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FORECASTING OF WHEAT PRODUCTION FOR PAKISTAN USING ADVANCE TIME SERIES MODELS

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ABSTRACT

It is a pillar of global food security because wheat is so full of nutrients-carbohydrates, proteins, fiber, vitamins (especially B vitamins), and important minerals. Worldwide, wheat continues to be the most common food grain. To guarantee food security, it is essential to comprehend and predict patterns in wheat production. The Department of Agriculture's Statistics Bureau provided the historical wheat production statistics for Pakistan from 1947 to 2019, which were the subject of this study's analysis. statistical techniques, Numerous methods, including moving averages, Holt's exponential smoothing, and autoregressive integrated moving average (ARIMA) models, were employed for a comprehensive analysis. The evaluation criteria, mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE), illustrate an increasing tendency among intrinsic historical data variations and demonstrate the durability of the forecasting skills of Holt's Exponential Smoothing approach. These results offer crucial information for strategic planning and policy decisions to maximize wheat output and maintain Pakistan's food security.

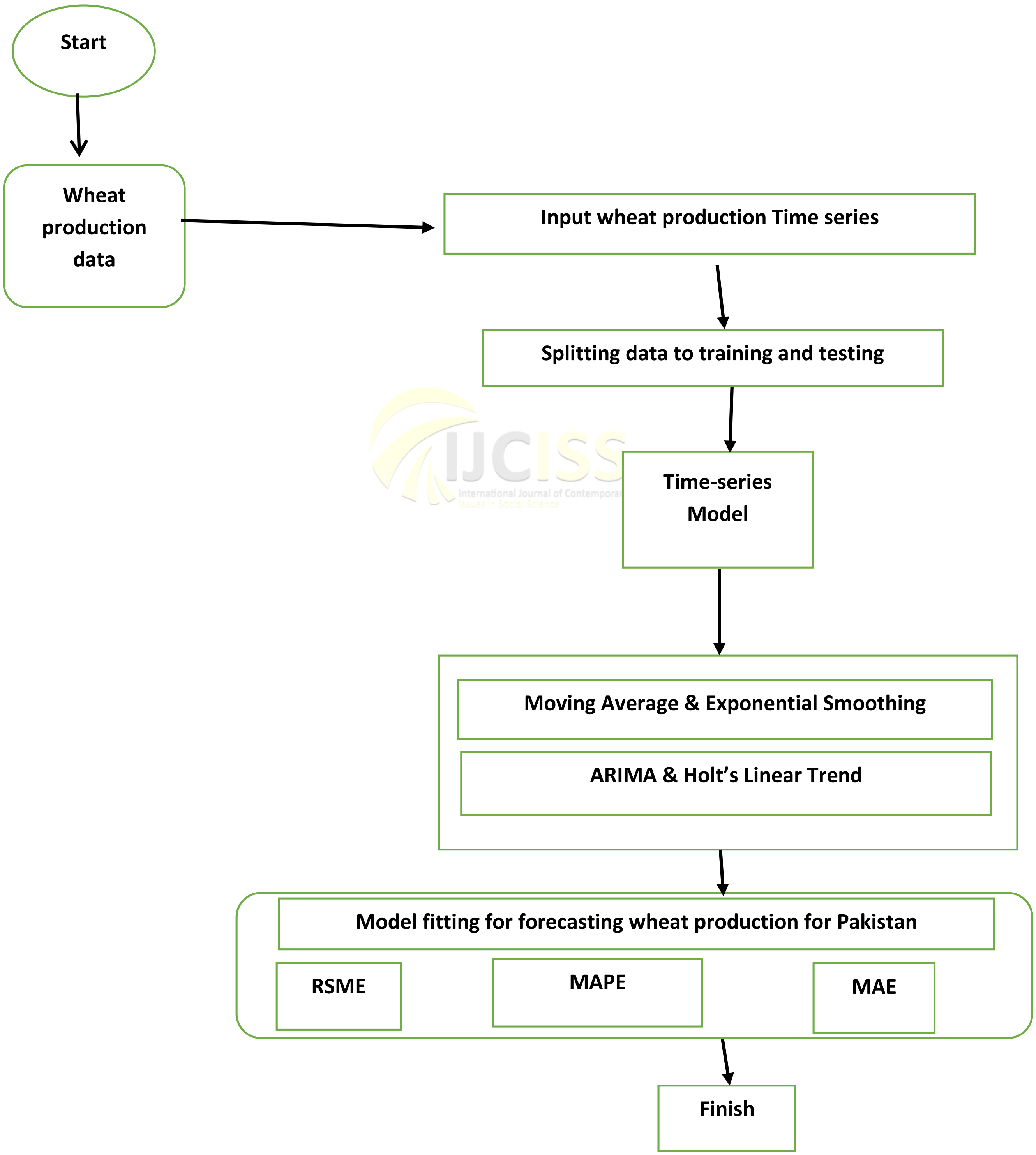
Keywords: Moving Average, Exponential Smoothing, ARIMA, Holt's linear Trend, Forecasting

