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Forecasting of Economic Indicators (Production, Consumption, Population) of Wheat Crop (A Case Study)

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ABSTRACT

Wheat is the most important food crop in Afghanistan, whether consumed by the bulk of the people or used in various sectors. The problem is that Afghanistan has a significant shortfall of wheat between domestic production and consumption. Thus, the present study looks at the issue of meeting self-sufficiency for the whole population due to wheat shortages. To do so, we employ time series analysis, which can produce a highly exact short-run prediction for a significant quantity of data on the variables in question. The ARIMA models are versatile and widely utilised in univariate time series analysis. The ARIMA model combines three processes: I the auto-regressive (AR) process, (ii) the differencing process, and (iii) the moving average (MA) process. These processes are referred to as primary univariate time series models in statistical literature and are widely employed in various applications. Where predicting future wheat requirements is one of the most important tools that decision-makers may use to assess wheat requirements and then design measures to close the gap between supply and consumption. The present study seeks to forecast Production, Consumption, and Population for the period 2002-2017 and estimate the values of these variables between 2002 and 2017. (2018-2030).

Keywords- Economic Indicators, Wheat crop, ARIMA Models, Forecasting, Afghanistan.

I. INTRODUCTION

In contrast to its neighbouring nations Tajikistan (2.97 Tons/Hectare) and Pakistan (2.82 Tons/Hectare), wheat is the principal staple food crop for the majority of Afghan families [Dreisigacker S et al., 2019]. As a result, it is necessary to boost output yield to close the existing deficit in wheat production and achieve self-sufficiency. As a result, it is required to produce wheat cultivars that are high yielding and stable throughout a wide range of locales to meet the needs of Afghanistan's people [Yashpal et al., 2017]. Unfortunately, food shortages are the consequence of low yields, climate change, financial restrictions, conflict, insecurity, and significant post-harvest losses [World Bank, 2011]. Over the last three decades, 95% of studies have resulted in enhanced output, while only 5% have resulted in lower post-harvest losses [Costa., 2014]. According to the initial dietary intake food item, wheat is farmed across the nation in a range of microclimatic conditions. There are only a few examples of the desert lowlands of Helmand province to the temperate high-altitude mountain valleys of Afghanistan's Ghor and Bamyan provinces. This crop is usually planted in the fall and harvested in the spring. More than half of wheat cultivation relies on rainfall, while irrigation is available in almost 45 percent of the total area, and irrigated wheat is farmed in nearly every province; nonetheless, total acreage is inadequate to guarantee national wheat self-sufficiency. Afghanistan is a very desert nation with large seasonal rainfall variability and a history of water scarcity [USDA., 2012]. During the primary growing season, there is only sporadic, if any, dependable rainfall to provide the bulk of the crop's water needs.

Afghanistan's farmland must be irrigated. Because the spring season is the principal source of irrigation in melting, flowing rivers, streams, and lakes that originate in the mountains, the Hindu Kush range is the primary storehouse for essential irrigation to their crops in the nation [Rout., 2008]. Due to a shortage of rainfall throughout the growing season, the length and duration of the yearly snowmelt phase is a critical element in determining the quantity of irrigation water and time available [USDA, 2008].

According to the Ministry of Agriculture, Irrigation, and Livestock (MAIL), Afghanistan will need up to seven million tonnes of wheat to achieve self-sufficiency by 2022 [Waziri et al., 2013]. However, the increase in wheat output of two million tonnes has been a success.

The present situation, in which just 45 percent of wheat is irrigated [MAIL., 2014], which is the country's principal source of wheat production, is exceedingly dark and miserable. To close the gap in wheat production, an appropriate strategy involving widespread application of improved seeds and fertilisers rebuilds infrastructures (irrigation canals, dams, and roads) that were destroyed during the war, as well as an effective research and extension system for better crop management [Waziri et al., 2013]. To fill the demand gap, about one-third of the country's domestic wheat needs are satisfied via imports. According to earlier research, Afghanistan produced 4.7 million tonnes and imported 2.1 million tonnes per year on average during the last five years. During this time, Afghanistan's wheat was mostly dispersed between Kazakhstan and Pakistan, with imports fluctuating from year to year. Pakistan, for

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example, prohibited wheat exports from 2008 to 2010. Wheat travels north from Kazakhstan via Uzbekistan, Afghanistan, and Tajikistan over the Silk Road. There are two primary border crossings into Afghanistan from Pakistan. [Chabot and Tondel, 2011] The railway is the primary mode of wheat transportation in the area. Afghanistan imports a substantial quantity of wheat and flour each year to bridge the gap between market supply and demand. Five essential concerns, including a poor financial situation, an ineffective irrigation system, farmers' illiteracy, a tiny quantity of land yield, and the farmers' uniqueness or individuality, have lost the country's wheat output. As a result, if the criteria mentioned above are not considered, Afghanistan will never achieve self-sufficiency [Kazimi., 2018].

