Y forecast +/- 1.0 SE
Level +/- 1.0 SE
Slope +/- 1.0 SE
Cycle +/- 1.0 SE
Autoregressive I +/- 1.0 SE
Loss functions
RMSE = 7495.20
MAE = 6352.26
MAPE = 19.98



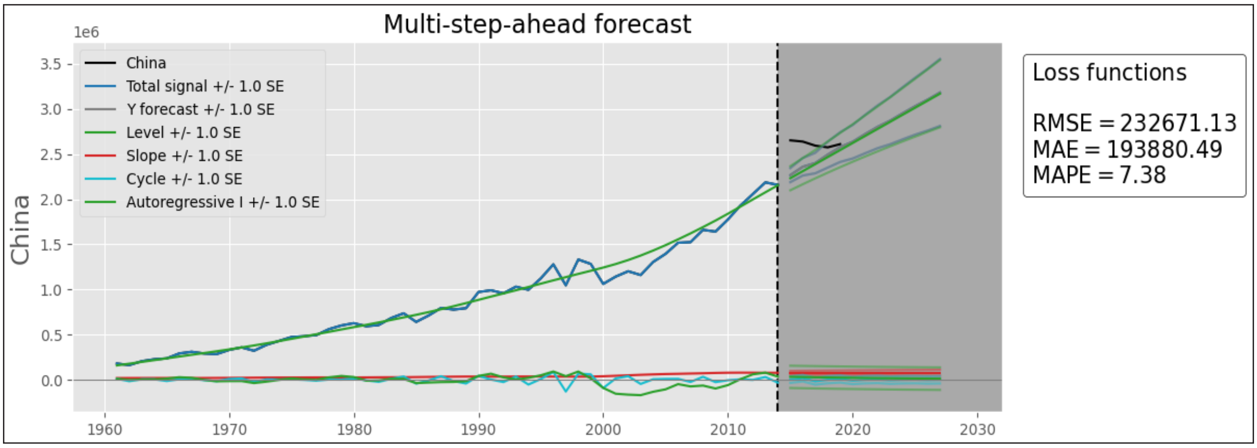
Residuals (Pred)
Standardized residuals (Pred)
Composite signal (Pred)
Trend + Cycles + ARs (Pred)
Cycles + ARs (Pred)
Bangladesh
Level (Smo)
Slope (Smo)
Cycle (Smo)
Autoregressive I (Smo)

