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Forecasting cereal food production in the Kingdom of Saudi Arabia using the autoregressive integrated moving average model

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Abstract

There is a shortage in cereal production in the Kingdom of Saudi Arabia (KSA) due to unsuitable climatic conditions and high temperatures. The purpose of this study was to predict cereal food production in Saudi Arabia and enable policymakers to develop future strategies regarding the sustainability of cereal production and food security. The World Bank Development Indicators have provided the data for cereal food production; this data was gathered during the period 1961 to 2021. To interpret the data, the autoregressive integrated moving average (ARIMA) model was used. Based on the results, ARIMA (0,1,1) was the optimal model to perform forecasting. The optimal model was used to evaluate in-sample and out-of-sample forecasts. Thus, the forecast value of cereal food production in 2021 was 1,171,166.24 metric tons, while the actual value was 1,187,241.77 metric tons; the relative error was about -1.39%. This means the selected model has a good fitting effect. The projected value of cereal food production in the year 2030 will be 1,292,721.18 metric tons. Therefore, the research suggested various solutions for improving cereal food production in the KSA. Reactivate the role of extension services by promoting the transfer of innovations and technologies to produce cereal varieties suitable for production in the climatic conditions of the KSA. Furthermore, expanding external agricultural investment is necessary to improve the sustainability of food production and food security.

1. Introduction

For most people around the world, cereals are their staple food. Therefore, the availability of cereal food represents the main aspect of every country's effort in its attempt to ensure food security. Many countries have tried to achieve self-sufficiency in producing cereal food to reduce the number of malnourished people. According to the Food and Agricultural Organization (2023), the forecast for world cereal production increased by 5.9 million tons during July 2023 parallel to the earlier months. In recent years, many researchers have focused on increasing cereal production to increase food security (Mughal and Sers, 2020; Grote *et al*., 2021; Raheem *et al*., 2021). However, cereal production is influenced by many factors, including climatic conditions such as temperature and precipitation (Xiang and Solaymani, 2022; Pickson *et al*., 2023). Similarly, as Mundia *et al*. (2019) argued, food production is influenced by a wide range of factors, including climate change, population expansion and economic growth, agricultural production, growing interest in other types of crops, lack of agricultural means, biodiversity, cultural bias, costs, and wars.

Saudi Arabia has made several efforts to achieve food security. However, the environmental conditions are not adequate for cereal production due to higher temperatures (Fiaz *et al*., 2018; Baig *et al*., 2022). On the other hand, water scarcity is the biggest obstacle to achieving food security (Baig *et al*., 2022). In contrast, climate change poses an additional risk to agriculture systems in Saudi Arabia. Therefore, increasing food production to meet growing demand in Saudi Arabia is extremely limited, thus, the gap between production and consumption is met through imports (Fiaz *et al*., 2018; Baig *et al*., 2022). Therefore, despite the KSA's efforts to increase cereal production, the production volume remains below the requirement for the reasons mentioned above. The monetary value of cereal exports from the European Union to Saudi Arabia increased from

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3.660 million euros in 2018 to 4,817 million euros in 2022 (General Directorate for Agriculture and Rural Development of the EU Commission, 2023).

Future strategic decisions to increase cereal production and ensure food security require obtaining future results based on historical data. Therefore, time series analysis with ARIMA is the best forecasting method. Time series analysis is applied to make observations and make decisions about upcoming periods. Therefore, the ARIMA model has been applied in several studies to predict crop production. In a study involving the prognostication of wheat production in Pakistan, Najeeb *et al*. (2005) and Masood *et al*. (2018) utilized the ARIMA model. They mentioned that ARIMA (2,1,2) is the best model to predict wheat production. Dasyam *et al*. (2015) and Nath *et al*. (2019), used an ARIMA (1,1,0) model to estimate wheat production in India. Madlul *et al*. (2020) used ARIMA (1,0,1) to predict the development of wheat production in Iraq until 2028. Ray *et al*. (2016) also used ARIMA (0,1,1), ARIMA (1,1,2), and ARIMA (2,1,1) models to predict food grains in India. Kasthuri and Selvakumar (2021) found that the ARIMA (0,1,1) model was the most accurate and effective method for predicting food grain production. Sharma *et al*. (2018) used a statistical model to forecast how much maize would be produced from 2017 to 2022 by using The ARIMA (2,1,0) model which was found to be the best for forecasting this data. Borkar (2017) modelled and predicted how much land will be used to grow rice in India in the future and how much rice will be produced in India in the future, and they discovered that ARIMA (0,1,1) was a suitable model to predict rice production. SenthamaraiKannan and Karuppasamy (2020) applied ARIMA to predict rice production in many selected states in South India. The researchers discovered that the predicted rice production values for the selected states were slightly different from the actual values. A new study by Ray *et al*. (2023) forecasts the output and yields of wheat, rice, maize, sorghum, and cotton crops. According to the study, wheat, rice, and cotton production are expected to increase, while jowar (a variety of sorghum) and maize production are expected to decrease. Two studies were recently conducted in Saudi Arabia to predict food production using ARIMA. In this context, Alderiny *et al*. (2020) examined the forecast of broiler production and imports and their impact on the expected self-sufficiency ratio in Saudi Arabia. They applied ARIMA (0,1,1) as the optimal model to predict broiler chicken production. Jayagopal *et al*. (2022) analysed the use of the ARIMA model to predict maize yield in Saudi Arabia.