Unemployment and underemployment are a concern in rural Afghanistan. There is also a poor absorption rate for it, in addition to the fact that Afghanistan's young population is rapidly growing, posing job challenges [Leao et al., 2018]. Wheat is the most important food crop in Afghanistan, whether consumed by the whole population or used in various sectors. Unfortunately, there is a significant imbalance between local production and demand in Afghanistan. As a result, the study looks at the issue of a lack of output to fulfil the needs of the people. As a result, estimating future wheat demands is an important tool that may assist decision-makers in determining wheat needs and devising effective strategies to close the gap between production and consumption and provide the required financial assistance.

Furthermore, most prediction systems are only good for a one-year forecast. On the other hand, moving prediction techniques have been discovered to measure and forecast the dependent variable's future movement. The present study attempts to predict Production, Consumption, and Population for the period (2002-2017) to anticipate the values of these variables in the future (2018-2030).

II. MATERIALS AND METHODS

2.1. Data Collection Method

Secondary data was gathered from a variety of sources, including the Ministry of Agriculture, Irrigation, and Livestock (MAIL), the National Statistics and Information Authority (NSIA), the United States Department of Agriculture (USDA), the Food and Agriculture Organization of the United Nations (FAO STAT), THE WORLD BANK, UNdata, and other data-publishing websites. We also employed specific references and investigations pertinent to the study topic for the present section of the study.

2.2. Analytical Approach

For a sufficiently large quantity of data on the relevant variables, time series analysis may offer a reasonably exact short-run prediction [Granger and Newbold, 1986]. The ARIMA models are versatile and widely utilised in univariate time series analysis. The ARIMA model combines three processes: the Autoregressive (AR) process, the Differencing (D) process, and the Moving-Average (MA) process. These processes are referred to as primary univariate time series models in statistical literature and are widely employed in various applications.

2.3. Autoregressive (AR) Model

An autoregressive model of order p, AR (p), can be expressed as:

$X_t = c + \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \cdots + \alpha_p X_{t-p} + \varepsilon_t;\ t = 1,2, \ldots T,$ …… (1)

Where is the error term in the equation; where ε_t a white noise process, a sequence of independently and identically distributed (iid) random variables with $E(\varepsilon_t) = 0$ and $var(\varepsilon_t) = \sigma^2$; i.e. $\varepsilon_t \sim iid\ N\ (0, \sigma^2)$. In this model, all previous values can have additive effects on this level and so on; so, it's a long-term memory model.

2.4. Moving-Average (MA) Model

A time-series $\{X_t\}$ is said to be a moving-average process of order q, MA (q), if:

$X_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}.,\ldots\ldots$ (2)

2.5. Forecasting using ARIMA models

This model is expressed in terms of past errors as explanatory variables. Therefore, only q errors will affect on X_t. However, higher-order errors don't affect on X_t; this means that it's a short memory model.

2.6. Autoregressive Moving-Average (ARMA) Model

A time-series $\{X_t\}$ is said to follow an autoregressive moving-average process of order p and q, ARMA (p, q), the process if:

$X_t = c + \alpha_1 X_{t-1} + \cdots + \alpha_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q}$……… (3)

This model can be a mixture of both AR and MA models above.

2.7. Arima Models

The ARMA models can further be extended to non-stationary series by allowing the differencing of the data series resulting in ARIMA models. The general non-seasonal model is ARIMA (p, d, q): Wherewith three parameters; p is the autoregressive order, d is the degree of differencing, and q is the order of moving average. For example, if X_t is non-stationary series, we will take a first-difference so that ΔX_t becomes stationary, then the ARIMA (p, 1, q) model is:

$\Delta X_t = c + \alpha_1 \Delta X_{t-1} + \cdots + \alpha_p \Delta X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q}$……….. (4)

where $\Delta X_t = X_t - X_{t-1}$. But if p = q = 0 in equation (1), then the model becomes a random walk model classified as ARIMA (1, 1, 2).

2.8. Box-Jenkins Approach

In time series analysis, [Box-Jenkins., 1970]. Approach, named after the statisticians George Box and Gwilym Jenkins, applies ARIMA models to find the best fit of a time series model to past time series values. See [Young, 1977; Frain., 1992; Kirchgässner et al., 2013; and Chatfield., 2016] for more details about Box-Jenkins time series analysis. (Figure. 1) shows the four

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iterative stages of modelling according to this approach.

2.9. Model Identification

Make sure that the variables are stationary, identify seasonality in the series, and use the Autocorrelation Function (ACF) and Partial Auto-Correlation Function (PACF) plots of the series autoregressive or moving average component should be used in the model.

2.10. Model Estimation

Using computation algorithms to arrive at coefficients that best fit the selected ARIMA Model. The most common methods use Maximum Likelihood Estimation (MLE) or nonlinear least-squares estimation.

