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ANALYZING THE BOX JENKINS METHODOLOGY: PREDICTING APPLE PRODUCTION IN PAKISTAN

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ABSTRACT

Utilizing the ARIMA model, this investigation explores the growth patterns of apple farming regions and outputs in Pakistan between 1959-60 to 2019-20. Moreover, it predicts future trends from 2021 to 2030. This study aims to provide an all-encompassing evaluation and future projection, particularly regarding apple farming as a significant contributor in the horticultural sector of Pakistan's economy. The purpose is to assist decision-makers by offering insightful guidance based on this pivotal role of agriculture. The study utilized time series data obtained from the Federal Bureau of Statistics and employed EViews software for analysis. Through this, they determined that the most effective model to use for forecasting was ARIMA (1,1,0). According to the findings, apple cultivation and production are projected to consistently expand in Pakistan over the next decade. This indicates a promising future for the country's apple farming industry. According to forecasts, the apple farming area will increase from 200.66 thousand hectares in 2021 to 247.02 thousand hectares by 2030 along with an estimated rise in production output from its current level of 6094.29 thousand tonnes to approximately 693 .98thousand tons during this period. The importance of accurate forecasting in agricultural planning is highlighted in this paper, along with the need to overcome sectoral obstacles and capitalize on growth prospects. By adding new insights to the field of agricultural prediction, this research highlights a promising future for apple farming in Pakistan.

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INTRODUCTION

Agricultural sector in Pakistan remains critical to the economy, providing vital food security for a rapidly growing population (Davies et al., 2024). However, recent years have been marked by significant fluctuations in GDP and per capita income (Haider et al., 2024). After peaking at 5.53% in 2018, GDP fell sharply to -0.47% in 2020 while per capita income followed suit with its own decline from previous highs of +2.87%. Despite these challenges, agricultural businesses remain important contributors accounting for over one-fifth (22%) of Pakistan’s overall economic activity as well as employing almost two-thirds (40%) of people working across different sectors nationwide; With growth rate hovering around an average annual increase roughly about four percent (4%), up significantly compared against last year which saw only marginal increases near 3.48% (Papanek, 2024).

The horticulture sector is a crucial part of Pakistan's agricultural industry and plays a significant role in satisfying both local demand for fruits and vegetables, as well as creating positive contributions to the nation's foreign exchange reserves through commodity exports (Chandio et al., 2024). Thanks to its diverse agroecological zones, Pakistan can readily cultivate various temperate, sub-tropical and Mediterranean crops that are ideally suited to their climatic needs (Kingra and Kukal, 2024). Currently producing 6963.57 thousand tonnes across 746.62 thousand hectares with an average yield of around 9.32 tonnes per hectare; this dynamic sector also generates more than twelve million tons annually by exporting high-value products: peaches, apples, dates cherries grapes citrus (kinnow), along other fruits like loquat pears plums guava - all presenting considerable export potential for Pakistani farmers who specialize in these types of produce (Maqbool et al., 2021).

Apples (Malus domestica) occupy a significant position among fruits in Pakistan, trailing behind only other noteworthy stone fruit varieties (Delaplane, 2021). These members of the Rosaceae family are recognized for their wide-ranging qualities—sweetness, juiciness, and fleshiness that come with an alluring flavor and aroma. Apples have earned global renown because of their crisp texture plus the range they offer: from sweetness to tart flavors. They rank as dietary staples due to abundant vitamin C—an excellent natural antioxidant regulating immune function along with wound healing properties—and fiber content promoting regulation around weight management besides helping digestive health while cholesterol reduction forms another key benefit (Basuray et al., 2024). Furthermore, apples provide essential nutrients like potassium complimenting heart health needs alongside various B vitamins aiding metabolic well-being by supporting energy production without high calorie-impact on consumed diets thanks largely in part through its mostly water-based composition supplemented with carbohydrates dietary Fiber multivitamins minerals making it perfect low-calorie nutritional supplement choice available so widely loved everywhere (Ballantyne, 2024).

