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Article

Future Projections of Iraq's Cereal Yields Using Wavelet-Arima Model

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Abstract

This study presents an enhanced forecasting methodology for Iraq`s cereal production by integrating wavelet denoising with ARIMA modeling. Using annual production data (58 observations from 1961-2018), we demonstrate that preprocessing with the Daubechies wavelet of order 2 and soft thresholding significantly improves forecast accuracy by isolating noise while preserving trends. Our proposed wavelet-ARIMA hybrid model outperforms classical ARIMA across some statistical criteria (RMSE and AIC), achieving an increase in predictive precision through optimized signal decomposition. Empirical results reveal that wavelet analysis constructs latent patterns in fluctuating agricultural data that traditional methods overlook, enabling more reliable long-term projections. Based on this framework, Iraq`s cereal yields are forecasted to stabilize approximately at 4.03 million metric tons annually for the years 2019-2025, with a narrower confidence interval than ARIMA alone. These results provide mainly two important contributions. Firstly, a procedure that was validated for denoising of non-stationary agricultural time series, which is often affected by random noise. Secondly, it brings useful recommendations for decision-makers to mitigate the risks that are related to food security, especially in dry climate areas. The adaptability of the proposed method indicates that it can also be applicable to other product forecasting, where the volatility in data makes traditional techniques less effective.

Keywords: Forecasting; Cereal Production; Wavelet-ARIMA; Box-Jenkins

1. Introduction

Agricultural production in Iraq remains one of the major parts of the national economy, offering employment and food sources for a large part of the population. As reported by the International Food and Agriculture Organization (FAO), the main cereal crops grown in Iraq are wheat, barley, rice, and other grains. The country's agriculture mostly depends on cereal crops to maintain both food availability and macroeconomic stability. However, Iraq has experienced difficulties in sustaining and raising cereal production due to various factors, including water scarcity, increasing soil salinity, and periods of political instability. Despite such challenges, significant progress has achieved by introducing modern farming methods, improving agricultural technologies, and adapting a high-yield variety of crops[1]. These developments have contributed to keeping the food supply and supporting rural livelihoods.

Several earlier studies have attempted to forecast agricultural production in Iraq using different methods. In 2016, one study was conducted to analyze the impacts of climate change time-series data on Iraq's agriculture sector, including pattern changes in rainfall and temperature. The research highlighted the importance of adaptation strategies to reduce the negative effects of climate change on crop productivity[2]. In the following year, a study applied the

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ARIMA model to forecast the wheat production in Iraq for 2017. The model achieved acceptable results in estimating yield under several market conditions [3]. In 2018, researchers used a grouped method for predicting cotton production depending on climate conditions, and the model performed effectively under different weather variations[4]. In the same year, the Box -Jenkins approach was employed to estimate Iraq's food production and the existing gap. The selected models were ARIMA (1,0,1) for the gap and ARIMA (4,1,3) for production data. Although production was increased, the food gap remained by 2025, which required continuing imports due to unmet demand[5].

Later studies emphasized the state support and introduction of modern agricultural technologies to boost cereal production and improve the food security situation in the country[6]. In 2020, the water footprint method was applied to examine cereal crops (wheat, rice, barley, and maize), showing that the import policy saved nearly 2,676 Mm^3 water yearly and recommending more water-saving farming practices[7]. In the same year, another research was carried out using the data from 1988 up to 2018, where the ARIMA (1,0,1) model was used for forecasting wheat production in Iraq. The results showed that this strategy is effective for agricultural time series forecasts, and it predicted about 0.94% yearly increase in wheat yield till the year 2028[8]. Another study that was done in 2023 investigated the food gap in Iraq from 2003 to 2020. It revealed that the country's major crops faced a deficit ranging between 48% and 100%, mostly due to improper policies, insufficient water availability, and the problem of national security. The conclusion of that study stated that economic restructuring is urgent and food security is at high risk[9]. Then, in 2024, other researchers developed a hybrid ARIMA-ML model to forecast the wheat production between 2024 and 2033 in Iraq. The results proved that the hybrid model gave more accurate predictions than traditional ARIMA, especially for nonlinear time-series data when evaluated using RMSE[10]. At a similar time, another study applied the ARIMA (0,1,1) model to predict the average annual cereal production for the upcoming three years. The findings confirmed that the ARIMA method has strong potential for agriculture policy decision-making[11]. Another study in 2024 applied ARIMA models to assess Iraq's barley self-sufficiency and food gap from 1990-2022. The best-fitting models, ARIMA (5,0,1) for self-sufficiency and ARIMA (8,0,8) for the food gap, both indicate a persistent domestic production deficit that requires targeted agricultural policies[12].