2.11. Model Checking

By testing whether the estimated model conforms to the specifications of a stationary Univariate process. In particular, the residuals should be independent of each other and Constant in mean and variance over time; plotting the ACF and PACF of the residuals are helpful to identify misspecification. If the estimation is inadequate, we must return to step one and attempt to build a better model. Moreover, the estimated model should be compared with other ARIMA models to choose the best model for the data. The two common criteria used in model selection: Akaike's Information Criterion (AIC) and Bayesian Information Criteria (BIC) which are defined by:

$$AIC = 2m - 2\ln(L^{\wedge}), BIC = \ln(n)\,m - 2\ln(L^{\wedge}) \ldots\ldots\ldots\ldots (5)$$

2.12. Forecasting Using Arima Models

Where $L^{\wedge}$ denotes the maximum value of the likelihood function for the model, is the number of parameters estimated by the model, and is the number of observations (sample size). AIC and BIC are used with the classical criterion: The Mean Squared Error (MSE).

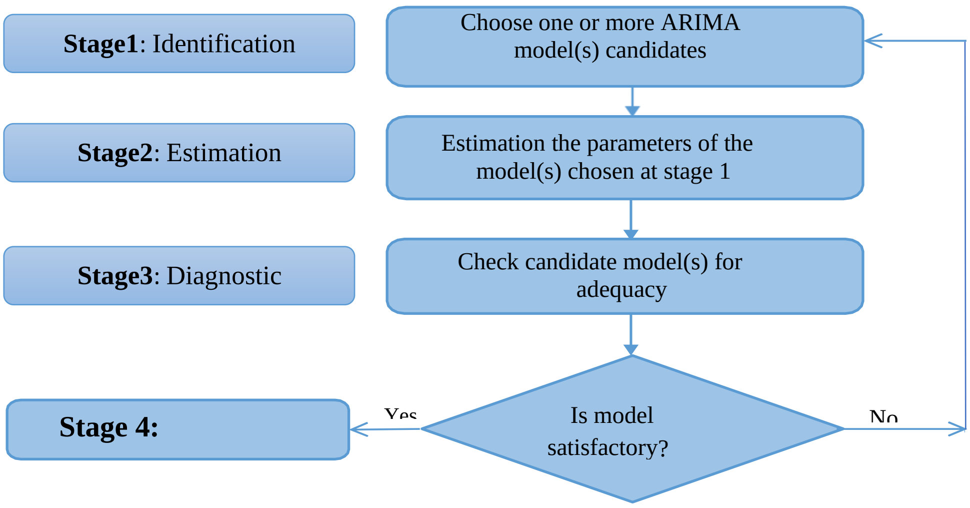


Figure 1: Stages in The Box-Jenkins Iterative Approach

2.13. Forecasting

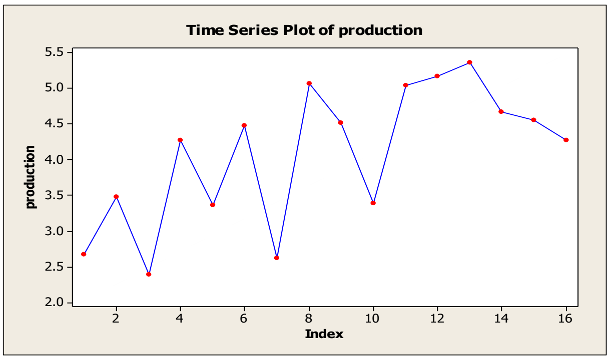
When the selected ARIMA model conforms to a stationary univariate process's specifications, we can use this model for forecasting.

III. RESULTS AND DISCUSSION

3.1. Production

3.1.1. Identification

The time-series data for wheat crop production is shown in the figure (Figure. 2). Applying the Auto-Correlation Function (ACF) and Partial-Correlation Function to determine data stability reveals that the data was not static owing to a decrease in the general trend, which demonstrates the average's instability. The importance of the Autocorrelation coefficient and partial correlation coefficient values is shown in (Table 1), indicating that the time series is not static [Singh et al, 2015; Khapedia et al, 2018]. Wheat output fluctuated mostly owing to changes in the area under wheat crops and their yield. According to [Goswami and Challa 2006], if the variability in both the area and yield components decreases, the variability in production will also decrease.