INTRODUCTION

There are two main types of wheat: one variety is used to make various wheat-based dishes, and the durum variety is used specifically for making pasta. In the Northern Hemisphere, most bread wheat is typically red, while in Australia, it is often white. Based on its protein concentration, wheat is categorized as "soft" or "hard". Lower in protein than hard wheat, soft wheat works well for sweet cakes and biscuits. Hard wheat, on the other hand, is perfect for baking bread because it has a high gluten and protein content. Wheat flour is a staple in a wide variety of dishes, such as bread, muffins, pasta, noodles, cakes, pastries, cereal bars, crackers, crispy breads, and sauces (Haros, 2017). Wheat is also used in the production of confectionery and alcoholic beverages. agricultural sector in Pakistan is heavily reliant on climatic conditions, particularly temperature and rainfall patterns. (Sarwar N. A., 2023) Unusual climate variations have increased vulnerability for farmers, with many struggling to meet their basic needs due to the impact on their livelihoods (Sultana, 2020). To mitigate these challenges, adopting climate adaptation strategies, such as adjusting sowing dates, modifying plant populations, and adopting new sowing and harvesting technologies, has been recommended (Anser, 2020). Additionally, the government of Pakistan has been urged to launch new funding programs to support the development of the agricultural sector, as the output of major field crops, including wheat, has a positive and significant relationship with the agricultural GDP of the country. Wheat is a prominent food crop in Pakistan, with the country being one of the top 10 wheat producers in the world (Kazmi, 2012). The durum variety is used to produce pasta, while the other variation is utilized to make various wheat-based foods (Mefleh, 2019). While bread wheat cultivated in Australia is frequently white, most bread wheat grown in the Northern Hemisphere is usually red. Wheat is categorized as "hard" or "soft" depending on how much protein it has when used to make bread. Hard wheat includes considerable amounts of gluten and is strong in protein, making it ideal for bread baking, whereas soft wheat is low in protein and can be processed into sweet biscuits and cakes (Pauly, 2013). The durum type is used to make pasta, while the other variety is utilized to make various wheat-based foods. The majority of bread wheat farmed in the Northern Hemisphere is typically red, but bread wheat in Australia is often white. Depending on how much protein it contains, wheat is classified as "hard" or "soft" for making bread (Khan, 2016). While soft wheat is low in protein and can be ground to make sweet biscuits and cakes, hard wheat is high in protein and also has a lot of gluten, making it perfect for baking bread. The floor is ready. Wheat is usually mixed into flour, followed by a wide range of foods, including bread, crumbs, muffins, noodles, pasta, biscuits, cakes, pastries, cereal bars, sweet and savory breakfast foods, crackers, crispy breads, and sauces. Used to create range and confectionery (such as alcohol) and other uses of wheat include: There are two main types of wheat: one variety is used to make various wheat-based dishes, and the durum variety is used specifically for making pasta. In the Northern Hemisphere, most bread wheat is typically red, while in Australia, it is often white (Romano, 2021). Wheat is classified as "soft" or "hard" based on the amount of protein it contains. For sweet cakes and biscuits, low-protein soft wheat works nicely. Based on its protein concentration, wheat is categorized as "soft" or "hard." Lower in protein than hard wheat, soft wheat works well for sweet cakes and biscuits. In contrast, hard wheat, which is high in protein and gluten, is ideal for baking bread wheat flour is an essential component of many dishes, such as bread, muffins, noodles, spaghetti, biscuits, cakes, pastries, cereal bars, breakfast items, crisp bread, and sauces. (Sarwar N. F.-S., 2021). Wheat is also used in the production of confectionery and alcoholic beverages. Wheat is the second most significant crop grown worldwide both in the United States and other nations. The wheat cereal crops were divided into five classes by us (Giraldo, 2019). The five classes that makeup categories of wheat are red hard spring, red hard winter, red soft winter, white, and durum wheat. Based on regional differences, cultivation trends vary for every class. Most red hard winter wheat is grown on the Great Plains, which stretch from Montana to Texas. The primary usage of this variety of wheat is for bread flour. Northern grassland areas primarily cultivate hard red spring wheat, though durum varieties are also available. The majority of wheat grows in Dakota and Montana; this variety is well-known for making pasta of the highest caliber, and it falls into the category of white wheat, which is what everyone wants for breakfast. In comparison to other crops, wheat is farmed on more than 240 million hectares, and the global trend for wheat production exceeds that of all other crops put together. The Food and Agriculture Organization (FAO) projected that global wheat production in 2020 will reach 771 million tons, representing a 6.8% rise over the previous year (Dadrasi, 2022). It demonstrates that wheat production has increased over the decrease from the previous year, reaching a record-breaking high (Vitale, 2020). Hard red spring wheat is mostly cultivated in northern grassland areas, while durum wheat, known for producing high-quality pasta, is mainly grown in Dakota and Montana. White wheat, preferred for breakfast, is another important category. Over 240 million hectares of wheat are cultivated globally, with wheat production surpassing that of all other crops combined (Shiferaw, 2013). The Food and Agriculture Organization (FAO) predicted that 771 million tons of wheat would be produced worldwide in 2020, a 6.8% rise from the year before and the greatest amount ever.