In very recent year specially in 2025, the authors used ARIMA modeling to forecast barley production in Iraqi Kurdistan. After stabilizing non-stationary data from 1981 to 2023, the ARIMA (1,2,1) model was selected. The forecasts for 2024-2030 predict a declining trend, highlighting a need for policy intervention[13]. Furthermore, in the most recent study in 2025, the ARIMA (1,1,1) model was used for the prediction of rice production in Iraq until 2027. This analysis underlined the existing uncertainty due to external factors and recommended using more improved models and sustainable approaches for achieving food safety [14]. In the same year, the researchers forecasted global barley production for 2025-2035 using country-level ARIMA models. The results show a geographic shift, with production shares rising in countries like Turkey, Russia, and Australia, while declining in traditional producers like the US, Germany, and Canada. This analysis underlined the existing uncertainty due to external factors and recommended using more improved models and sustainable approaches for achieving food safety[14].

This study is driven by the urgent need of more precise forecast of cereal production in Iraq, as a support for future food security strategies. Also, it comes due to the current limitation of ARIMA models in dealing with non-stationary data, which is very common in agricultural time series. In addition, the wavelet decomposition technique is proposed as it can enhance prediction accuracy and still keep interpretability. The study's remaining sections are arranged as follows. The study's methodology will be covered in sections 2 and 3. The actual data will be subjected to the Box-Jenkins methodology and wavelet analysis in Section 4. Section 5 will end with a few conclusions as well as recommendations.

2. Box-Jenkins Method

The Box-Jenkins technique is a systematic strategy for selecting, fitting, and validating autoregressive integrated moving average (ARIMA) models for time series data. This method consists of three main stages: identification, estimation, testing, and application [15] [16].

2.1. Stages of Box-Jenkins Methodology

2.1.1. Identification

The Box-Jenkins approach initiates with data preparation, involving cleaning data from outliers, transformations to stabilize variance, and differencing to achieve stationarity in mean, or both if required. Subsequently, an optimal time series model is identified by specifying the autoregressive order(p), differencing degree(d), and moving average order(q). The key diagnostic tools for model selection include the autocorrelation function (ACF) and partial autocorrelation function (PACF). The autoregressive integrated moving average model, denoted as ARIMA(p,d,q), provides a structured framework for this analysis. This systematic process ensures robust time series forecasting[17],

$$\emptyset(\beta)\,(1-\beta)^d\,Y_t = \theta(\beta)\,\varepsilon_t \qquad (1)$$

Here, Y_t is observed time series data at time t, β is the backshift operator ($\beta\, Y_t = Y_{t-1}$), both $\phi(B)$ and $\theta(B)$ represent the autoregressive AR and moving average MA operators, respectively, ε_t is a white noise error term at time t,[15].

2.1.2. Estimation and Testing

Following model identification, the parameter estimation phase commences. The procedure employs either least squares estimation (LSE) or maximum likelihood estimation (MLE) as primary techniques. Subsequently, the ARIMA model`s mathematical formulation is derived, representing the time series structure through its characteristic AR and MA components.

$$Y_t = C + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_q\varepsilon_{t-q} \qquad (2)$$

Here: c is a constant term, $\emptyset$ and θ are unknown parameters, the p and q terms represent the lagged values of AR and MA, respectively, and ε_t represents the error term. The best model will be selected depending on suitable criteria such as the Root Mean Square Error RMSE, and Akaike`s Information criterion AIC [15],[18]. After parameter estimation, the model must be checked to guarantee that its residuals are white noise. This includes checking the residuals' ACF and PACF plots and doing the Ljung-Box Q test to ensure there is no substantial autocorrelation left [19], [20], [21].

2.1.3. Application

The forecasting phase generates future values. This includes point estimates and confidence intervals using the validated model. The final stage applies the derived time series patterns to produce statistically sound predictions. Rigorous validation and evaluation of forecasts are critical to ensure model reliability and practical utility. Ultimately, this process transforms analytical insights into actionable projections while maintaining statistical robustness [22].