Source: Calculated from Table 1 in the Appendix 1

Figure 2: Time Series Plot of Wheat Production

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Table. 1: Autocorrelation and partial correlation of wheat production

<table>
<tr><th>Prob</th><th>Q-Stat</th><th>PAC</th><th>AC</th><th></th><th>Partial Correlation</th><th>Autocorrelation</th></tr>
<tr><td>0.001</td><td>10.411</td><td>-0.777</td><td>-0.777</td><td>1</td><td>******| . |</td><td>******| . |</td></tr>
<tr><td>0.001</td><td>13.360</td><td>-0.523</td><td>0.397</td><td>2</td><td>****| . |</td><td>. |***. |</td></tr>
<tr><td>0.003</td><td>14.316</td><td>-0.530</td><td>-0.217</td><td>3</td><td>****| . |</td><td>. **| . |</td></tr>
<tr><td>0.005</td><td>15.011</td><td>-0.462</td><td>0.176</td><td>4</td><td>.***| . |</td><td>. |* . |</td></tr>
<tr><td>0.010</td><td>15.049</td><td>0.101</td><td>-0.039</td><td>5</td><td>. |* . |</td><td>. | . |</td></tr>
<tr><td>0.014</td><td>15.941</td><td>0.005</td><td>-0.179</td><td>6</td><td>. | . |</td><td>. *| . |</td></tr>
<tr><td>0.011</td><td>18.247</td><td>-0.051</td><td>0.268</td><td>7</td><td>. | . |</td><td>. |** . |</td></tr>
<tr><td>0.012</td><td>19.660</td><td>-0.061</td><td>-0.195</td><td>8</td><td>. | . |</td><td>. *| . |</td></tr>
<tr><td>0.017</td><td>20.073</td><td>-0.176</td><td>0.096</td><td>9</td><td>. *| . |</td><td>. |* . |</td></tr>
<tr><td>0.026</td><td>20.309</td><td>-0.117</td><td>-0.065</td><td>10</td><td>. *| . |</td><td>. | . |</td></tr>
<tr><td>0.039</td><td>20.503</td><td>-0.072</td><td>0.051</td><td>11</td><td>. *| . |</td><td>. | . |</td></tr>
<tr><td>0.057</td><td>20.547</td><td>-0.208</td><td>-0.020</td><td>12</td><td>. **| . |</td><td>. | . |</td></tr>
</table>

Source: Calculated from Table 1 in the Appendix 1

Also, if we draw the original data for the ACF, we obtain (Figure 3), and if we draw the original data for the PACF for wheat crop production, we get (Figure 4). The findings demonstrated the importance of the Partial Auto-correlation Coefficient (PACF), which indicates rejecting the fundamental premise "that the sum of the squares of single correlation coefficients is significant," implying that there exist correlations, and is referred to as a general test.

3.1.2. Estimation

To examine the PACF, we use historical data (Figure. 4). We find that this parameter falls outside the boundaries of the confidence interval at one gap. Therefore, the Auto-regression model (AR) and the moving average model (MA) must be applied. Finally, the best model is shown in (Table. 2).

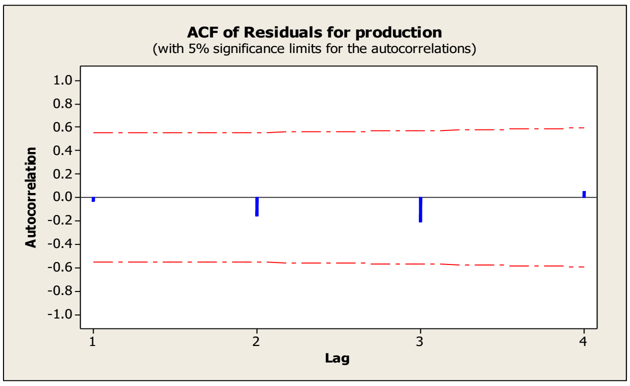
Table 2: Final estimates of parameters for production (1-1-2)

Type	Coef	SE Coef	T	P-value
AR 1	-0.1291	0.9079	-0.14	0.889
MA 1	1.3544	0.9868	1.37	0.197
MA 2	-0.3974	1.0864	-0.37	0.721
Constant	0.15644	0.01992	7.85	0.000

Source: Calculated from Table 1 in the Appendix 1

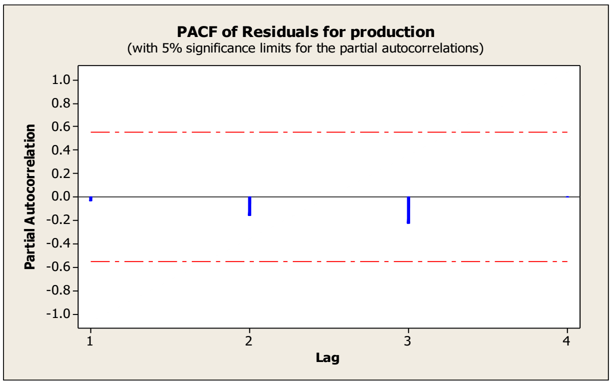
3.1.3. Diagnostic checking

For checking the (PACF) and (ACF) Residuals estimated models (ei), it was found that they were in confidence limits shown in (Figure. 3 and Figure. 4) that there is no specific behavioural pattern for the PACF and ACF of the Residuals, and this indicates the quality of the model [Khapedia et al., 2018].