This study aimed to use the ARIMA model to forecast cereal food production in Saudi Arabia for the next nine years, starting from 2021. In addition, the study is expected to present some recommendations to achieve sustainability in food production and food security.

2. Materials and methods

2.1 Data collection

Data on cereal production in Saudi Arabia from 1961 to 2021, measured in tons, was collected from the World Bank Development Indicators database in 2023. According to the World Bank, this data comes from officially recognized sources in Saudi Arabia. Similarly, in agreement with the World Bank (2023), cereal production statistics only apply to crops harvested for dry grain. As a result, cereal crops used for grazing, hay production, or green harvesting for food, feed, or silage have not been included in this category. Table 1 presents data on cereal production in Saudi Arabia from 1961 to 2021, measured in metric tons.

2.2 Data analysis using autoregressive integrated moving average model

Box and Jenkins developed the ARIMA model in the 1976s, a highly accurate forecasting method for time series data AR, I, and MA make up the model. The moving averages are represented by MA, the integration is represented by (I), and the AR stands for the autoregressive model. The ARIMA (p, d, q) model combines the ARIMA (p, q) model with differential operation, which is also known as unit root testing (Fan and Zhang, 2009; Box *et al*., 2015). The Augmented Dickey-Fuller (ADF) test is a unit root test that is used to determine if a time series is stationary (Dickey and Fuller, 1979). If the series is not stationary, the difference operation is used to convert it into a stationary sequence (Ma *et al*., 2018).

Vantuch and Zelinka (2014) provided the general formula for the ARIMA (p, d, q) model, which can be written as follows:

$$y_t = \mu + \sum_{i=1}^{p}(\sigma y_{t-1}) + \sum_{i=1}^{q}(\theta \varepsilon_{t-1}) + \varepsilon_t \quad (1)$$

where µ: the mean value of the time series data, *p*: the number of autoregressive lags, *σ*: autoregressive coefficients (AR), *q*: the number of lags of the moving average process, *θ*: moving average coefficients (MA), *ε*: the white noise of the time series data.

d: the number of differences is given in equation (2)

$$\Delta y_t = y_t - y_{t-1} \quad (2)$$

A key step in using the ARIMA model is to choose the best values for p, d, and q.

To choose the appropriate values for p, d, and q in the ARIMA model, we can look at the autocorrelation

Table 1. Time series data of cereal food production (CFP) (metric tonnes) in the Kingdom of Saudi Arabia from 1961 to 2021.

Year	CFP	Year	CFP	Year	CFP	Year	CFP
1961	360800	1979	349887	1997	2338534	2015	1616813
1962	360320	1980	266238	1998	2201566	2016	1507153
1963	393748	1981	294042	1999	2454119	2017	1493955
1964	397300	1982	488520	2000	2167394	2018	1498372
1965	419300	1983	874586	2001	2591615	2019	1293633
1966	424450	1984	1443643	2002	2852747	2020	1181780
1967	424174	1985	2187821	2003	2948817	2021	1187241.77
1968	431700	1986	2460924	2004	3189319		
1969	430000	1987	2929420	2005	3006637		
1970	433000	1988	3692086	2006	3042777		
1971	314678	1989	3931967	2007	2960073		
1972	109952	1990	4136772	2008	2431704		
1973	113102	1991	4574269	2009	1585994		
1974	300236	1992	4702572	2010	1565155		
1975	289186	1993	5042521	2011	1414016		
1976	282106	1994	4859501	2012	1084597		
1977	294271	1995	2668863	2013	881553		
1978	301519	1996	1931516	2014	1568940		

function (ACF) and partial autocorrelation function (PACF) of the time series. (Pindyck and Rubinfeld, 1991) If two of the three terms are zero, the model can be simplified by dropping the corresponding term. For example, ARIMA (1,0,0) means that AR is equal to 1, ARIMA (0,1,0) means that d is equal to 1, and ARIMA (0,0,1) means that MA is equal to 1 (Ma *et al*., 2018)