Apple cultivation in Pakistan encounters numerous obstacles, such as disease outbreaks, low productivity rates, challenging marketing conditions and high input expenses (Garwi et al., 2024). Energy shortages also pose difficulties along with insufficient cold storage facilities and financial constraints - all of which lead to a decrease in cultivated land. Despite the various benefits it brings forth; strategic measures must be put into place if we are to overcome these challenges successfully because apple growth has proven crucial for both domestic consumption as well as exporting purposes (Khan et al., 2024). Accurately predicting agricultural production trends, specifically in the apple industry, is crucial for prospective decision-making among policymakers, researchers and producers (Siegle et al. 2024). Techniques like utilizing Box-Jenkins methodology and ARIMA models allow extrapolation of future behaviors through past data analysis that enables early planning efforts including policy creation or implementation strategies (Vianna, Gonçalves, and Souza 2024). By leveraging these predictive methodologies to optimize resource allocation while mitigating risks stakeholders can enhance productivity levels driving sustainable development in agriculture with concurrent economic benefits (Vărzaru, 2024).

METHODOLOGY

Data

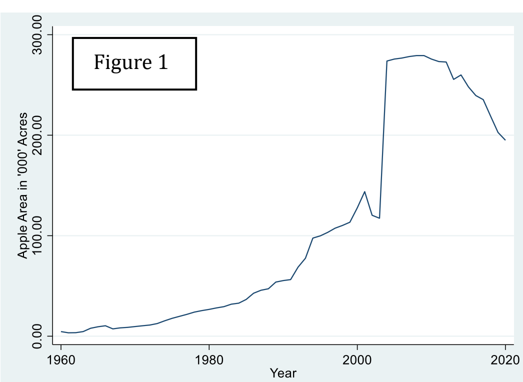
This study utilized time series data from two distinct sets, encompassing the area and production of apple from 1959- 60 to 2019-20. These datasets were sourced from the Pakistan Bureau of Statistics. The analysis and processing of the data were conducted using EViews, version 9, leading to the generation of forecasts covering the decade from 2021 to 2030. For model construction and forecasting the annual figures for apple cultivation area and production, the study applied the ARIMA model. Originally introduced by Box and Jenkin in 1976, the ARIMA model stands as a comprehensive framework for predicting time series data. This model's regression equations are formulated as follows:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \dots\dots\dots\dots.. + \rho_p \varepsilon_{t-p} + \varepsilon_t - \rho_1 \varepsilon_{t-1} - \rho_2 \varepsilon_{t-2} - \dots\dots\dots\dots.. - \rho_q \varepsilon_{t-q}$$

RESULTS AND DISCUSSION

Table 1 presents the study descriptive statistics in detail. Results show that the average crop area is 104.10 thousand hectares with a median of 55.35 thousand hectares, varying widely as indicated by the standard deviation of 102.20. The skewness and kurtosis values suggest that the area's distribution is slightly skewed towards larger sizes and flatter than a normal curve, with the Jarque-Bera test confirming a deviation from normality (Prob = 0.016). Production averages 272.53 thousand tonnes and also exhibits a broad range, though with a more symmetrical distribution and less peakiness, with a mild deviation from normality noted by the Jarque-Bera test (Prob = 0.053).