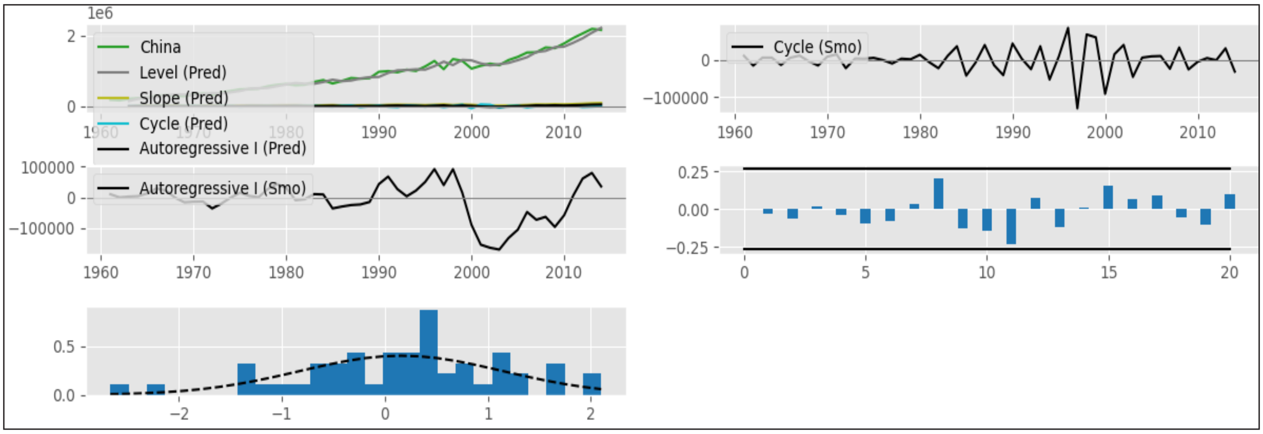


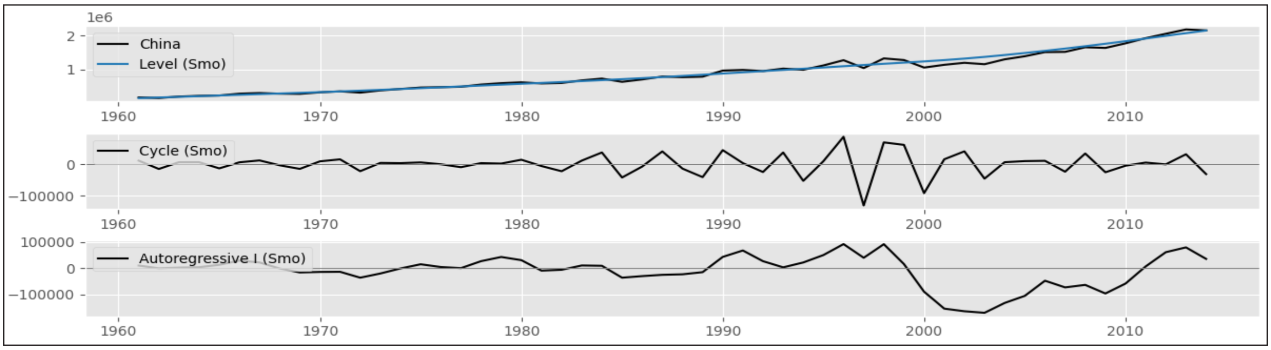
Multi-step-ahead forecast
Bhutan
Level +/- 1.0 SE
Slope +/- 1.0 SE
Cycle +/- 1.0 SE
Autoregressive I +/- 1.0 SE
Bhutan
Y forecast +/- 1.0 SE
Total signal +/- 1.0 SE
Loss functions
RMSE = 187.80
MAE = 153.80
MAPE = 26.95

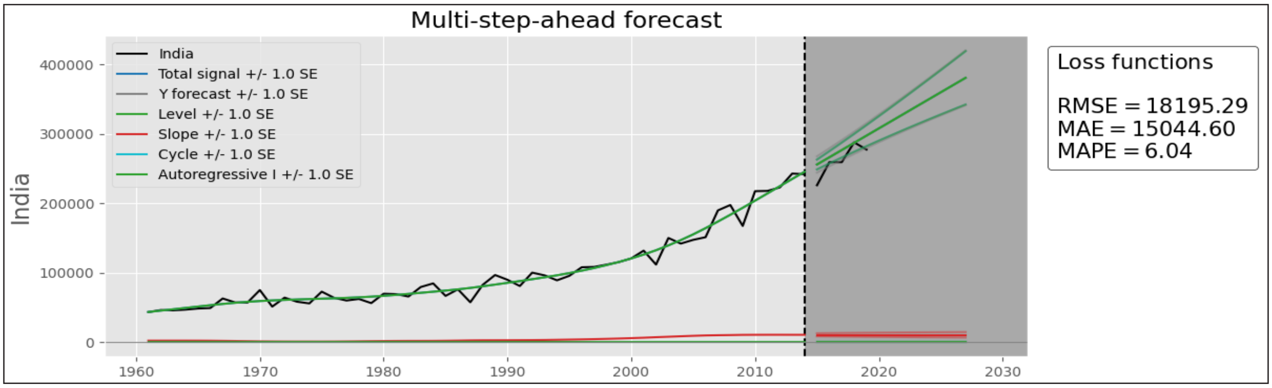


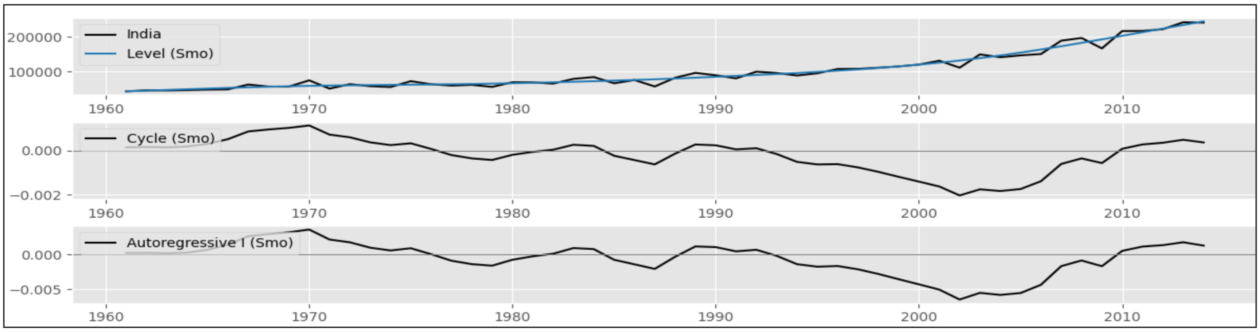
Bhutan
Level (Smo)
Residuals (Pred)
Standardized residuals (Pred)
Cycle (Smo)
Autoregressive I (Smo)
Bhutan
Level (Smo)
Slope (Smo)
Cycle (Smo)
Autoregressive I (Smo)
Composite signal (Smo)
Trend + Cycles + ARs (Smo)
Cycles + ARs (Smo)
Standardized residuals (Pred)
Residuals (Pred)