Ma *et al*. (2018) described the following steps for forecasting cereal food production (CFP) using the ARIMA model:

I. The Identification of the CFP Time Series' Stationarity. To identify whether the cereal food production (CFP) time series is stationary, we can look at the line graph, autocorrelation function (ACF), and partial autocorrelation function (PACF) plots of the series, as well as perform the Augmented Dickey-Fuller (ADF) test. The ADF test checks for seasonality, trend, and volatility in the series, and can also be used to determine stationarity. If the CFP series is not level stationary, we need to take differences (d). The order of a single integer is shown by the number of differences.

II. ARMA Simulation. The sequence's autocorrelation coefficient (ACF) and partial autocorrelation coefficient (PACF) are calculated. Additionally, the ARMA model's autocorrelation order p and moving average order q values can be estimated.

III. Parameter Estimation Execution. The number of autocorrelation coefficients and partial autocorrelation coefficients with impressively significant levels is determined using the CFP autocorrelation and partial autocorrelation graphs. Several models are then roughly created. Therefore, to choose the best model, we consider the following criteria, we minimize the value of AIC (Akaike Information Criterion), SBC (Schwarz's Bayesian Information Criterion), S.E. Regression (Standard error of the regression), and maximize the adjusted R -squared.

IV. Diagnostic and Optimization Test. We checked the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals after a white noise test.

V. ARIMA forecasting method. The optimal ARIMA model was evaluated using the in-sample forecast (predicted CFP value for 2021) and the out-of-sample forecast (predicted CFP values from 2022 to 2030).

3. Results and discussion

3.1 Stationarity test

The cereal food production (CFP) data series from 1961-2021 was plotted in Figure 1. Table 2 shows the results of the Augmented Dickey-Fuller (ADF) test for stationarity on the data. The Augmented Dickey-Fuller (ADF) test statistic in Table 2 (-1.876869) was greater than the critical value at all significance levels (0.01, 0.05, and 0.1). This indicated that the original cereal food production series was not stationary. The first step in making the cereal food production (CFP) series

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stationary by taking the first-order difference of the series, which we call the DCFP series. Then we test the DCFP series by using the Augmented Dickey-Fuller test (ADF test).

The results shown in Table 3 indicate that because the Augmented Dickey-Fuller (ADF) test statistic for the DCFP series (-5.080400) was less than the critical values at all significance levels (0.01, 0.05, and 0.1), the DCFP series was stationary at the first-order difference. This means the original CFP sequence was a first-order single that is, DCFP ~ I (1).

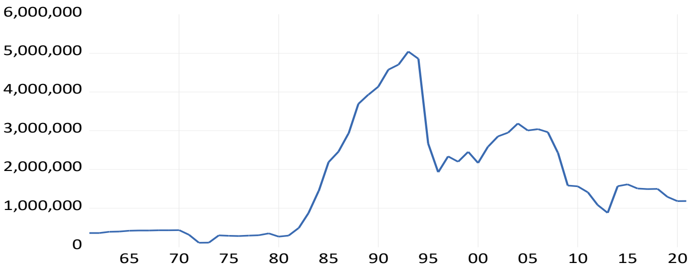

Figure 1. Cereal food production data series during 1961-2021.

Table 2. Augmented Dickey-Fuller unit root test on CFP series using trend and intercept.

		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-1.876869	0.3408
Test critical values:	1% level	-3.546099	
	5% level	-2.911730	
	10% level	-2.593551	

Table 3. Augmented Dickey-Fuller unit root test on DCFP series using trend and intercept.

		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-5.080400	0.0001
Test critical values:	1% level	-3.546099	
	5% level	-2.911730	
	10% level	-2.593551	

3.2 Model identification

Figure 2 shows the autocorrelation and partial autocorrelation function graphs of the DCFP series. It can be observed that at a lag of 1, the autocorrelation coefficient for the DCFP series was significantly different from zero. For lag orders greater than 1, the autocorrelation coefficient of the DCFP series is within the confidence band, which suggests that q can be considered as: 1. At a lag order equal to 1, the partial autocorrelation coefficient is significantly nonzero, and when the lag order is equal to 2, it is similarly significantly different from 0, hence p=1 or p=2 can be taken into consideration. Even though the evaluation was based on subjectivity, various ARIMA models (p, d, and q) are built to create an accurate model by correctly relaxing the range of p and q's values (Ma *et al*., 2018). The processed sample data undergoes the autoregressive moving average pre-estimation in the order of 0, 1, and 2. The performance of the ARIMA model with different values of the parameters p, d, and q is shown in Table 4. The adjusted R-squared, AIC, BIC, and standard error of the regression (SE) are all important factors to consider when selecting the best ARIMA model.