Identification of ARIMA Model: Estimation diagnostic checking, and forecasting. The first step is to determine the stationarity and normality of the data (Ahmar et al., 2023). Tables 2 to 5, display the dataset's partial autocorrelation function (PACF) and autocorrelation function (ACF) charts (Alkhayyat et al., 2023). Table 2's correlogram indicates strong positive autocorrelation for the apple cultivation area with initial AC at 0.958 for lag 1, persisting across all 15 lags (Bjørnland et al., 2024). This suggests the need for differencing to achieve stationarity for ARIMA modelling, as shown by high Q-Statistics and zero p-values confirming significant autocorrelation (Wabomba, Mutwiri, and Fredrick 2016). Identifying the appropriate AR and MA terms for the ARIMA model is guided by the ACF and PACF plots (Aljandali et al. 2018). Forecasting involves ensuring the model's residuals are normally distributed with mean zero and constant variance over time (Mills 2019; Hansen et al., 2022). Table 3 displays a correlogram of the first-differenced area under apple cultivation with low autocorrelation (AC) starting at 0.106 at lag 1 and oscillating around zero thereafter (Amin et al., 2024). Partial autocorrelation (PAC) similarly fluctuates within a narrow range from -0.158 to 0.128. The Ljung-Box Q-Statistics are not significant, with all probabilities (Prob) above 0.05, indicating no substantial autocorrelation at all considered lags (Chandra, 2023). These findings suggest that the first-differenced time series is essentially random, indicating that initial trends in the original data have been effectively removed by differencing (Rupassara et al., 2023). Table 4. correlogram for apple production shows high autocorrelation at lag 1 (AC = 0.930) that decreases with distance but remains significantly positive, suggesting persistent autocorrelation (Sawadogo et al., 2023). The PAC starts at 0.930 and fluctuates, implying a need for an autoregressive model term. High Q-Statistics (starting at 55.398 and rising to 366.83) with p-values of 0.000 across all lags indicate strong non-random autocorrelation. These findings suggest an ARIMA model with differencing may be needed to address non-stationarity (Ajobo et al., 2024). However, Table 5. showcases the correlogram for first-differenced apple production with significant autocorrelation at lag 1 (AC = -0.532, PAC = -0.532) and alternating AC and PAC values across the subsequent lags. The Q-Statistics are high for all lags with corresponding probabilities at or near zero, signifying strong autocorrelation. This pattern, especially the negative autocorrelation at lag 1, suggests the need for both autoregressive and moving average terms in an ARIMA model to capture the observed fluctuations in apple production (Amin et al., 2024). Table 3. shows no significant autocorrelation in the first-differenced area for apple cultivation, as indicated by Ljung-Box Q-Statistic probabilities above 0.05. This suggests that the series may be random and not require complex ARIMA modelling. On the other hand, Table 5. reveals significant autocorrelation in the first-differenced apple production data, particularly at lag 1, with strong negative values for both AC and PAC. The low probabilities for the Q-Statistics suggest a need for an ARIMA model incorporating both autoregressive and moving average terms (Agyare, Odoi, and Wiah 2024). Table 3. points to a potentially simpler modelling approach, while Table 5. indicates the necessity for a more detailed ARIMA model.



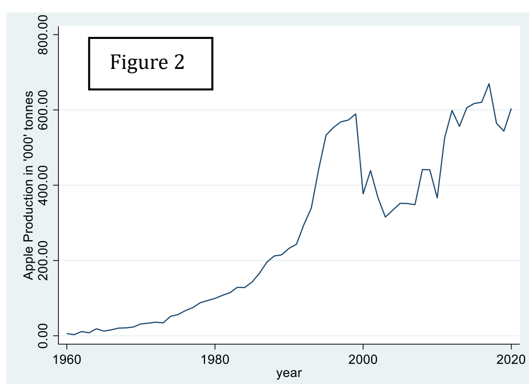


Figure 1 depicts a steady increase in apple farming area from 1960 until a peak in the early 2000s, followed by a sharp decline and subsequent stabilization at a lower level. Figure 2 shows a general upward trend in apple production over the same period, with notable increases correlating with the peak area of cultivation, followed by fluctuations but not as pronounced a decline as seen in the cultivation area, suggesting improved yields or efficiency in production.

Stationarity Test

Table 6 illustrates the ADF test results, where the area is non-stationary at level (ADF: -1.687, p-value: 0.433) but becomes stationary after first differencing (ADF p-value: 0.000). Production is non-stationary at level per ADF (-2.241, p-value: 0.194) but is stationary according to PP (-4.179, p-value: 0.002). Both variables achieve stationarity at first differencing (ADF: -3.774, p-value: 0.005; PP:-12.481, p-value: 0.000). A second differencing confirms stationarity (ADF: -8.724; PP: -46.144, p-values: 0.000).

ARIMA modelling requires only the first difference for both, despite discrepancies in production's initial stationarity assessment.

Table 1. Presents descriptive statistics of Pakistan's apple output and area between 1959–1960 To 2019–20.

Parameter	Mean	Median	Max	Min	SD	Skew	Kurtosis	JB	Prob
Area(A)	104.10	55.350	279.23	3.40	102.20	0.705	1.882	8.216	0.016
Produce (P)	272.53	232.40	669.91	3.00	221.09	0.289	1.594	5.874	0.053

Table 2. Correlogram @ level for area under apple.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.958	0.958	58.829	0.000
		2	0.906	-0.152	112.30	0.000
		3	0.853	-0.020	160.52	0.000
		4	0.805	0.033	204.21	0.000
		5	0.766	0.076	244.51	0.000
		6	0.729	-0.037	281.61	0.000
		7	0.689	-0.043	315.43	0.000
		8	0.640	-0.127	345.17	0.000
		9	0.592	0.008	371.03	0.000
		10	0.542	-0.041	393.17	0.000
		11	0.491	-0.070	411.68	0.000
		12	0.438	-0.068	426.70	0.000
		13	0.383	-0.048	438.44	0.000
		14	0.330	-0.019	447.34	0.000
		15	0.280	-0.002	453.87	0.000