Source: Table 1 in the Appendix 1

Figure 3: ACF for Wheat Production



Source: Table 1 in the Appendix 1

Figure 4: PACF for Wheat Production

3.1.4. Forecasting

Besides, to use the appropriate and previously estimated model, forecasting is performed for 13 years, ensuring that the most suitable model can predict in Table.3 and Table. 4.

Table 3: Forecasts from period 2018-2030 for production 95% limits

Period	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Forecast	5.85	5.35	5.57	5.70	5.84	5.98	6.12	6.25	6.39	6.53	6.67	6.81	6.95
Lower	4.32	3.64	3.86	3.98	4.12	4.26	4.40	4.54	4.67	4.81	4.95	5.09	5.22
Upper	7.39	7.05	7.28	7.41	7.55	7.69	7.83	7.97	8.11	8.25	8.39	8.53	8.67

Source: Calculated from Table 1 in the Appendix 1

Table 4: Modified box-pierce (Ljung-box) chi-square statistic forecasts from period 2018-2030 for production 95% limits

Lag	12	24	36	48
Chi-Square	5.0	*	*	*
DF	8	*	*	*
P-Value	0.759	*	*	*

Source: Calculated from Table 1 in the Appendix 1

3.2. Consumption

3.2.1. Identification

Besides the drawing, the time series data for the wheat crop consumption is shown in (Figure. 5). It indicates that the data was not static due to an increase of the general trend, which shows the instability of the average, by using Auto-Correlation Function (ACF) and Partial-Correlation Function to detect stability of the data. The results indicate in (Table. 5) the significance of the Autocorrelation coefficient and partial correlation coefficient values, which indicates that the time series is not static [Khapedia et al., 2018; Abid., 2019].

Source: Calculated from Table 1 in the Appendix 1

Figure 5: Time Series Plot of Wheat Consumption

Table. 5: Autocorrelation and partial correlation of wheat consumption

Prob	Q-Stat	PAC	AC		Partial Correlation	Autocorrelation
0.002	9.3420	0.698	0.698	**1**	. |***** |	. |***** |
0.001	14.350	0.013	0.493	**2**	. | . |	. |**** |
0.002	15.377	-0.260	0.215	**3**	. **| . |	. |** . |
0.004	15.504	0.022	0.073	**4**	. | . |	. | . |
0.008	15.538	-0.015	-0.036	**5**	. | . |	. | . |
0.015	15.700	-0.021	-0.075	**6**	. | . |	. *| . |
0.028	15.738	0.252	0.035	**7**	. |** . |	. | . |
0.046	15.747	-0.183	0.015	**8**	. *| . |	. | . |
0.066	16.020	-0.309	-0.081	**9**	. **| . |	. *| . |
0.026	20.366	-0.290	-0.301	**10**	. **| . |	. **| . |
0.002	28.751	0.045	-0.382	**11**	. | . |	.***| . |
0.000	39.251	0.165	-0.382	**12**	. |* . |	.***| . |

Source: Calculated from Table 1 in the Annex

Also, by drawing the original data for the ACF, we got (Figure. 6), and by pulling of PACF original data for the consumption of wheat crop, we get (Figure. 7). The results showed the significance of the Partial Auto-correlation Coefficient (PACF), which means rejecting the fundamental assumption “that the sum of the squares

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of single correlation coefficients are significant" it is mean there are correlations, and it is called a general test.

3.2.2. Estimation

Besides, to investigate the PACF with historical data as shown (Figure. 7), we find that this parameter falls outside the boundaries of the confidence interval at one gap. Therefore, the Auto-regression model (AR) and the moving average model (MA) must be applied. Finally, the best model is shown in (Table. 6)

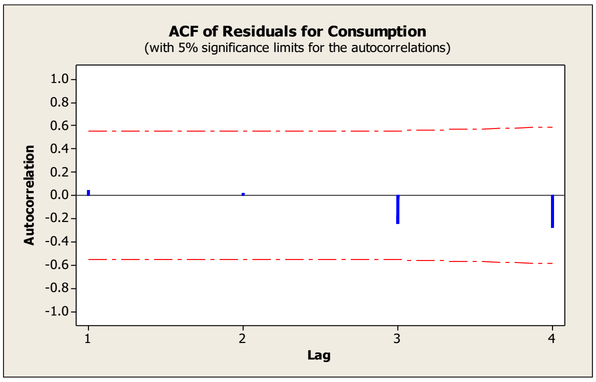
Table 6: Final estimates of parameters for consumption (1-1-2)

Type	Coef	SE Coef	T-value	P-value
AR 1	-0.2990	1.1487	-0.26	0.799
MA 1	0.7783	1.0787	0.72	0.486
MA 2	0.6688	1.3247	0.50	0.624
Constant	0.370561	0.000698	530.59	0.000