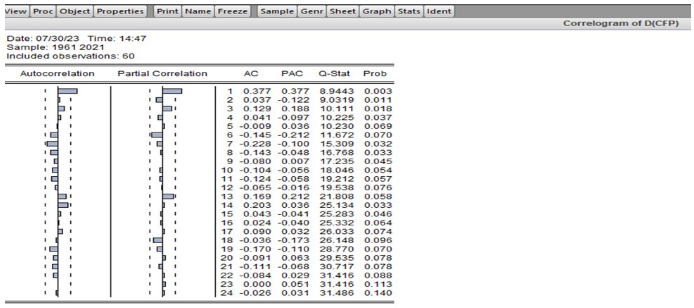

Figure 2. Autocorrelation and partial autocorrelation function graphs of the DCFP series.

Table 4 indicates the output of various ARIMA (p, d, q) models. The AIC value and the BIC value are used to determine the best model to utilize. The minimum AIC and BIC values, however, are insufficient prerequisites for the ARMA model with the most suitable performance. The suitable model is built on the smallest AIC and BIC values, a higher adjusted R-squared, the relevance of the parameters, and the residual randomness test, according to Ma *et al*. (2018). Consequently, the chosen ARIMA model of CFP is (0,1,1), as shown by "*" in Table 4. This points out that the model is successful at the parameter significance and residual randomness tests, and that it has a minimum AIC value and BIC value, together with a higher adjusted R-squared.

Table 4. Test results of ARMA (p, d, q) for cereal food production in KSA.

ARIMA (p,d,q)	Adjusted R-squared	AIC	BIC	S.E. of regression
(1,1,0)	0.111714	28.64910	28.75382	392396.4
(0,1,1)*	0.153669	28.60332	28.70803	383017.6
(1,1,1)	0.150184	28.62435	28.76397	383805.5
(1,1,2)	0.139018	28.63620	28.77583	386318.6
(2,1,1)	0.138558	28.63665	28.77627	386421.7
(2,1,2)	0.051956	28.83143	28.97106	427019.1

3.3 Model examination

Table 5 shows the estimation results of the ARIMA (0,1,1) model. ARIMA (0,1,1) was the most suitable model of the D (CFP) series. The exact mathematical formulation of the model is provided in equation 3. The number in brackets below the equation is the t-test statistic of the parameter.

$$DCFP = 13506.10+0.511750\ CFP_{t-1}$$

T-Test = (3.809253)

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Table 5. Estimation results of the ARIMA (0,1,1) model.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	13506.10	96453.56	0.140027	0.8891
MA(1)	0.511750	0.134344	3.809253	0.0003
SIGMASQ	1.39E+11	1.53E+10	9.116805	0.0000
R-squared	0.182358	Mean dependent var		13774.03
Adjusted R-squared	0.153669	S.D. dependent var		416340.4
S.E. of regression	383017.6	Akaike info criterion		28.60332
Sum squared resid	8.36E+12	Schwarz criterion		28.70803
Log likelihood	-855.0995	Hannan-Quinn criter.		28.64428
F-statistic	6.356334	Durbin-Watson stat		2.075937
Prob(F-statistic)	0.003221			
Inverted MA Roots	-0.51			

The estimated value of the S.E. of regression is equal to 383017.6

The parameter coefficient's t-statistics appear to be significant at 1%. In order to fit the DCFP data, the model was applied, and the outcome is depicted in Figure 3. The data of the actual and fitted values are represented by the top solid lines, while the model residual is represented by the lower line.

The residuals of the fitted ARIMA (0,1,1) model are subjected to a white noise test. The residual series' autocorrelation and partial autocorrelation function graphs are represented in Figure 4. The remnant seems to be white noise which indicates that the model has been fitted and is ready for forecasting.