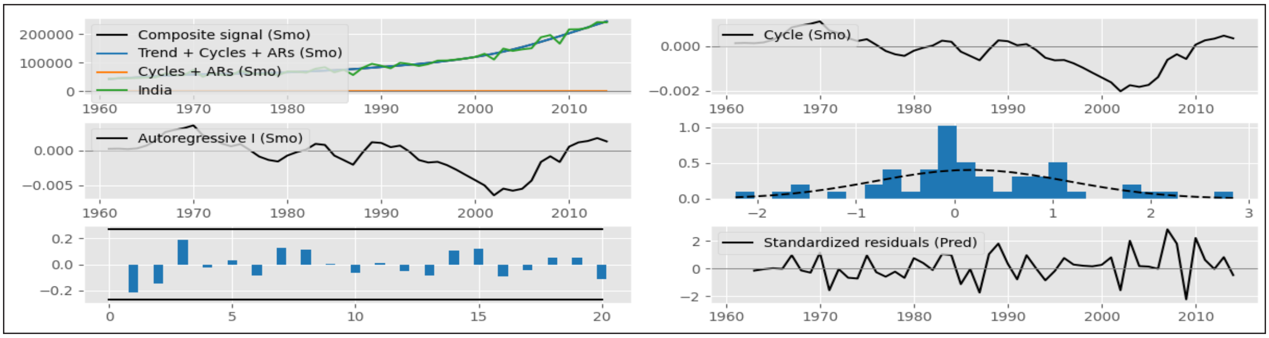

Multi-step-ahead forecast
China
China
Total signal +/- 1.0 SE
Y forecast +/- 1.0 SE
Level +/- 1.0 SE
Slope +/- 1.0 SE
Cycle +/- 1.0 SE
Autoregressive I +/- 1.0 SE
Loss functions
RMSE = 232671.13
MAE = 193880.49
MAPE = 7.38

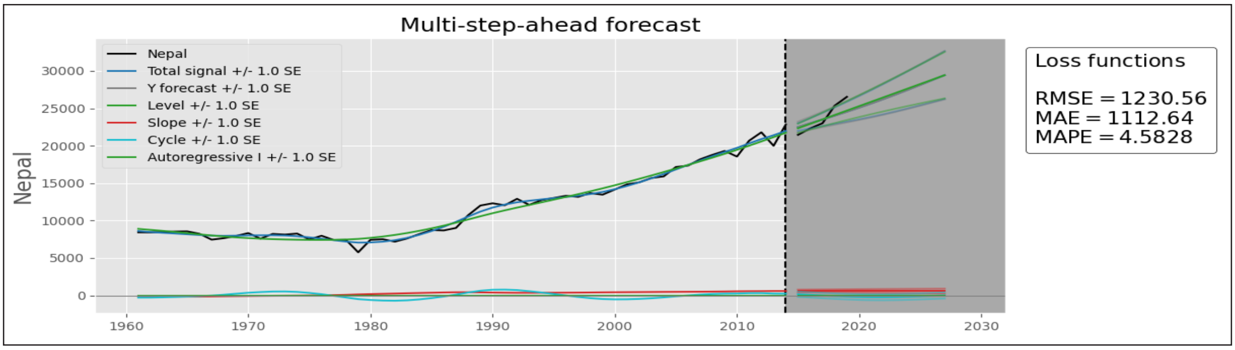

China
Level (Pred)
Slope (Pred)
Cycle (Pred)
Autoregressive I (Pred)
Autoregressive I (Smo)
Cycle (Smo)