3. Wavelet Analysis Method

Wavelet analyses have become an essential tool for simultaneously examining signals in both time and frequency domains, offering valuable multidimensional insights [23]. Wavelet analysis overcomes Fourier analysis`s key limitation by providing localized time-frequency representations, unlike Fourier`s global mapping, which lacks frequency-specific-temporal resolution for non-stationary processes. This enables a more precise characterization of transient signal features. [24]. According to [25], wavelet analysis is a mathematical technique that transforms time-domain signals into alternative representations for enhanced processing. This method proves particularly effective for non-stationary data characterized by time-varying means and autocorrelations. Given that, most time series data, including agricultural datasets, exhibit nonstationary behavior, wavelet transforms have become essential analytical tools for such applications.

Morlet originally formulated wavelets as a family generated through translations and dilations of a signal "mother wavelet". If the x(t) represents a signal, the wavelet transform can be expressed as:

$$\Psi_*^{\psi}(x,a) = \int x(t).\psi_{b,a}^*\,(t)d(t) \qquad (3)$$

Where:

$$\psi^*{}_{b,a}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)\ ; a,b \in R; a \neq 0 \qquad (4)$$

When substituting this description in equation (3) gives the definition of the continuous wavelet transform CWT.

$$CWT_x^{\psi}(b,a) = \frac{1}{\sqrt{a}} \int x(t).\psi\left(\frac{t-b}{a}\right) d(t) \qquad (5)$$

The degree of compression is measured by the parameter " a" often known as the scaling parameter or scale (dilation). The translation parameter (shift), denoted by " b," establishes the wavelet's time frame location. The wavelet in " a " is a compressed form of the mother wavelet $\psi(t)$ (reduced support in the time domain) and mostly corresponds to higher frequencies if $\lfloor a \rfloor < 1$. $\psi_{a,b}(t)$ correlates to lower frequencies and has a wider time width than $\psi(t)$ when $\lfloor a \rfloor > 1$. The effectiveness of Morlet wavelets in signal processing and time-frequency analysis stems from their frequency-adaptive time widths, which enable precise localization of signal features across varying temporal and spectral scales.

The wavelet transform is implemented using a multiresolution pyramidal decomposition approach. By applying a pair of complementary filters, a high-pass filter (HiF-D) and a low-pass filter (LoF-D), a recorded digital time signal $S(n)$ can be decomposed into its detailed $cD1(n)$ and approximation $cA1(n)$ components, respectively. Analogous to the discrete Fourier transformation in spectral analysis, the discrete wavelet transformation (DWT) serves as the foundational tool for wavelet-based time series analysis [26]. For discrete-time applications, the discrete wavelet transform (DWT) is used. This transform is grounded in sub-band coding, enabling efficient computation of wavelet transforms. This method is computationally economical, requiring minimal resources and reduced processing time. For a given real-world dataset $\{Y_j\}$, dynamic decomposition can be performed by defining the scale parameter "a" as 2^{-j} and the translation parameter "b" as $K.2^{-j}$, where $j, k \in Z$. Under this framework, a discrete wavelet function can be mathematically expressed as follows:

$$\psi_{j,k}(t) = \frac{1}{2^j}\psi\left(\frac{1-K2^j}{2^j}\right) \qquad (6)$$

3.1. Combined Wavelet-Arima Model

Since ARIMA models require stationary input data, noise in time series significantly degrades forecasting accuracy [27]. To address this limitation, a wavelet-based denoising framework is proposed. The selection of decomposition levels is critical, as it directly influences model performance in wavelet space [28]. The following steps outline the wavelet-enhanced ARIMA methodology [29]:

1. Decomposition: The observed time series is transformed into wavelet space using (DWT).
2. Thresholding: Wavelet coefficients are modified via a selected shrinkage function and threshold criterion. Coefficients below the threshold are either reduced or zeroed to suppress noise.
3. Reconstruction: The denoised coefficients are inverted via inverse (DWT) ($IDWT$), yielding a smoothed signal with minimized noise.
4. Modeling: The ARIMA model is applied to the refined data.

Figure 1, summarizes this hybrid denoising and modeling framework. By isolating and filtering high-frequency noise, wavelet preprocessing enhances ARIMA`s robustness to non-stationarity while preserving structural patterns.