1. Material and Methods

Data on Pakistan's wheat production from 1947 to 2019 were gathered for this study from the FAO (www.pbs.gov.pk). To estimate and forecast wheat production, ARIMA, and Holt's linear trend models were used to estimate and forecast the average movement average of exponential smoothing. Because they are simple to use and produce reliable forecasts, these models are often used for modeling and forecasting. When applied to time series data or any other type recorded at regular intervals, like time series data, a moving average is a simple yet powerful technique (Anderson, 2011).



2.1 Moving Average

It is used to smooth data to reveal trends and can also serve as a forecasting technique. A moving average calculates the average of different subsets of a complete data set, allowing for focused analysis (Bisgaard, 2011). To reduce volatility, a moving average of three, five, or seven years can be calculated. I decided to make K an even number in this instance, precisely K = 3 years. This method can then be used to construct the 3-year moving averages.

$$\hat{Y}_{t-1} = \frac{Y + Y_{t-1} + \cdots Y_{t-p+1}}{p} \tag{1}$$

Where Yt+1 is forecasting yield for year t + 1, Yt is reported for year $t$and p is the number of terms specified in the moving averaging techniques.

2.2 Exponential Smoothing:

By minimizing deviations unrelated to the present trend, exponential smoothing is a statistical technique that aids in understanding the significance of trends (Yang, 2015). This method smooths the data by giving more weight to recent observations and less weight to older ones, which is known as adequate smoothness. As new data becomes available, it receives gradually increasing importance while older data's influence diminishes. This technique also referred to as average is commonly used for short-term forecasting (Lu, 2020).

$$s_t = a_t + (1-a)s_{t-1} \tag{7}$$

OR

$$s_1 = Y_1$$

$$s_t = Y_t + (1-a)s_{t-1} \tag{8}$$

OR

$$F_t = F_{t-1} + a(A_{t-1} - F_{t-1}) \tag{9}$$

where

F = Forecast α = Coefficient t = time A = Actual value

2.3 ARIMA

The ARIMA model proposed by Box and Jenkins is also known as the Box-Jenkins method in the literature (Loganathan, 2010). The ARMA combination is produced by integrating a moving average (MA) model with an autoregressive (AR) model. The ARIMA model is used with non-stationary series, whereas the AR and MA models work well with stationary series.

(Cheng, 2015) to generate Holt's ARIMA (p, d, q) models, the data must first be stabilized by differencing it d-times. Only then can an ARMA (p, q) mode be fitted.