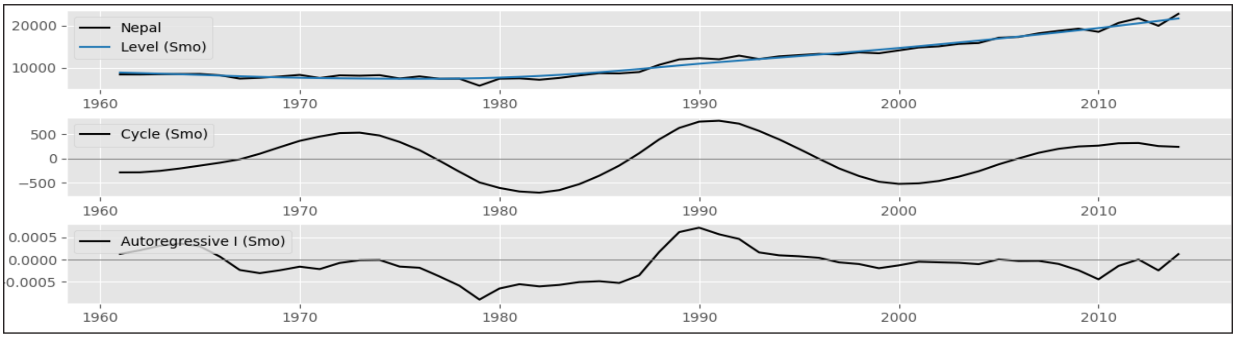

China
Level (Smo)
Cycle (Smo)
Autoregressive I (Smo)

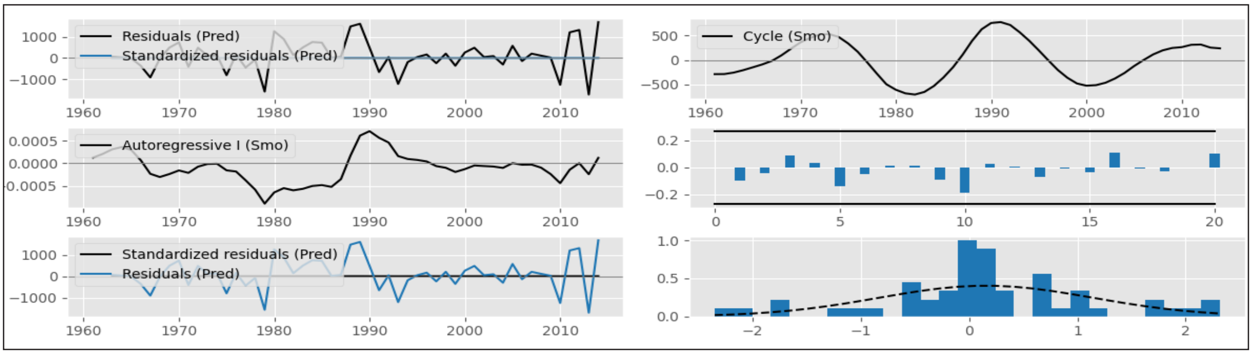

Multi-step-ahead forecast
India
India
Total signal +/- 1.0 SE
Y forecast +/- 1.0 SE
Level +/- 1.0 SE
Slope +/- 1.0 SE
Cycle +/- 1.0 SE
Autoregressive I +/- 1.0 SE
Loss functions
RMSE = 18195.29
MAE = 15044.60
MAPE = 6.04

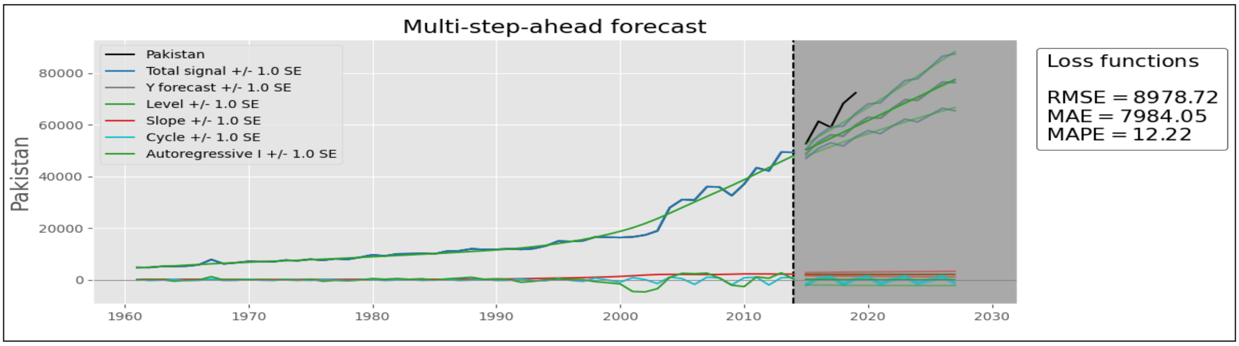

India
Level (Smo)
Cycle (Smo)
Autoregressive I (Smo)