Source: Calculated from Table 1 in the Appendix 1

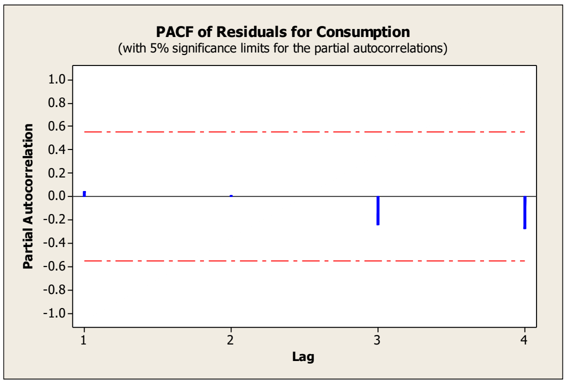
3.2.3. Diagnostic checking

Through checking of the (PACF) and (ACF) Residuals estimated models (ei), it was found that they were in confidence limits shown in (Figure. 6 and Figure. 7) that there is no specific behavioural pattern for the PACF and ACF of the Residuals, and this indicates the quality of the model.



Source: Table 1 in the Appendix 1

Figure. 6: ACF for Wheat Consumption



Source: Table 1 in the Appendix 1

Figure. 7: PACF for Wheat Consumption

3.2.4. Forecasting

Besides using the appropriate and previously estimated model, forecasting is performed for 13 years, ensuring that the most suitable model can predict in (Table. 7 and Table. 8).

Table 7: Forecasts from period 2018-2030 for consumption 95% limits

Period	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Forecast	7.48	7.83	8.10	8.39	8.67	8.96	9.24	9.53	9.81	10.10	10.38	10.67	10.95
Lower	6.47	6.82	6.99	7.24	7.47	7.71	7.94	8.18	8.42	8.67	8.91	9.15	9.40
Upper	8.49	8.85	9.20	9.54	9.87	10.2	10.54	10.9	11.2	11.53	11.86	12.18	12.51

Source: Calculated from Table 1 in the Appendix 1

Table 8: Modified box-pierce (Ljung-Box) chi-square statistic forecasts from period 2018-2030 for consumption 95% limits

Lag	12	24	36	48
Chi-Square	5.7	*	*	*
DF	8	*	*	*
P-Value	0.679	*	*	*

Source: Calculated from Table 1 in the Appendix 1

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3.3. Population

3.3.1. Identification

Besides the drawing, the time series data for annual growth of the population in Afghanistan is shown in (Figure. 8). It indicates that the data is not static due to an increasing yearly growth of the people, which shows the instability of the average, by using Auto-Correlation Function (ACF) and Partial-Correlation Function to detect the stability of the data. The results indicate in (Table. 9) the significance of the Autocorrelation coefficient and partial correlation coefficient values, which indicates that the time series is not static [Singh et al., 2015; Khapedia et al., 2018; Abid., 2019].

Source: Calculated from Table 1 in the Appendix 1

Figure 8: Time Series Plot of Population

Table 9: Autocorrelation and partial correlation of population

Prob	Q-Stat	PAC	AC		Partial Correlation	Autocorrelation
0.001	11.594	0.777	0.777	**1**	. |******|	. |******|
0.000	18.877	-0.022	0.595	**2**	. | . |	. |**** |
0.000	22.855	-0.080	0.424	**3**	. *| . |	. |***. |
0.000	24.502	-0.092	0.262	**4**	. *| . |	. |** . |
0.000	24.925	-0.057	0.127	**5**	. | . |	. |* . |
0.000	24.925	-0.105	-0.004	**6**	. *| . |	. | . |
0.001	25.470	-0.121	-0.130	**7**	. *| . |	. *| . |
0.001	27.404	-0.084	-0.232	**8**	. *| . |	. **| . |
0.000	31.354	-0.079	-0.310	**9**	. *| . |	. **| . |
0.000	37.456	-0.056	-0.357	**10**	. | . |	.***| . |
0.000	46.045	-0.078	-0.386	**11**	. *| . |	.***| . |
0.000	57.553	-0.077	-0.400	**12**	. *| . |	.***| . |

Source: Calculated from Table 1 in the Appendix 1

Also, by drawing the original data for the ACF, we got (Figure. 9), and by drawing of PACF original data for the annual growth of population, we got (Figure. 10). The results showed the significance of the Partial Auto-correlation Coefficient (PACF), which means rejecting the fundamental assumption "that the sum of the squares of single correlation coefficients are significant" it is mean there are correlations, and it is called a general test.

3.3.2. Estimation

To investigate PACF compared with the historical data as shown (Figure. 10), we found that this parameter falls outside the boundaries of the confidence interval at one gap. Therefore, the Auto-regression model (AR) and the moving average model (MA) must be applied. Finally, the best model is shown in (Table. 10).