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots . + \varphi_p Y_{t-p} + \alpha_1 - \theta_1 \alpha_{t-1} - \alpha_2 - \theta_2 \alpha_{t-2} - \cdots - \alpha_q - \theta_q \alpha_{t-q} \tag{2}$$

2.4 Box-Jenkins Method

The Box-Jenkins Model is a mathematical model that uses inputs from a given time series to forecast data ranges. Multiple time series data types can be analyzed by the Box-Jenkins Model in order to make forecasts. Differentiations between data points are used in its process to calculate results. With the use of seasonal differencing, moving averages, and auto regression, the methodology enables the model to make predictions and detect trends (Makridakis, 1997). Important step to be follow:

- **Identification**: Plot the series, check for stationarity, use ACF and PACF to identify model type.
- **Estimation**: Fit the model by choosing AR, I, and MA parameters.
- **Diagnostics**: Analyze residuals to ensure they are white noise.

- **Forecasting**: Use the validated model to make forecasts and calculate confidence intervals.

2.5 Holts Linear Trend:

One method for predicting data that shows a trend is Holt's model, often known as linear exponential smoothing (Pongdatu, 2018). Three separate equations make up the Holt model, which combines them to produce a comprehensive forecast.

Level equation $$l_t = ay_t + (1-a)(l_{t-1} + b_{t-1}) \quad (3)$$

Trend equation $$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \quad (4)$$

Forecast equation $$\hat{Y}_t = l_t + hb_t \quad (5)$$

The Holt method, or double exponential smoothing, uses three equations to forecast time series data. The first adjusts the current level estimate l_t with a smoothing parameter a. The second updates the trend estimate b_t using a trend-smoothing parameter β, adapting to changing conditions. Forecasts are derived from these estimates, making them effective for predicting future values based on historical trends.

2.6 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is a widely used metric to assess how well a model predicts the future. It is computed as the mean of the absolute deviations between the observed and anticipated values. The average error of the forecasts is indicated by the MAE. Regression problems and other scenarios involving predictive modeling are where it shines. It is simple to read because it is expressed in the same unit as the actual and anticipated values.

2.7 Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is another widely used statistic to assess a forecasting or prediction model's performance. It is computed by averaging the absolute percentage of mistakes in the predictions and is given as a percentage. Compared to absolute measurements like MAE, MAPE offers a clear prediction accuracy measure expressed as a percentage, making it potentially easier to grasp. When evaluating how many models perform on the same dataset, it is really helpful.

2.8 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is a commonly used metric to assess how well a model predicts the future. The square root of the average squared discrepancies between the observed and anticipated values is what it stands for.