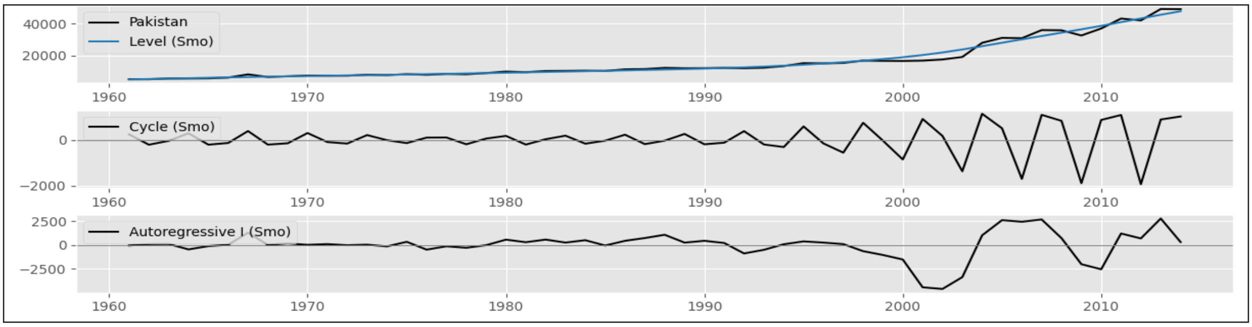

Composite signal (Smo)
Trend + Cycles + ARs (Smo)
Cycles + ARs (Smo)
India
Cycle (Smo)
Autoregressive I (Smo)
Standardized residuals (Pred)

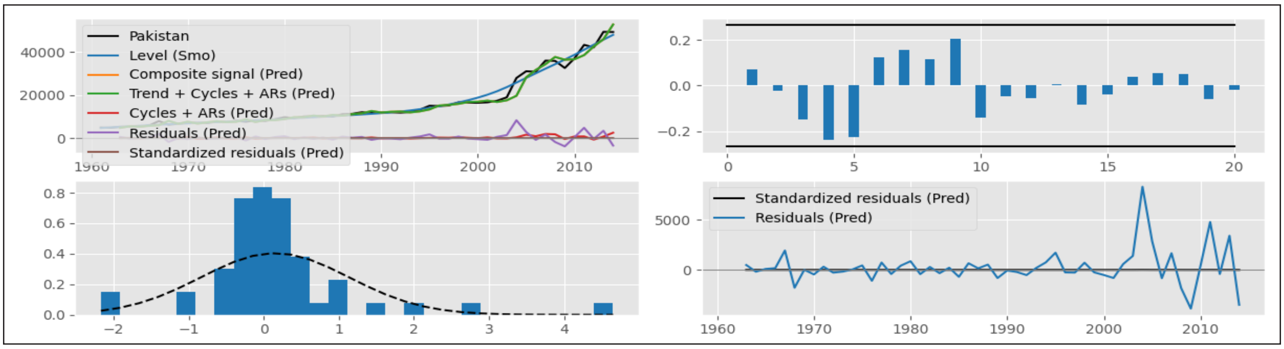

Multi-step-ahead forecast
Nepal
Total signal +/- 1.0 SE
Y forecast +/- 1.0 SE
Level +/- 1.0 SE
Slope +/- 1.0 SE
Cycle +/- 1.0 SE
Autoregressive I +/- 1.0 SE
Loss functions
RMSE = 1230.56
MAE = 1112.64
MAPE = 4.5828

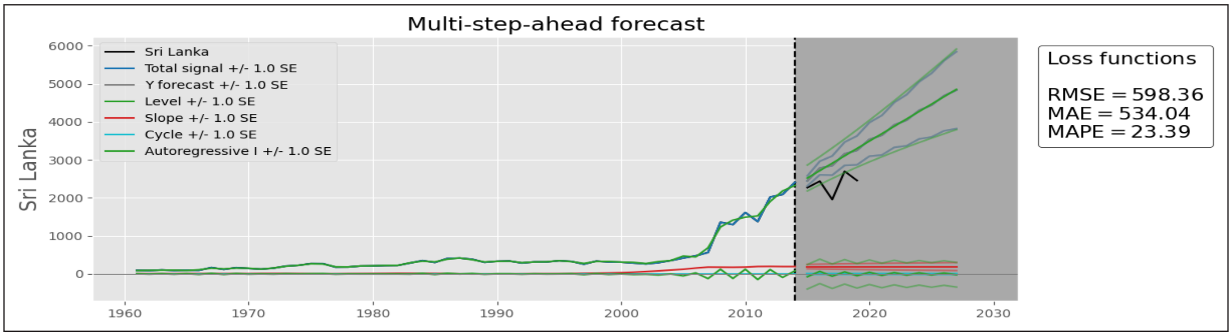

Nepal
Level (Smo)
Cycle (Smo)
Autoregressive I (Smo)