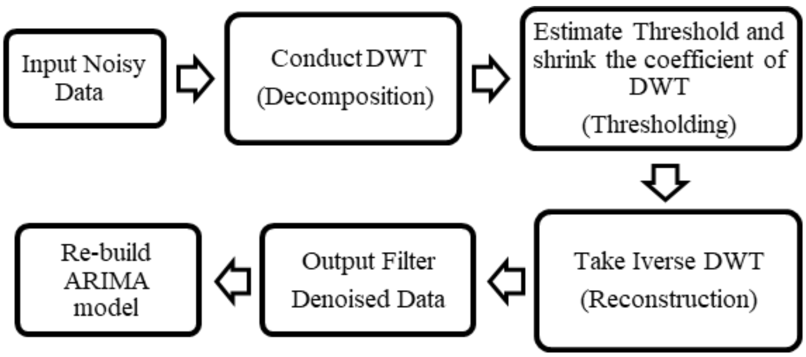

Figure 1. Building ARIMA model using wavelet denoising

3.2. Combined Wavelet-Arima Model

The wavelet transform possesses a decorrelation property, such that coefficients across different levels exhibit minimal to no correlation. This occurs because the transformation from the original series to wavelet coefficients to each level effectively functions as a pass-band filter (Wavelet Threshold Estimators for Data with Correlated Noise (PDFDrive), n.d.) Consequently, a distinct threshold λj must be established for each decomposition level j. Various thresholding strategies exist, including the Rigorous SURE, Minimax, and Universal approaches. This study employs the Rigorous SURE threshold (RST), also known as SURE shrink, which utilizes Stein's Unbiased Risk Estimate criterion to derive a statistically unbiased threshold. The (RST) algorithm optimizes threshold selection by minimizing the estimated risk, making it suitable for noise reduction in wavelet-based signal processing [31].

3.3. Hard and Soft Thresholding

Wavelet coefficients at level *j* are subjected to either hard or soft thresholding after threshold estimation. Hard thresholding follows a "keep or kill" principle: Coefficients below the threshold are set to zero while others remain unchanged. In contrast, soft thresholding shrinks all nonzero coefficients toward zero, yielding a smoother denoised [32]. Empirical evidence demonstrated that soft thresholding achieves lower variance compared to hard thresholding [33]. Consequently, this study exclusively uses soft thresholding to optimize the ARIMA model`s performance on the dataset. The approach enhances noise reduction while preserving essential signal characteristics, which improves forecasting accuracy.

3.4. Using Wavelet Families

Various wavelet families (e.g., Haar, Daubechies, Coiflets) are applicable for denoising. This study employs the Daubechies wavelet. This is an extension of the Haar wavelet with multiresolution levels, selected for its advantageous properties: smoothness, orthogonality, vanishing moments, and compact support. These features enable effective pattern extraction and noise reduction in annual cereal data, ensuring robust analysis [34].

4. Application on Real Data

The study analyzes annual cereal yield data from Iraq (1961-2018), comprising (58) observations as shown in figure2. The dataset retains actual values for 2019-2022 to validate forecast accuracy through comparison with predicted values. Source data were obtained from the United Nations Database (Metadata-Countries, World Bank). This temporal division enables robust model evaluation while maintaining sufficient observations for statistical significance.

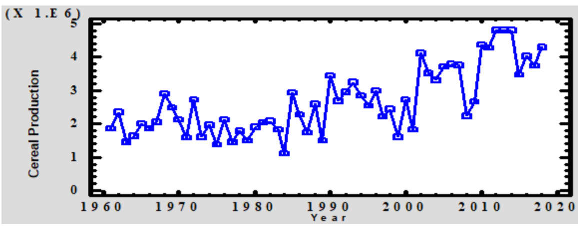

Figure 2. Annual time series for cereal yields in Iraq

Figure 2 reveals non-stationary characteristics in Iraq`s cereal production time series, exhibiting both oscillatory behavior and a consistent upward trend. Initial production of (1847205) tons in 1961 rose sharply to (2332325) tons in 1962, ultimately reaching (4290625) tons in 2018. The ACF as shown in Figure 3 demonstrates gradually decaying autocorrelation coefficients, while the PACF as presented in Figure 4 shows an abrupt cutoff after two significant lags, both indicative of non-stationarity. This is further confirmed by the Ljung-Box Portmanteau test (Q = 154.694, $p < 0.01$ at 19 lags), demonstrating highly significant autocorrelation. These diagnostic results collectively suggest the need for differencing to achieve stationarity before modeling.