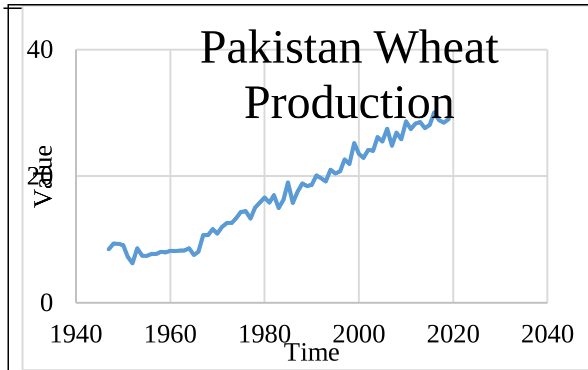


Figure1: Wheat Production of Pakistan

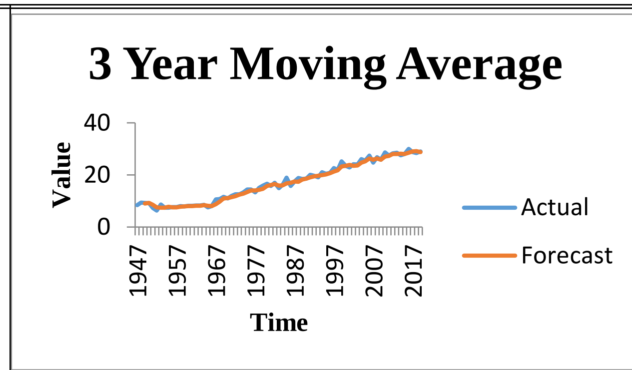


Figure2: : 3-Year Moving Average Forecast of Wheat Production of Pakistan

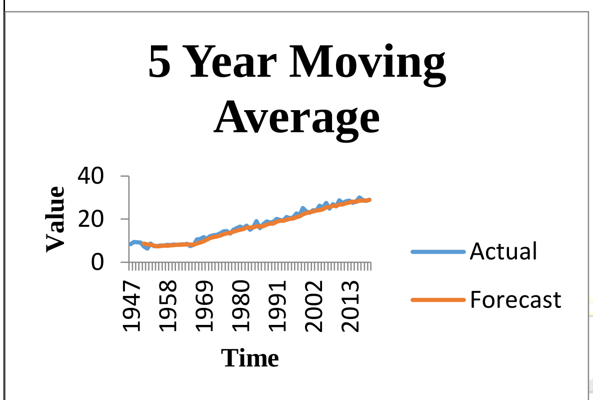


Figure3: 5-Year Moving Average Forecast of Wheat Production of Pakistan

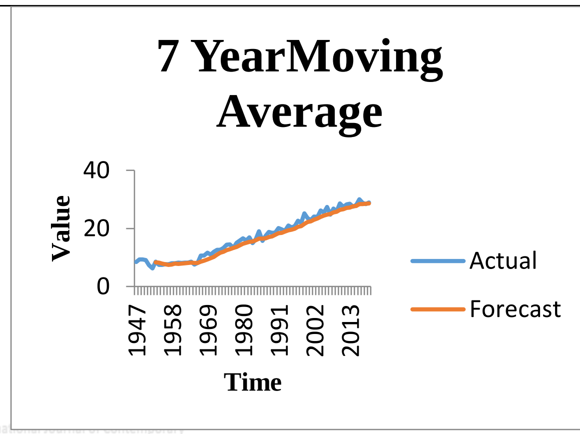


Figure4: 7-Year Moving Average Forecast of Wheat Production of Pakistan

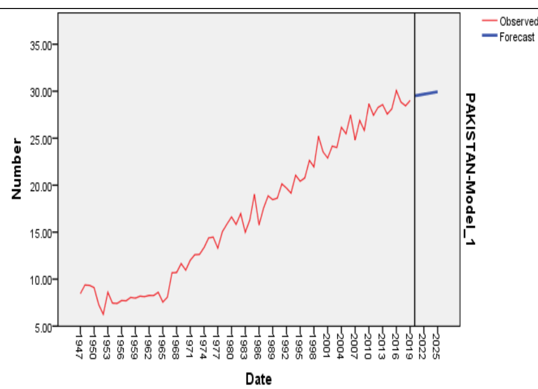


Figure5: Forecasting of Wheat Production of Pakistan by Using Holt's Method

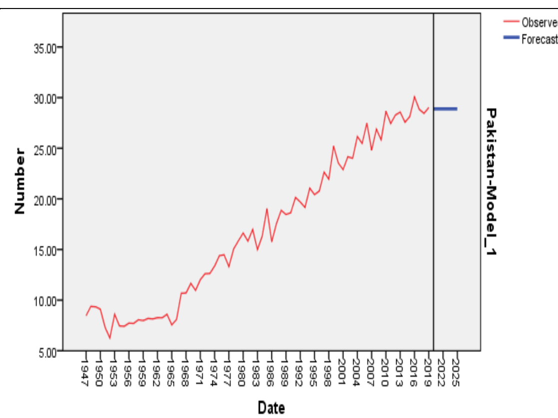


Figure6: : Forecasting of Wheat Production of Pakistan by Using Simple Exponential Smoothing Method

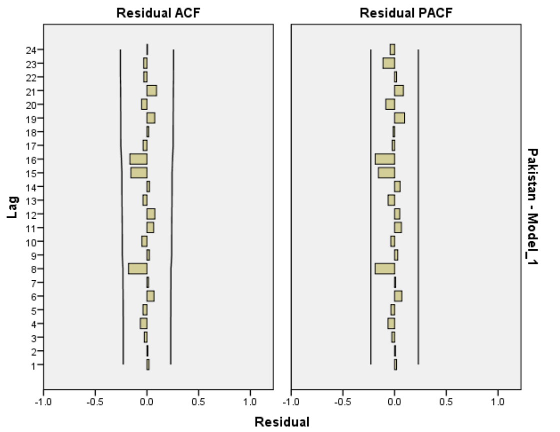


Figure7: Residual plots of ACF and PACF by Using Holt's Method

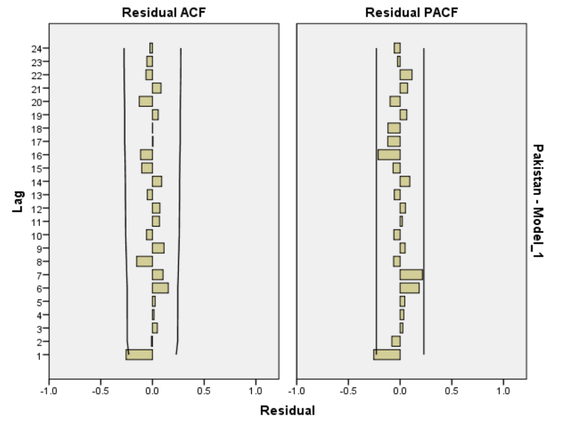


Figure8: Residual plots of ACF and PACF by Using Simple Exponential Smoothing Method