Table 10: Final estimates of parameters for the population (1-1-2)

Type	Coef	SE Coef	T-value	P-value
AR 1	0.3833	0.2524	1.52	0.157
MA 1	-0.0019	0.3153	-0.01	0.995
MA 2	0.9694	0.2733	3.55	0.005
Constant	0.41455	0.01270	32.64	0.000

Source: Calculated from Table 1 in the Appendix 1

3.3.3. Diagnostic checking

Through checking of the (PACF) and (ACF) Residuals estimated models (ei), it was found that they were in confidence limits shown in (Figure. 9 and Figure. 10) that there is no specific behavioural pattern for the PACF and ACF of the Residuals, and this indicates the quality of the model.

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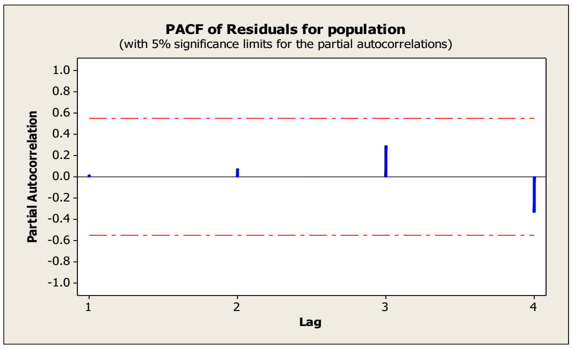
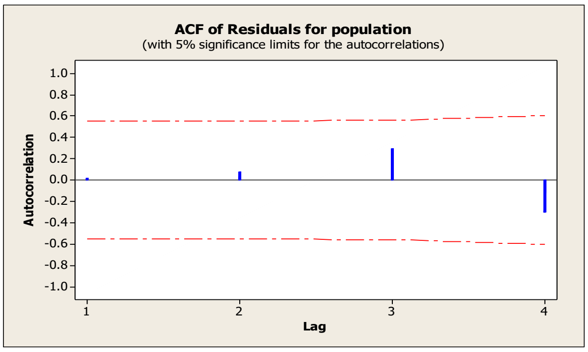


Source: Table 1 in the Appendix 1
Figure 9: ACF for Population



Source: Table 1 in the Appendix 1
Figure 10: PACF for population

3.3.4. Forecasting

Besides using the appropriate and previously estimated model, forecasting is performed for 13 years, ensuring that the most suitable model can predict in (Table. 11 and Table. 12).

Table 11: Forecasts from period 2018-2030 for population 95% limits

Period	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Forecast	34.77	35.31	35.94	36.59	37.25	37.92	38.59	39.27	39.94	40.61	41.28	41.95	42.63
Lower	34.447	34.75	35.34	35.99	36.66	37.32	37.99	38.67	39.34	40.01	40.68	41.35	42.02
Upper	35.10	35.88	36.53	37.19	37.85	38.52	39.20	39.88	40.54	41.21	41.88	42.56	43.23

Source: Calculated from Table 1 in the Appendix 1

Table 12: Modified box-pierce (Ljung-box) chi-square statistic forecasts from period 2018-2030 for population 95% limits

Lag	12	24	36	48
Chi-Square	8.1	*	*	*
DF	8	*	*	*
P-Value	0.427	*	*	*

Source: Calculated from Table 1 in the Appendix 1

VI. CONCLUSION

According to this research, wheat is an important and staple food crop in Afghanistan, production and consumption. Because it accounts for over 59% of daily calorie intake and 164 kg of consumption per capita in the nation. As a result of the world's fast population expansion, food scarcities and the prospect of poverty in Afghanistan are critical current and future challenges. Unfortunately, over the last three decades, Afghanistan has had a significant imbalance between production and consumption. As a result, the study looks at the issue of a lack of output to fulfil the needs of the people. As a result, estimating future wheat demands is an essential tool that may assist decision-makers in determining needs and developing effective strategies that can help close the gap between production and consumption by giving the required financial assistance.

Furthermore, the majority of prediction algorithms are only accurate for one year. On the other hand, moving prediction techniques have been discovered to measure and forecast the dependent variable's future movement. By the way, the present study's objectives were to forecast Production, Consumption, and Population for the period (2002-2017) and the values of these variables during that time (2018-2030). So, using the Autocorrelation function (ACF) and Partial Correlation to detect the stability of the time series, the results of the time-series data for production, consumption, and annual population growth were not static, due to increasing or decreasing of the general trend, which means the average was unstable. The importance of the Autocorrelation coefficient and partial correlation coefficient data further demonstrated that the time series is not static.

REFERENCES

[1] Abid, S., 2019. Trends and variability of wheat crop in Pakistan: J. 1005/2018.8.2/1005.2.153.159. https://doi.org/10.18488/.