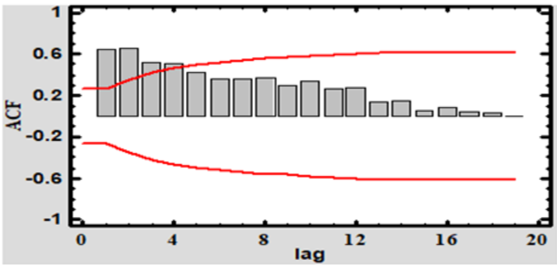

Figure 3. ACF of annual cereal yields in Iraq

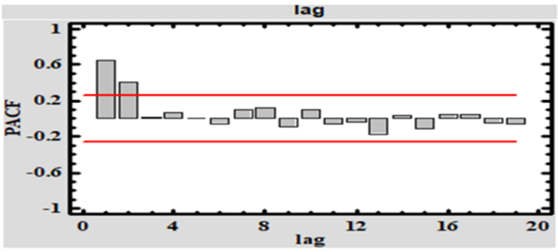

Figure 4. PACF of annual cereal yields in Iraq

4.1. Stationarity test for the time-series data

The stationarity of time series data is evaluated using the augmented Dicky-Fuller (ADF) test, complemented by ACF/PACF analysis [35]. The test examines two hypotheses:
H_0: The series contains a unit root (non-stationary)
H_1: The series lacks a unit root (stationary)
The ADF stationary patterns test findings are displayed in Table 1.

Table 1. Findings of the ADF test

Significant Level		Alpha = 0.05
Time Series	**ADF**	**After the First Difference**
Cereal Production Data	**-2.872**	**-4.951**
P-Value	**0.223**	**0.010**

The ADF test results as presented in Table 1 indicate non-stationarity in cereal production data (test statistic = -2.872, p = 0.223 at α = 0.05). The first differencing achieved stationarity (test statistic = -4.951, p = 0.01). Preliminary Levene`s test revealed significant variance non-stationarity (L = 13.169, p = 0.001), requiring logarithmic transformation before differencing. Post-transformation ACF/PACF examination confirmed that first differencing is still required to stabilize the mean.

Figures 5-6 present the transformed series and corresponding correlogram after these preprocessing steps. This two-stage stabilization approach, logarithmic transformation for variance stabilization followed by differencing for mean stabilization, aligns with standard time series preprocessing protocols when handling multiplicative non-stationarity. The final transformed series demonstrates characteristics suitable for subsequent ARIMA modeling, with both variance and mean fluctuations now appropriately controlled. The methodological validity in addressing both variance and mean non-stationarity ensures more reliable parameter estimation and forecasting performance.