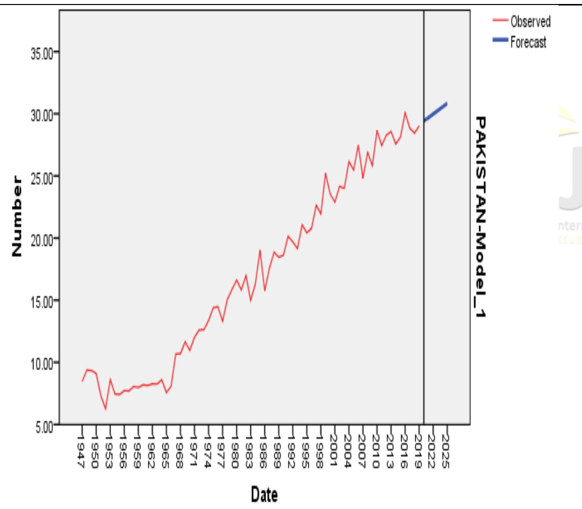


Figure9: Forecasting of Wheat Production of Pakistan by Using ARIMA Model

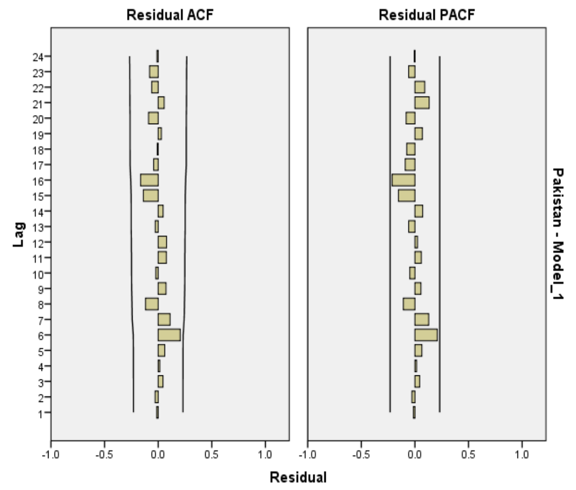


Figure10: Residual plots of ACF and PACF by Using ARIMA Model

Figures 1, 2, 3, and 4 show the rise in wheat production from 1947 to 2019. Figure 1 demonstrates the time series plot of Pakistan's wheat production, which displays a distinct upward trend and a minor curve that accelerates the increase over time.Figure 2 uses a three-year average (e.g., 1947-1950, 2017-2019), with the X-axis as time and the Y-axis as production, showing a steady rise in actual and forecasted production. Figure 3 uses a five-year average (e.g., 1947-1951, 2015-2019), also showing a consistent rise. Figure 4 uses a seven-year average (e.g., 1947-1953, 2013-2019), showing a regular increase in production over time.

Figures 5 to 10 show wheat production forecasts from 1947 to 2019 using Holt's Method, simple exponential smoothing, and the ARIMA model. Holt's Method indicates a steady rise with wide intervals, and residuals confirm model adequacy. Simple exponential smoothing shows a similar upward trend with minor residual issues at lag 1. The ARIMA model, addressing non-stationarity, shows a rising trend with ARIMA (1,1,1) as the best fit, and residuals validate the model.