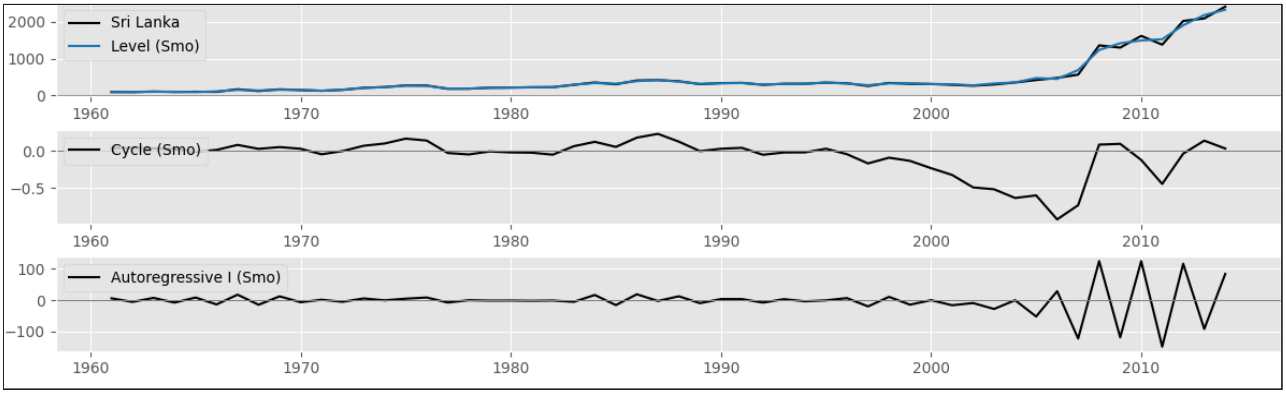

Residuals (Pred)
Standardized residuals (Pred)
Cycle (Smo)
Autoregressive I (Smo)
Standardized residuals (Pred)
Residuals (Pred)


Multi-step-ahead forecast
Pakistan
Total signal +/- 1.0 SE
Y forecast +/- 1.0 SE
Level +/- 1.0 SE
Slope +/- 1.0 SE
Cycle +/- 1.0 SE
Autoregressive I +/- 1.0 SE
Loss functions
RMSE = 8978.72
MAE = 7984.05
MAPE = 12.22


Pakistan
Level (Smo)
Cycle (Smo)
Autoregressive I (Smo)


Pakistan
Level (Smo)
Composite signal (Pred)
Trend + Cycles + ARs (Pred)
Cycles + ARs (Pred)
Residuals (Pred)
Standardized residuals (Pred)


Multi-step-ahead forecast
Sri Lanka
Total signal +/- 1.0 SE
Y forecast +/- 1.0 SE
Level +/- 1.0 SE
Slope +/- 1.0 SE
Cycle +/- 1.0 SE
Autoregressive I +/- 1.0 SE
Loss functions
RMSE = 598.36
MAE = 534.04
MAPE = 23.39


Sri Lanka
Level (Smo)
Cycle (Smo)
Autoregressive I (Smo)

State Space Models are flexible to capture different specifications of complex non-linearity nature of the data series, structural breaks, shifts, time-varying parameters, missing data and stationarity is not required in these models, State Space Models are also suited to dynamic time-series Models that include unobserved components, whilst Stationary is required in the ARIMA Models and it may be necessary to remove the trend, seasonal effects in ARIMA Models using differencing (*Devi et al.* 2021).

The table 5 show us that Maize production in China is expected to reach 3180958 thousand tonnes in 2027. With a growth rate of 20.67% during the period 2020-2027. Maize production in India is expected to reach to 380438.1 thousand tonnes in 2027 with a growth rate of 23.66% during the period 2020-2027. Maize production in Nepal is expected to reach to 29430.82 thousand tonnes in 2027 with a growth rate of 17.34% during the period 2020-2027. Maize production in Pakistan is expected to reach to 76409.31thousand tonnes in 2027 with a growth rate of 21.51% during the period 2020-2027. Maize production in Sri Lanka is expected to reach to 4833.18 thousand tonnes in 2027 with a growth rate of 36.54% during the period 2020-2027. Maize production in Bhutan is expected to reach to 792.6657 thousand tonnes in 2027 with a growth rate of 5.61% during the period 2020-2027. Maize production in Bangladeshis expected to reach to 41003.83 thousand tonnes in 2027 with a growth rate of 42.96% during the period 2020-2027. Maize production in Afghanistan is expected to reach to 3596.347 thousand tonnes in 2027 with a growth rate of 11.62% during the period 2020-2027.