Table 3. Correlogram @ 1st difference for area under apple

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.106	0.106	0.7078	0.400
		2	-0.145	-0.158	2.0591	0.357
		3	-0.164	-0.134	3.8161	0.282
		4	-0.002	0.008	3.8165	0.431
		5	0.020	-0.024	3.8440	0.572
		6	0.101	0.084	4.5428	0.604
		7	-0.011	-0.030	4.5509	0.715
		8	-0.012	0.017	4.5615	0.803
		9	-0.038	-0.019	4.6643	0.863
		10	0.121	0.128	5.7476	0.836
		11	0.061	0.032	6.0265	0.872
		12	0.065	0.080	6.3563	0.897
		13	-0.062	-0.029	6.6650	0.919
		14	-0.068	-0.033	7.0383	0.933
		15	-0.010	0.015	7.0463	0.956

Table 4. Correlogram @ level for apple production.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.930	0.930	55.398	0.000
		2	0.859	-0.045	103.44	0.000
		3	0.806	0.100	146.51	0.000
		4	0.746	-0.093	184.00	0.000
		5	0.701	0.107	217.75	0.000
		6	0.644	-0.151	246.70	0.000
		7	0.591	0.051	271.53	0.000
		8	0.543	-0.052	292.87	0.000
		9	0.490	-0.017	310.60	0.000
		10	0.442	-0.028	325.34	0.000
		11	0.402	0.041	337.75	0.000
		12	0.362	-0.034	348.01	0.000
		13	0.317	-0.055	356.06	0.000
		14	0.273	-0.023	362.15	0.000
		15	0.237	0.023	366.83	0.000

Table 5. Correlogram @ 1st difference for apple production

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.532	-0.532	17.854	0.000
		2	0.392	0.151	27.689	0.000
		3	-0.188	0.099	30.001	0.000
		4	0.146	0.049	31.420	0.000
		5	-0.008	0.107	31.425	0.000
		6	-0.017	-0.013	31.445	0.000
		7	0.013	-0.052	31.457	0.000
		8	0.059	0.090	31.708	0.000
		9	-0.101	-0.068	32.450	0.000
		10	0.096	-0.018	33.136	0.000
		11	-0.097	-0.012	33.849	0.000
		12	0.135	0.079	35.259	0.000
		13	-0.045	0.101	35.422	0.001
		14	0.034	0.019	35.515	0.001
		15	-0.017	-0.035	35.538	0.002

Table 6. Stationary test for apple area and production.

Parameter		ADF	P-Value	PP	P-Value	Remarks
Area	Level	-1.687	0.433	-1.923	0.320	
	1st Diff.	-7.088*	0.000	-7.086*	0.000	*I(0)*
Production	Level	-2.241	0.194	-4.179*	0.002	
	1st Diff.	-3.774*	0.005	-12.481*	0.000	
	2nd Diff.	-8.724*	0.000	-46.144*	0.000	*I(0)*

Source: Authors own calculation. Note: Significance at the 5% level is indicated by an asterisk (*).

Table 7. ARIMA models fitted for Apple area and production, and matching criterion for selection

Criteria	Model	ARIMA	AIC	BIC	HQ	Log Likelihood	$Sigma^2$
Area	*A*	*(1,1,1)*	*-0.721*	*-0.582*	*-0.667*	*25.645*	*0.025*
	B	(1,1,0)	-0.747	-0.643	-0.706	25.422	0.025
	C	(0,1,1)	-0.752	-0.647	-0.711	25.560	0.025
Production	A	(1,1,1)	-0.171	-0.032	-0.117	9.144	0.042
	B	(1,1,0)	-0.109	-0.004	-0.068	6.257	0.047
	C	(0,1,1)	0.066	0.171	0.107	1.017	0.056
	D	*(2,1,1)*	*-0.258*	*-0.118*	*-0.203*	*11.743*	*0.039*

Source: Authors own calculation

For both model estimation and analytical assessment, various versions were tested for the area and production of apple, utilizing different p and q values in the ARIMA framework. The ARIMA (1,1,0) model emerged as the optimal choice for both parameters, selected on the grounds of the lowest Akaike Information Criterion (AIC), Schwarz Bayesian Information Criterion (BIC), and Hannan-Quinn Information Criterion (HQ) scores, as detailed in Table 7.