Table 1: Computation of Moving Averages of Wheat Production for Pakistan

Year	Pakistan	3 year moving average	5 year moving average	7 year moving average
1947	8.45			
1948	9.38			
1949	9.34			
1950	9.1	9.06		
1951	7.3	9.27		
1952	6.27	8.58	8.71	
1953	8.61	7.56	8.28	
1954	7.45	7.39	8.12	8.35
1955	7.42	7.44	7.75	8.21
1956	7.73	7.83	7.41	7.93
1957	7.7	7.53	7.50	7.70
1958	8.06	7.62	7.78	7.50
1959	7.98	7.83	7.67	7.61
1960	8.19	7.91	7.78	7.85
1961	8.14	8.08	7.93	7.79
1962	8.27	8.10	8.01	7.89
1963	8.26	8.20	8.13	8.01
1964	8.6	8.22	8.17	8.09
1965	7.56	8.38	8.29	8.21
1966	8.08	8.14	8.17	8.14
1967	10.68	8.08	8.15	8.16

1968	10.7	8.77	8.64	8.51
1969	11.66	9.82	9.12	8.88
1970	10.96	11.01	9.74	9.36
1971	12.02	11.11	10.42	9.75
1972	12.61	11.55	11.20	10.24
1973	12.63	11.86	11.59	10.96
1974	13.36	12.42	11.98	11.61
1975	14.39	12.87	12.32	11.99
1976	14.48	13.46	13.00	12.52
1977	13.31	14.08	13.49	12.92
1978	15.05	14.06	13.63	13.26
1979	15.86	14.28	14.12	13.69
1980	16.62	14.74	14.62	14.15
1981	15.83	15.84	15.06	14.72
1982	16.98	16.10	15.33	15.08
1983	14.99	16.48	16.07	15.45
1984	16.31	15.93	16.06	15.52
1985	19.03	16.09	16.15	15.95
1986	15.77	16.78	16.63	16.52
1987	17.55	17.04	16.62	16.50
1988	18.87	17.45	16.73	16.64
1989	18.46	17.40	17.51	17.07
1990	18.63	18.29	17.94	17.28
1991	20.14	18.65	17.86	17.80
1992	19.69	19.08	18.73	18.35

1993	19.16	19.49	19.16	18.44
1994	21.05	19.66	19.22	18.93
1995	20.42	19.97	19.73	19.43
1996	20.77	20.21	20.09	19.65
1997	22.64	20.75	20.22	19.98
1998	21.95	21.28	20.81	20.55
1999	25.2	21.79	21.37	20.81
2000	23.53	23.26	22.20	21.60
2001	22.89	23.56	22.82	22.22
2002	24.16	23.87	23.24	22.49
2003	24.01	23.53	23.55	23.02
2004	26.16	23.69	23.96	23.48
2005	25.48	24.78	24.15	23.99
2006	27.47	25.22	24.54	24.49
2007	24.8	26.37	25.46	24.81
2008	26.88	25.92	25.58	25.00
2009	25.83	26.38	26.16	25.57
2010	28.66	25.84	26.09	25.80
2011	27.45	27.12	26.73	26.47
2012	28.28	27.31	26.72	26.65
2013	28.57	28.13	27.42	27.05
2014	27.57	28.10	27.76	27.21
2015	28.12	28.14	28.11	27.61
2016	30.08	28.09	28.00	27.78
2017	28.84	28.59	28.52	28.39

2018	28.45	29.01	28.64	28.42
2019	29.02	29.12	28.61	28.56

The table displays the wheat production in Pakistan from 1947 to 2019 and the actual production and three-, five-, and seven-year moving averages. To emphasize longer-term trends, moving averages smooth out short-term volatility. For instance, the production of 1949, 1950, and 1951 is averaged to get the 3-year moving average for 1950, which comes out to 8.58. The production during each of the designated periods is averaged to calculate the 5-year and 7-year moving averages. By lessening the effect of yearly changes, these averages aid in the identification of trends. The numbers smooth out and highlight longer-term trends as the moving average's period lengthens, but it also responds more slowly to current changes. The understanding of wheat production trends over time provided by this analysis is helpful for agricultural planning and policy-making.

Table 2 Evaluation of the Performance of Different Methods in Predicating the Wheat Production of Pakistan

Models	Model fit Statistics			Ljung-BoxQ(18)		
	RSME	MAPE	MAE	Statistics	DF	Sig
Holt Model	1.043	5.932	0.803	9.987	16	0.867
Simple Exponential Smoothing Model	1.210	5.971	0.909	15.389	17	0.567
ARIMA Model	1.107	6.059	0.826	12.452	16	0.712