Forecasting

After developing the best models, forecasting is carried out for Maize production in 8 countries (China, India, Nepal, Pakistan, Sri Lanka, Bhutan, Bangladesh, Afghanistan). The residuals of the chosen models were found stationary and white noise for all time series. The predicted values from "2020" to "2027", using best-fitted models are shown in the Figures. The figures showed the predicted values, all forecasted lines in the figures are close to the actual values, which highlight the value of the selected models. From the forecasted figures, it can be seen that Maize production of all countries to be in increasing trend.

CONCLUSION

In this study, state-space models and ARIMA models were fitted to forecast the trend of maize production over the period 1961 to 2027 in eight countries of the region of South-Asia which is Afghanistan, Bangladesh, Bhutan, China, India, Nepal, Pakistan and Sri Lanka. Statistically, the main results show that state-space models outperform the ARIMA models in terms of forecasting accuracy. According to the forecast estimation, the eight countries could expect an increasing trend in production, which could relax policymakers to enhance their strategies and devote themselves to developing the rest of the crops, such as rice and wheat, to achieve the target of food security.

REFERENCES

Ahmad, I., Saeed, U., Fahad, M., Ullah, A., Habib ur Rahman, M., Ahmad, A. and Judge, J. 2018. Yield forecasting of spring maize using remote sensing and crop modeling in Faisalabad-Punjab Pakistan. *J. Indian Soc. Remote Sens.*, **46**(10): 1701-1711.

Akhtar, S. 2016. Malnutrition in south Asia- A critical reappraisal. *Critical Reviews in Food Science and Nutrition,* **56**(14): 2320-2330.

Bishwajit, G., Sarker, S., Kpoghomou, M.A., Gao, H., Jun, L., Yin, D. and Ghosh, S. 2013. Self-sufficiency in rice and food security: a South Asian perspective. *Agric. Food Sec.*, **2**(1): 1-6.

Box, G.E.P., Jenkins, G.M., Reinsel, G.C. and Ljung, G.M. 2015. Time series analysis: Forecasting and control (5th ed). Hoboken, New Jersey: John Wiley & Sons.

Chen, X., Feng, L., Yao, R., Wu, X., Sun, J. and Gong, W. 2021. Prediction of Maize Yield at the City Level in China Using Multi-Source Data. *Remote Sens.*, **13**(1): 145-146.

Choudhury, A.K., Molla, M., Zahan, T., Sen, R., Biswas, J.C., Akhter, S., Ishtiaque, S., Ahmed, F., Maniruzaman, M., Hossain, M.B. and Sarker, P.C. 2021. Optimum Sowing Window and Yield Forecasting for Maize in Northern and Western Bangladesh Using CERES Maize Model. *Agronomy*, **11**(4): 634-635.

Dev, S.M. 2000 Economic liberalisation and employment in South Asia. *Econ. Polit. Weekly*, **35**(1/2): 40-51.

Devarajan, S. and Nabi, I. 2006. Economic growth in South Asia: promising, unequalising, sustainable?. *Econ. Polit. Week*, **41**(33): 3573-3580.

Devi, M., Kumar, J., Malik, D.P. and Mishra, P. 2021. Forecasting of wheat production in Haryana using hybrid time series model, *J. Agric. Food Res.*, 100175.

Devi, M., Mishra, P., Malik, D.P., Mehala, V., Mehta, V.P and Bhardwaj, N. 2019. Study of climatic factors affecting the productivity of cotton and its instability. *Econ. Aff.,* **64**(4): 761–767.

Grote, U., Fasse, A., Nguyen, T.T. and Erenstein, O. 2021. Food security and dynamics of wheat and maize value chains in Africa and Asia. *Front Sustain. Food Syst.*, **4**.

Hellin, J., Krishna, V.V., Erenstein, O. and Boeber, C. 2015. India's poultry revolution: Implications for its sustenance and the global poultry trade. *Int. Food Agribus. Manag. Rev.*, **18**: 151-164.

Iqra, S., Kadir, K., Makarovskikh, T., Abotaleb, M., Syed Aflake Hussain Gardazi and Mishra, P. 2021. Machine Learning-based Covid-19 Forecasting: Impact on Pakistan Stock Exchange. *Int. J. Agric. Stat. Sci.*, **17**(1): 53-61.