There have been many efforts to predict the area and production of various commodities across different nations. Despite this, there remains a gap in the existing literature. To our knowledge, there has not yet been a forecast of apple area and production utilizing the ARIMA model by any researchers (Chaudhary et al., 2021). In a related study, (Ullah, Khan, and Zheng 2018) projected the production of mangoes in Pakistan for the years 1982 to 2004. The findings of their research indicated that the ARIMA (1,1,1) model provided the most accurate forecasts. (Naz 2012) determined that, out of five projected models for the area used for mango production in Pakistan between 1961 and 2009, the ARIMA (0,1,0) model was the best option. Additionally, they evaluated the ARIMA (1,1,0) model, aligning with our study's optimal ARIMA model findings. However, their selection favored the ARIMA (0,1,0) model, chosen for its lower Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Criterion (HQ) values. Likewise, (Ahmad et al., 2005) used the ARIMA model to predict Pakistan's kinnow production for the period spanning 1990–1991 to 2001–2002. They selected the ARIMA (3,1,2) model as the most appropriate for their analysis. Similarly, Rahman et al (2016) investigated Bangladesh's black gram pulse production region and output, covering years from 1967-68 to 2013-14, and determined that the ARIMA (0,1,0) model was the best fit for their data series. (Pirzado et al., 2021) roughly two models, ARIMA (1,1,1) and ARIMA (2,1,2) for wheat production and for the wheat area, specifically in Pakistan. Additionally, (Biswas et al. 2014) conducted an analysis on wheat yield, production, and area in Punjab through forecasting techniques, identifying ARIMA (0,1,1) for yield and production and ARIMA (0,1,0) for area as the most effective models in their study. After the ARIMA (1,1,0) model was found to be the most accurate predictor of apple area and production, our study advances to examine the diagnostic checks of the model's residuals.

Residual Diagnostics

Descriptive statistics and line graph of the standardised residuals for the estimated models' normality test are shown in Figures 3 and 4. At the 5% level of significance, this test finds that there is no autocorrelation among the residuals of the fitted ARIMA (1,1,0) models for apple production or area. Additionally, the "portmanteau test" is often linked to George E. P. Box and David A. Pierce, who introduced it in a 1970 paper, marking a key development in statistical model validation. (Table 8) Portmanteau tests in statistics are designed to evaluate the adequacy of a model by detecting a range of potential deviations from the null hypothesis, without specifying a particular alternative hypothesis. These tests are valuable for identifying whether a model may be missing key aspects of the data's structure, prompting further investigation.

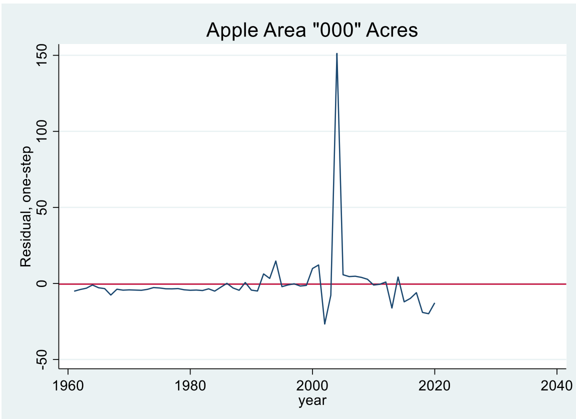


Figure 3.

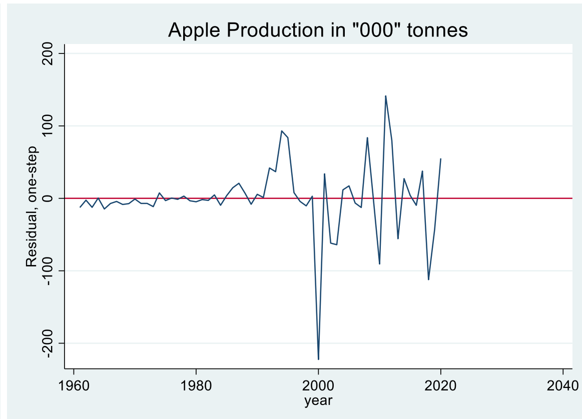


Figure 4.

Diagnostics for white noise

White noise, characterized by a constant power spectral density across all frequencies, is pivotal in diagnostics for system identification and noise-cancelling techniques. By analyzing a system's response to white noise, researchers can elucidate its characteristics, enhancing diagnostic tools and signal processing by improving signal-to-noise ratios (SNR). This methodology underscores the utility of white noise in facilitating precise measurements and analysis across various domains (Quqa et al., 2021).