[2] Box. GEP, Jenkins GM., 1970. Times Series Analysis Forecasting and Control, Holden-Day San Francisco.

[3] C. Chatfield., 2016. The Analysis of Time Series: An Introduction, CRC Press.

[4] Central Statistics Organization of Afghanistan. Annual Trade Bulletin. Kabul, Afghanistan: CSO.

[5] Chabot P, & Tondel, F., 2011. A regional view of wheat markets and food security in Central Asia: International Development Famine Early Warning Systems Network.

[6] Costa S. J., 2014. Reducing Food Losses in Sub-Saharan Africa - An Action Research evaluation trail from Uganda and Burkinafaso. http://documents.wfp.org/stellent/groups/public/documents/special_initiatives/WFP2652 05.pdf.

[7] Dreisigacker S., 2019. Tracking the Adoption of Bread Wheat Varieties in Afghanistan Using DNA Fingerprinting: BMC Gene. 20, 1–13.

[8] Goswami, S. N., & Challa, O. (2006). Socio-economic factors affecting land use in India. Agri. Situ. India, 60(10), 615-623. view at Goole scholar / view at publisher.

[9] J. Frain., 1992. Lecture Notes on Univariate Time Series Analysis and Box Jenkins Forecasting, Economic Analysis: Research and Publications.

[10] Kazimi, Z., 2018. Wheat Market Instability in Afghanistan: A Case Study of Kabul, Mazar-e-Sharif, Bamyan and Ghor Provinces, 122–127.

[11] Khapedia, H. L., Sharma, S. K., Sikarwar, R., & Mridha, I. S, 2018. Forecasting Wheat Productivity and Production of Madhya Pradesh , India , Using Autoregressive Integrated Moving Average Models, (7), 4693–4705.

[12] Kirchgässner G, Wolters J, Hassler U., 2013. Univariate stationary processes, in Introduction to Modern Time Series Analysis, Springer, Berlin, Heidelberg.;27-93.

[13] Leao. I, Ahmed, M., and Kar A, 2018. Jobs from Agriculture in Afghanistan: International Development in Focus. Washington, DC: World Bank.

[14] Ministry of Agriculture Irrigation and Livestock., 2013. Agriculture Prospect http://mail.gov.af/Content/files/mail_Agriculture_Prospects_Report_2013%20DECEMBER (1).pdf.

[15] Rout Bob., 2008. How the Water Flows, A Typology of Irrigation Systems in Afghanistan: Afghanistan Research and Evaluation Unit Issue Paper Series. Kabul, Afghanistan.

[16] Saharawat Yashpal, 2017. Genotype × environment interaction and identification of high yielding wheat genotypes for Afghanistan: J. Exp. Biol. & Agric. Sci. 5, 25–34.

[17] Singh, Netajit, L., Darji, V. B., Parmar, D. J., Vbdarji, 2015. Forecasting of Wheat Production and Productivity of Ahmedabad Region of Gujarat State by Using ARIMA Models. Ind. J. of Econ and Dev. 3(6), 2015.

[18] USDA, 2012. Wheat Production Forecast at Near-Record Levels: Commodity intelligence report Afghanistan.

[19] US Department of Agriculture, Foreign Agricultural Service., 2008. Afghanistan Severe Drought Causes Major Decline in Wheat Production: Commodity Intelligence Report.

[20] Waziri A, Habibi A., Manan A R, 2013. Making Afghanistan wheat secure by 2022: Wheat, J. Inf. Ser. 116, 12-14.

[21] World Bank, 2011. Missing Food, the Case of post-harvest Grain Losses in Sub-Saharan African: WB (Vol. 60371-AFR). http://siteresources.worldbank.org/INTARD/Resources/MissingFoods10_web.pdf.

[22] W. L. Young., 1977. The Box-Jenkins Approach to Time Series Analysis and Forecasting: Principles and Applications, RAIRO-Operations Research Recherche Opérationnelle. 11, 129-143. https://doi.org/10.1051/ro/1977110201291.

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***Annex**:* Economic variables of wheat crop growing in Afghanistan over the period 2002-2017

Year	Production/Million-Ton	Consumption/Million-Ton	Population/Million
2002	2.67	3.19	23.6
2003	3.48	3.80	25.1
2004	2.39	3.29	25.7
2005	4.27	4.30	26.3
2006	3.37	4.40	27.15
2007	4.48	5.50	27.39
2008	2.62	5.85	27.71
2009	5.07	6.05	28.48
2010	4.52	5.40	29.12
2011	3.39	4.50	29.76
2012	5.05	6.04	30.42
2013	5.17	6.04	31.11
2014	5.37	6.20	31.83
2015	4.68	6.80	32.56
2016	4.56	6.90	33.34
2017	4.28	6.95	34.13

Source: 1- Central Statistics Organization of Afghanistan (CSO), Different yearly Book; 2- World Bank, Different Issues