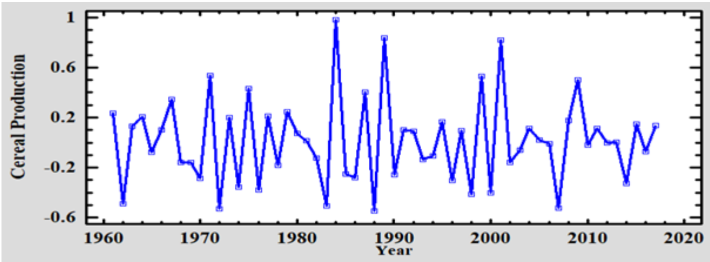

Figure 5. The transformed series

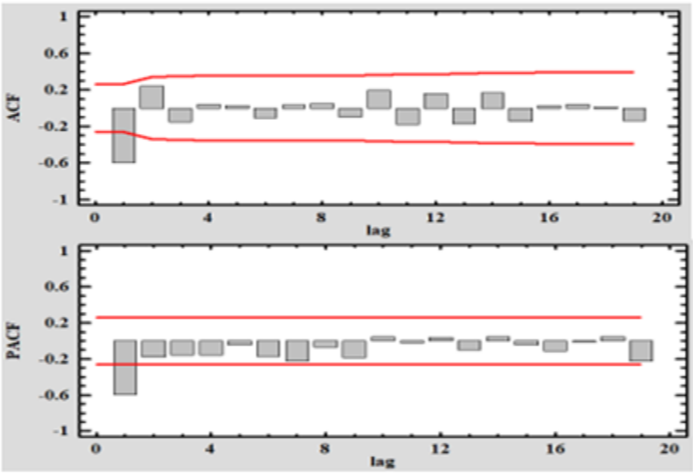

Figure 6. ACF and PACF of log of data after 1st differencing

4.2. Building an ARIMA Model

4.2.1. Model Identification Stage:

Following stationarity confirmation and analysis of ACF/PACF patterns as presented in Figure 5, multiple candidate models were evaluated. After testing various ARIMA model specifications, ARIMA (0,1,1) emerged as the best fit. It consistently delivered the lowest AIC and RMSE values, meaning it was not only simpler but also more accurate in its predictions compared to alternatives like ARIMA (1,1,1) and (1,1,0). This balance of simplicity and precision led us to select it for the final analysis. In other words, the ARIMA (0,1,1) specification demonstrated superior performance, exhibiting lowest RMSE (696931) and AIC (26.943) values among competing models as shown in Table 2. These selection criteria confirm its optimal balance of model simplicity and predictive accuracy for the analyzed time series.

Table 2. The chosen model relied on statistical criteria with the lowest values

Model	Criteria	
	RMSE	AIC
ARIMA (0,1,1)	**696931**	**26.943**
ARIMA (1,1,1)	**704717**	**27.001**
ARIMA (1,1,0)	**701264**	**26.956**

4.2.2. Model Estimation Stage:

The ARIMA (0,1,1) model was selected based on ACF/PACF analysis and statistical criteria. As presented in Table 3, its moving average (MA) parameter is statistically significant ($p<0.05$), confirming the model`s robustness for the stationary time series.

Table 3. Results of estimating the best model

The Ideal Model	Parameter	Standard Error S.E.	T-Value	P-Value
ARIMA (0,1,1)	**MA = 0.729**	**0.092**	**7.940**	**0.000**

4.2.3. Model diagnosis Stage:

Figure 7 demonstrates that the standardized residuals of the ARIMA (0,1,1) model exhibit random dispersion around zero, with ACF/PACF values statistically dominant within 95% confidence bounds. The Ljung-Box test (Q =12.515, p = 0.820) confirms no significant residual autocorrelation (α = 0.05). These diagnostic results collectively validate the model`s adequacy for characterizing Iraq`s cereal production dynamics, as all assumptions of white noise residuals are satisfied.

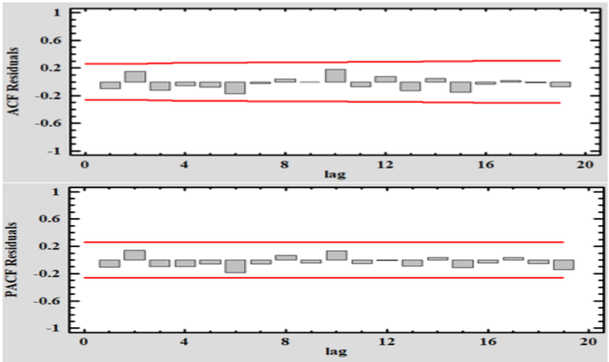

Figure7: Standard residuals of ACF and PACF for ARIMA (0,1,1) model

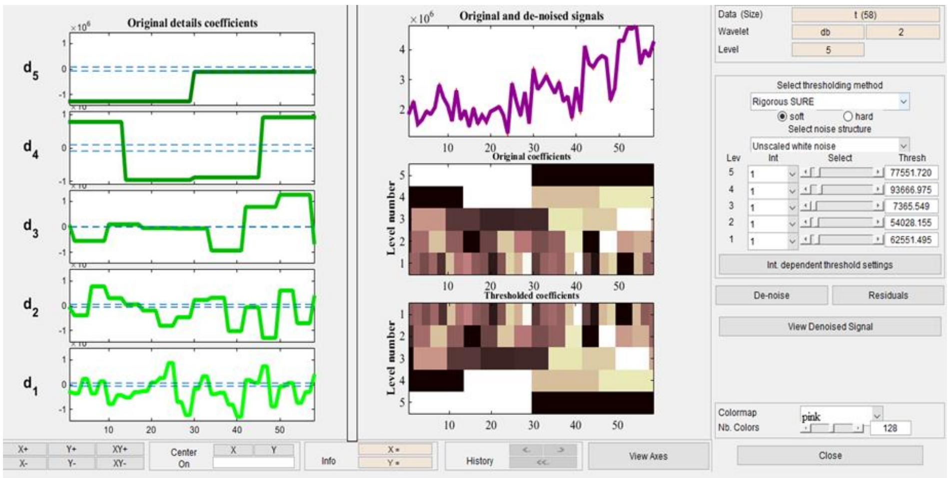

Figure 8. Daubechies2 wavelet with Rigorous SURE threshold at level 5 and soft rules for the cereal yields data