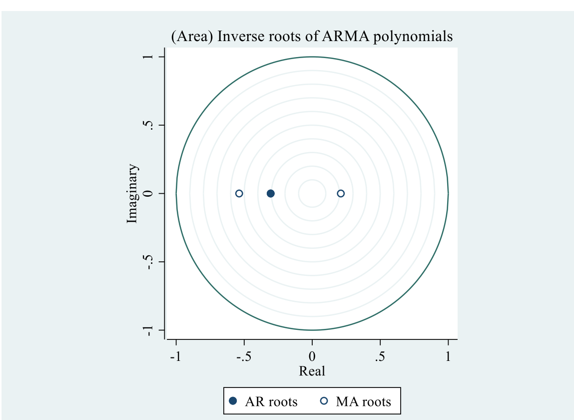


Figure 5.

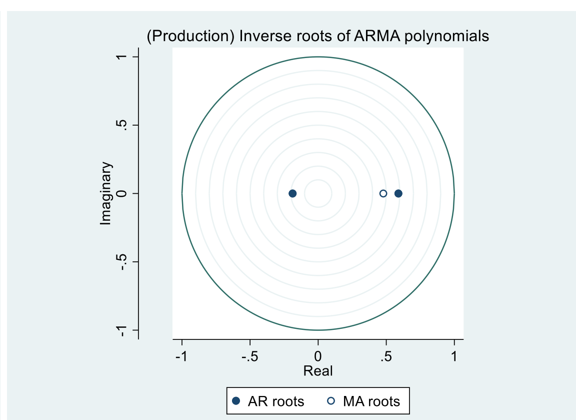


Figure 6.

Figure 5. All the eigenvalues lie inside the unit circle. The AR parameters satisfy stability condition in area. Figure 6. All the eigenvalues lie inside the unit circle. The MA parameters satisfy invertibility conditions in production (Ali et al. 2020). Table 8. presents results from a diagnostic test for white noise in two parameters, with Area showing an average change of -0.45, a high standard deviation, and a P-value of 0.99 against a Chi-squared distribution with 28 degrees of freedom, while Production exhibits an average change of 0.03, a high standard deviation, and a P-value of 0.54, both of which suggest no evidence of systematic patterns or trends in

the dataset for either parameter, indicating that the variations are random and do not provide predictive information. Portmanteau test confirms that the residuals have white noise.

Table 8. Portmanteau test for diagnose white noise.

Parameter	Mean	S.D	Min	Max	Portmanteau (Q)	P> $Chi^2(28)$
Area	-0.45	21.08	-26.68	151.24	7.72	0.99
Production	0.03	49.50	-222.41	141.39	26.68	0.54

Source: Authors own calculation

Projected Area and Production for Apple Using ARIMA Model

Table 10 presents the projections and estimates for Pakistan's apple production and area based on ARIMA (1,1,0) for the next ten years. The area and production of apples are expected to expand year over year, from 200.66 thousand hectares in 2021 to 247.02 thousand hectares in 2030, according to forecasted statistics. Similarly, apple production is forecasted to rise from 604.29 thousand tonnes in 2021 to 693.98 thousand tonnes in 2030, showing a consistent upward trend. The data suggests that both the area dedicated to apple farming and the total apple production are expected to expand annually during this decade.

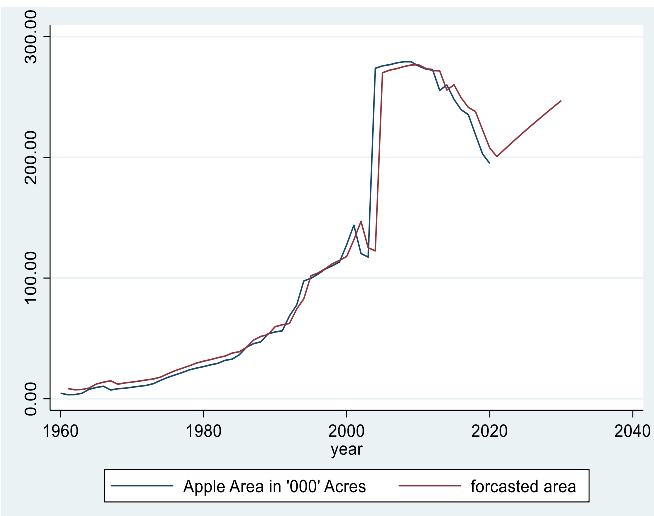


Figure 7.