Kalman, R.E. 1960. A new approach to linear filtering and prediction problems. *J. Basic Engineer* (Trans. ASME, ser. D), **82**(3): 35–45.

Lee, S.K., Song, J.H., Baek, S.B. and Kwon, Y.U. 2015. Status of maize production and distribution in South East Asia. *Korean J. Crop Sci.*, **60**(3): 318-332.

Matsuura, K., Gaitan, C.F., Hsieh, W. and Cannon, A. 2014. Maize yield forecasting by linear regression and artificial neural networks in Jilin, China. *J. Agric. Sci.*,

Mishra, P., Abotaleb M., Karakaya, K., Mostafa, A., Yonar, H., Blbas, H.T.A., Rahman, U.H. and Das, S.S. 2022. State of the Art in COVID-19 in the SAARC Counties and Chinausing BATS, TBATS, Holt's Linear and ARIMA Model. *J. Agric. Biol. Appl. Stat.*, **1**(1): 1-24.

Mishra, P., Matuka, A., Abotaleb, M.S.A., Weerasinghe, W.P.M.C.N., Karakaya, K. and Das, S.S. 2022. Modeling and forecasting of milk production in the SAARC countries and China. *Model Earth Syst. Environ.*, **8**(1): 947-959.

Mishra, P., Yonar, A., Yonar, H., Kumari, B., Abotaleb, M., Das, S.S. and Patil, S.G. 2021. State of the art in total pulse production in major states of India using ARIMA techniques, *Curr. Res. Food Sci.*, **4**: 800-806.

Pandey, E., Supriya, Mishra, P., Mehta, V., Karakaya, K. and Abotaleb, M. 2021. Growth Rate of Pulses in Eastern Uttar Pradesh a Zone-wise Analysis. *Econ. Aff.*, **66**(3): 377-382.

Pasuquin, J.M., Pampolino, M.F., Witt, C., Dobermann, A., Oberthür, T., Fisher, M.J. and Inubushi, K. 2014. Closing yield gaps in maize production in Southeast Asia through site-specific nutrient management. *Field Crops Res.*, **156**(1): 219-230.

Prasanna, B.M. 2011 Maize in the developing world: Trends, challenges and opportunities. Presented at 11th Asian Maize Conference Nanning, China, pp. 26-38.

Sahu, P.K. and Mishra, P. 2014. Instability in production scenario of maize in India and forecasting using ARIMA model. *Int. J. Agric. Stat. Sci.*, **10**(2): 425-435.

Sharma, P.K. 2018. Forecasting maize production in India using ARIMA model. *Agro Economist*, **5**(1): 1-6.

Shiferaw, B., Prasanna, B.M., Hellin, J. and Banziger, M. 2011. Crops that feed the world: past successes and future challenges to the role played by maize in global food security. *Food Sec.*, **3**(1): 307-327.

Tahir, A. and Habib, N. 2013. Forecasting of maize area and production in Pakistan. *Crop Prod.*, **2**(2): 11-18.

Tesfaye, K., Zaidi, P.H., Gbegbelegbe, S., Boeber, C., Rahut, D.B., Getaneh, F., Seetharam, K., Erenstein, O. and Stirling, C. 2017. Climate change impacts and potential benefits of heat-tolerant maize in South Asia. *Theoretical and Appl. Climatology*, **130**(3): 959-970.

Tiwari, Y.K. and Yadav, S.K. 2019. High temperature stress tolerance in maize (*Zea mays* L.): physiological and molecular mechanisms. *J. Plant Biol.*, **62**(2): 93-102.

Verma, S. 2018. Modelling and forecasting maize yield of India using ARIMA and state space models. *J. Pharmacognosy and Phytochemistry*, **7**(5): 1695-1700.

Wali, N., Agho, K. and Renzaho, A.M.N. 2019. Past drivers of and priorities for child undernutrition in South Asia: A mixed methods systematic review protocol. *Systematic Rev.*, **8**(189).

Xiong, W., Matthews, R., Holman, I., Lin, E., and Xu, Y. 2007. Modelling China's potential maize production at regional scale under climate change. *Climatic Change*, **85**(3): 433-451.

Yadav, S., Kadi, A., Ray, S., Rawat, D., Biswas, T., Singh, P.K. and Abotaleb, M. 2022. Modeling and Forecasting of Producer Price Index (PPI) of Cheese Manufacturing Industries. *J. Agric. Biol. Appl. Stat.*, **1**(1): 39-49.

Zhai, F. and Zhuang, J. 2009. Agricultural impact of climate change: A general equilibrium analysis with special reference to South East Asia. ADBI working paper 13. Tokyo.