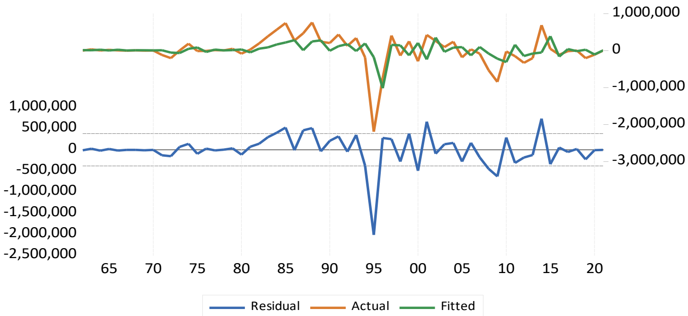
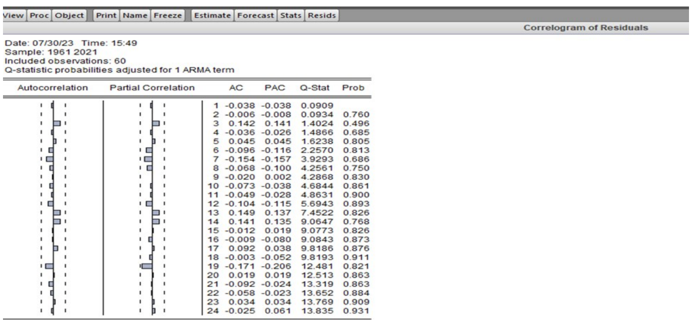


Figure 3. Actual series, fitted series and residual series of the DCFP sequence.



	AC	PAC	Q-Stat	Prob
1	-0.038	-0.038	0.0909	
2	-0.006	-0.008	0.0934	0.760
3	0.142	0.141	1.4024	0.496
4	-0.036	-0.026	1.4866	0.685
5	0.045	0.045	1.6238	0.805
6	-0.096	-0.116	2.2570	0.813
7	-0.154	-0.157	3.9293	0.686
8	-0.068	-0.100	4.2561	0.750
9	-0.020	0.002	4.2868	0.830
10	-0.073	-0.038	4.6844	0.861
11	-0.049	-0.028	4.8631	0.900
12	-0.104	-0.115	5.6943	0.893
13	0.149	0.137	7.4522	0.826
14	0.141	0.135	9.0647	0.768
15	-0.012	0.019	9.0773	0.826
16	-0.009	-0.080	9.0843	0.873
17	0.092	0.038	9.8186	0.876
18	-0.003	-0.052	9.8193	0.911
19	-0.171	-0.206	12.481	0.821
20	0.019	0.019	12.513	0.863
21	-0.092	-0.024	13.319	0.863
22	-0.058	-0.023	13.652	0.884
23	0.034	0.034	13.769	0.909
24	-0.025	0.061	13.835	0.931

Figure 4. Autocorrelation and partial autocorrelation function graphs of the DCFP residual series.

3.4 Data forecasting

First, the model (0,1,1) was applied to determine the predicted CFP value in 2021 using in-sample forecast. The prediction value in 2021 was 1171166.24 metric tons while the actual value was 1187241.77 metric tons, and the relative percentage difference (relative error) was equal to 1.36%. This shows that the predicted value in 2021 was quite accurate, suggesting that the model was a good fit for the data. On the other hand, the dynamic forecasting method was used to predict the values of CFP from 2022 to 2030 (out-of-sample forecast). The results are shown in Table 6. It turns out that the predicted value of cereal food production in 2030 will be 1292721.18 metric tons. The overall results illustrate that cereal food production increases slightly over time.

Table 6. Forecasting of the cereal food production (CFP) in Kingdom of Saudi Araba from 2022 to 2030.

Year	Forecasting cereal food production (CFP)
2022	1184672.35
2023	1198178.45
2024	1211684.56
2025	1225190.66
2026	1238696.76
2027	1252202.87
2028	1265708.97
2029	1279215.08
2030	1292721.18

4. Conclusion

Forecast results using the ARIMA (0,1,1) model show that cereal food production will increase slightly over time. Given Saudi Arabia's significant problems increased cereal food production will not be enough to meet demand. Consequently, cereal production requires painstaking and precise efforts by policymakers to adapt future strategic decisions to increase local production and achieve food security. Therefore, the research suggests various solutions for improving cereal food production in the KSA. Reactivate the role of extension services by promoting the transfer of innovations and technologies that promote the introduction of cereal varieties that can withstand harsh temperatures and unsuitable climate conditions. Furthermore, external agricultural investments need to be expanded to improve the sustainability of food production and food security.

Conflict of interest

The author declares no conflict of interest.

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