Table 2 The effectiveness of several forecasting techniques in projecting Pakistan's wheat production is assessed in the table. The Holt Model, the Simple Exponential Smoothing Model, and the ARIMA Model are the models evaluated. A variety of statistical measures and the Ljung-Box Q test are used to assess each model. In comparison to the other models, the Holt model has a better fit and fewer mistake, with an RMSE of 1.043, a MAPE of 5.932%, and an MAE of 0.803. With a significance level of 0.867 and a Ljung-Box Q value of 9.987, the residuals do not show any discernible autocorrelations. Higher errors are displayed by the Simple Exponential Smoothing Model, which has an RMSE of 1.210, MAPE of 5.971%, and MAE of 0.909. With a significance level of 0.567 and a Ljung-Box Q statistic of 15.389, it appears to be devoid of substantial autocorrelations. The RMSE, MAPE, and MAE of the ARIMA Model are 1.107, 6.059%, and 0.826, respectively. With a significance level of 0.712 and a Ljung-Box Q statistic of 12.452, there are no discernible autocorrelations.

Table 4: Forecast Values of Wheat Production of Pakistan						
Models	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**
Holt Model Forecast	29.51	29.60	29.69	29.77	29.86	29.95
UCL	31.59	31.74	31.95	32.23	32.58	33.00
LCL	27.43	27.46	27.42	27.32	27.14	26.89
Simple Exponential Smoothing Model						
Forecast	28.89	28.89	28.89	28.89	28.89	28.89
UCL	31.30	31.73	32.10	32.44	32.75	33.03
LCL	26.47	26.04	25.67	25.33	25.03	24.74
ARIMA Model Forecast	29.43	29.69	29.98	30.27	30.55	30.84
UCL	31.63	32.04	32.56	33.04	33.50	33.96
LCL	27.22	27.34	27.40	27.50	27.60	27.71

Table 4 The Holt Model, the Simple Exponential Smoothing Model, and the ARIMA Model are the three models that are used to anticipate wheat production figures for Pakistan from 2020 to 2025. To show the range within which actual values are predicted to fall with 95% certainty, the Holt Model, an extension of simple exponential smoothing, predicts production levels alongside Upper Control Limits (UCL) and Lower Control Limits (LCL). For instance, the Holt Model predicts 29.60 million tons of production in 2021, with an LCL of 27.46 million tons and a UCL of 31.74 million tons. Using weighted averages of past data, the Simple Exponential Smoothing Model predicts similarly and provides UCL and LCL estimates for each year to indicate the degree of prediction uncertainty.

Table 3: Parameter of the Model of the Wheat Production in Pakistan					
Model	Parameter	Estimate	SE	T	Sig
Exponential Smoothing Average	Alpha (Level)	.137	.057	2.405	.019
	Gamma (Trend)	.775	.370	2.097	.040
Holt	Alpha (Level)	.625	.109	5.733	.000
ARIMA	Constant	-6771.05	16.64	-40.31	.000
	Numerators	.347	.008	41.339	.000

The ARIMA Model anticipates production and contains LCL and UCL values. It combines autoregressive, integrated, and moving average components. These projections, which provide insights into possible output levels and associated uncertainties across the forecast horizon, are essential for policy planning, resource allocation, and market expectations.

Conclusion:

This study provides an in-depth analysis of wheat production in Pakistan using advanced time series forecasting models. Data from 1947 to 2019 were gathered from the Food and Agriculture Organization (FAO) to model and forecast wheat production. Three main forecasting techniques were employed: Moving Average, Exponential Smoothing, and ARIMA models. The Moving Average method smoothed the data by calculating averages over three-year periods, which helped in identifying underlying trends and reducing volatility. Exponential Smoothing assigned more weight to recent observations, capturing the significance of recent trends while gradually decreasing the influence of older data. ARIMA models combined autoregressive and moving average components to forecast future values, adjusting for any non-stationary behavior in the time series data. The performance of these models was evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Among the models, Holt's Linear Trend method showed a reasonable upward trend with wide prediction intervals, reflecting historical variability. The Exponential Smoothing model demonstrated a more stable trend, while the ARIMA model forecasted an increasing trend with broader confidence intervals. The results of this study indicate that wheat production in Pakistan has shown a significant increase over the analyzed period. The Holt model was found to have the least generalization error, making it the most accurate for forecasting wheat production in this context. These findings are crucial for policymakers to anticipate cultivation trends, manage wheat supply and demand, and make informed decisions regarding imports and support for farmers. Ensuring optimal yields will be essential for expanding wheat output in the future.

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