4.3. Enhancing the ARIMA model with the use of a wavelet filter for the cereal yields data

Following the ARIMA model selection for cereal yield data, wavelet denoising was applied to reduce noise contamination in the time series. MATLAB facilitated wavelet analysis using Haar, Daubechies, and Coiflets filters, coupled with the Rigorous SURE Threshold (RST) method under soft thresholding. The denoised series was then reconstructed for ARIMA forecasting. Figure 8 illustrates the Daubechies-2 wavelet filter implementation with RST and the soft threshold rule. This hybrid approach enhances signal clarity by suppressing high-frequency noise while preserving structural patterns, thus improving forecast reliability.

The time series data were transformed into the frequency domain and processed with wavelet filters of varying orders and threshold levels, employing both hard and soft thresholding approaches. In most cases, the filtering preserved the original observations, resulting in statistically equivalent model performance. However, a subset of configurations yielded below-ideal performance results compared to the unfiltered data. Notably, a single configuration Daubechies-2 wavelet decomposition at level 5 with a Rigorous SURE threshold (RST) under a soft thresholding rule demonstrated statistical improvement. For this optimal case, the ARIMA (0,1,1) model fitted to filtered data showed enhanced performance metrics: the Akaike Information Criterion AIC decreased from (26.943) to (26.790), while the Root Mean Square Error RMSE reduced from (696931) to (645569). These improvements indicate superior predictive accuracy relative to the classical model. Table 4 presents a comparative analysis of the original and filtered models' statistical criteria, specifically highlighting the efficacy of the second-order Daubechies wavelet with RST under soft thresholding at level 5. This finding suggests that the selective application of wavelet denoising can enhance ARIMA model performance. However, the effect is highly dependent on the specific filter configuration and thresholding parameters. The results highlight the importance of methodical parameter selection in wavelet-based preprocessing for time series analysis.

Table 4: The criteria values of the original ARIMA (0,1,1) model and filtered model

Model	RMSE	AIC
ARIMA (0,1,1) Original	**696931**	**26.943**
ARIMA (0,1,1) Using RST Daubechies 2-Soft	**645569**	**26.790**

4.4. Forecasting using a wavelet – ARIMA model

Table 5. shows the forecast values till 2025 with their lower and upper confidence interval.

Table 5. Forecast values using the Wavelet - ARIMA (0,1,1) model

Year	True Value	Forecast	Lower Limit 95%	Upper Limit 95%
2019	5934964	4034420	2467620	6596060
2020	2901824	4034420	2418600	6729750
2021	5302192	4034420	2372350	6860960
2022	3421743	4034420	2328560	6989980
2023		4034420	2286970	7117080
2024		4034420	2247380	7242460
2025		4034420	2074670	7843810

Table 5 presents projected cereal yields for Iraq (2019-2025) using the ARIMA (0,1,1) model, validated against observed values (2019-2022). The 2019 prediction (4034420 metric tons) closely approximates the actual yield (5934964 tons), with all observed values falling within a 95% confidence interval. This alignment confirms the hybrid wavelet-ARIMA (0,1,1) model`s suitability for Iraqi cereal production forecasting. Projections indicate an average annual output of (4034420 tons) during 2019-2025. The model`s robustness is evidenced by its consistent performance across both historical and prediction periods, suggesting reliability for medium-term agricultural planning.

5. Conclusions and Recommendations

5.1. Conclusions

The study concludes that:

1. The optimal model for forecasting Iraq`s annual cereal yields is ARIMA(0,1,1).
2. Wavelet-enhanced ARIMA (0,1,1) using Daubechies-2 with Rigorous SURE Threshold (RST) based on soft thresholding rule significantly improves forecast accuracy.
3. Projected cereal production (2019-2025) averages (4034420 metric tons) annually, demonstrating the model`s robustness for agricultural planning.

5.2. Recommendations

1. Implement forecast-strategic policies to enhance cereal yield sustainability and food security.
2. Maintain model accuracy through periodic updates with recent observational data.
3. Conduct a comparative employing alternative methods (e.g., artificial neural networks, ANN) to validate and improve forecasting reliability.
4. Adding simulations in future studies to test the model`s performance with artificial data, ensuring reliability before real-world use.