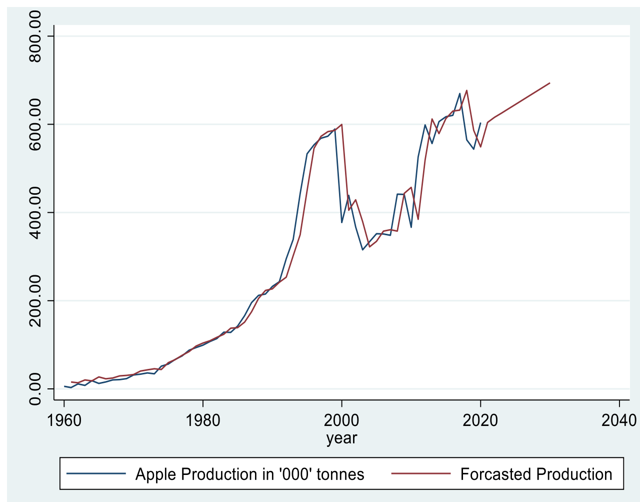


Figure 8.

The Figures show a line graph representing the historical and forecasted trends for apple area in thousand acres and apple production in thousand tonnes from 1960 to around 2040. In Figure 7, graph shows the historical trend for the Apple area illustrating a gradual increase until about the year 2000, then a sharp spike, followed by a decline and stabilization. The forecast trend, indicated by the red line, aligns with the historical data up to the present and then predicts a steady increase into the future. The Fig: 8 graph depicts a consistent upward trajectory in apple production, with some variability over the years. The forecasted production, also in red, follows the historical pattern until the present day and then projects a continual rise. Taken together, the graphs indicate that the forecast models project an optimistic outlook for apple cultivation, anticipating continued growth in both the cultivation area and production, in line with past trends.

Table 9 shows a forecast for apple cultivation area and production from 2021 to 2030. The area is projected to grow from 200.66 thousand hectares in 2021 to 247.02 thousand hectares in 2030, indicating a steady increase year over year. Similarly, apple production is forecasted to rise from 604.29 thousand tonnes in 2021 to 693.98 thousand tonnes in 2030, showing a consistent upward trend. The data suggests that both the area dedicated to apple farming and the total apple production are expected to expand annually during this decade.

Table 9. Forecasts for Apple area and production next 10 years.

Years	Area “000” hectares	Production “000” tonnes
2021	200.66	604.29
2022	206.22	615.86
2023	211.66	625.32
2024	216.99	635.18
2025	222.22	644.97
2026	227.34	654.77
2027	232.38	664.57
2028	237.34	674.37
2029	242.22	684.17
2030	247.02	693.98

Source: Authors own calculation

CONCLUSION

The research paper presents a comprehensive analysis of the trends in apple cultivation area and production in Pakistan from 1959-60 to 2019-20, employing the ARIMA (Autoregressive Integrated Moving Average) model for forecasting future trends from 2021 to 2030. The study highlights the significant role of apple farming within Pakistan's agriculture sector, emphasizing its contribution to the economy and potential for growth in both domestic and international markets. Through extensive data analysis, including stationarity tests and model diagnostics, The ARIMA (1,1,0) model is found in the article to be the most appropriate for predicting Pakistan's apple production and area.

Over the next ten years, the ARIMA's findings model predicts a continuous increase in the area used for apple production as well as cultivation. Specifically, the area is projected to grow from 200.66 thousand hectares in 2021 to 247.02 thousand hectares in 2030, and production is forecasted to rise from 604.29 thousand tonnes in 2021 to 693.98 thousand tonnes in 2030. These findings suggest a positive outlook for the apple farming industry in Pakistan, indicating an ongoing expansion and potential for enhanced economic contributions through increased production and cultivation areas.

The research underscores the importance of accurate forecasting in agricultural planning and policy-making, providing valuable insights for stakeholders to make informed decisions. It also points to the need for addressing challenges within the sector, such as disease outbreaks, marketing issues, and environmental shifts, to fully capitalize on the growth opportunities identified through the forecasts. Overall, the paper contributes to the body of knowledge on agricultural forecasting in Pakistan and highlights the promising future of apple cultivation as a means of economic growth and food security.

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