References

1. FAO Crop Prospects and Food Situation; FAO, 2022;
2. Kader, J.; Al-Khaza'aleh, A.M.; Al-Shamma'a, R.M. Climate Change Impact on Agriculture in Iraq: A Review. Journal of Environmental Science and Health **2016**, 51, 131–144.
3. Jaber, R.M.; Al-Hussaini, E.; Al-Bakri, A.H. Agricultural Production Forecasting Using ARIMA Model: Case Study of Wheat Crop in Iraq. Journal of Agricultural Economics and Development **2017**, 6, 1–10.
4. Al-Ani, H.M.; Al-Bayati, M.A.; Al-Rawi, J.M. Weather Forecasting and Crop Yield Prediction for Cotton in Iraq Using Ensemble Approach. Journal of Agricultural Engineering Research **2018**, 24, 241–253.
5. Mustafa, I.K.; Jbara, O.K. FORECASTING THE FOOD GAP AND PRODUCTION OF WHEAT CROP. Iraqi Journal of Agricultural Sciences **2018**, 4, 560–568.
6. Sultan, W.; Mohammed, B.; Rasheed, M.; Ali, Y. The Reality of the Production of the Main Cereal Crops in Iraq and Their Impact on Food Security for The Period (1995-2016). Tikrit Journal for Agricultural Sciences **2019**, 19, 80–90, doi:10.25130/tjas.19.3.11.
7. Ewaid, S.H.; Abed, S.A.; Al-Ansari, N. Assessment of Main Cereal Crop Trade Impacts on Water and Land Security in Iraq. Agronomy **2020**, 10, doi:10.3390/agronomy10010098.
8. Salah Madlul, N.; Al-Najjar, Y.; Tariq Baker, Y.; Irhaim, F.I. USING THE ARIMA MODELS TO PREDICT WHEAT CROP PRODUCTION IN IRAQ. Int. J. Agricult. Stat. Sci **2020**, 16, 121–127.
9. Hameed, O. The Food Gap of the Most Important Agricultural Products in Iraq for the Period 2003-2020 and Ways to Face It. Journal of Namibian Studies **2023**, 33.
10. Al-Sammarraie, H.K.R.; Hameed, L.M.A. Using a Hybrid Model (EVDHM-ARIMA) to Forecast the Average Wheat Yield in Iraq. Journal of Economics and Administrative Sciences **2024**, 30, 517–536, doi:10.33095/6afw4112.
11. Abdulqader, Q.M.; Ahmed, N.M. Forecasting The Annual Cereal Production of Iraq Using Arima Methodology. In Proceedings of the Proceedings of International Conference of Applied Physics and Mathematics, Budapest, Hungary; Research world, October 2024; pp. 1–5.
12. Nouri, H.H.; Gasim, O.A. Predicting the Food Gap and the Amount of Self-Sufficiency for the Barley Crop in Iraq for the Period (2024-2035). In Proceedings of the IOP Conference Series: Earth and Environmental Science; Institute of Physics, 2024; Vol. 1371.
13. Kızılcan, N.K.; Altuntaş, B. Global Barley Production 2025–2035: Forecasting Market Shifts and Policy Implications for Emerging Producers. Journal of Agricultural Faculty of Gaziosmanpasa University **2025**, 42, 274–283, doi:10.55507/gopzfd.1709119.
14. Mahmood, M.M.; Yasin, M.R.; Rasul, K.M.A.; Surchy, S.M. Forecasting Rice Production in Iraq (1961-2022) Using the ARIMA Model. European Journal of Theoretical and Applied Sciences **2025**, 3, 131–141, doi:10.59324/ejtas.2025.3(1).12.

15. Salie Ayalew, S.A. Comparison of New Approach Criteria for Estimating the Order of Autoregressive Process. IOSR Journal of Mathematics **2012**, 1, 10–20, doi:10.9790/5728-0131020.
16. Wei, W.W.S. Time Series Analysis _ Univariate and Multivariate Methods; 2nd edition.; Pearson, 2006; ISBN 0-321-32216-9.
17. Box, G.E.P.; Jenkins, G.M.; C, R.G.; Ljung, G.M. Time Series Analysis: Forecasting and Control; Fifth edit.; WILEY, 2015; ISBN 9781118675021.
18. Polhemus, N.W. Time Series Analysis Using Statgraphics Centurion; 2011;
19. Hamilton, J.Douglas. Time Series Analysis James D. Hamilton; Princeton University Press, 2006; ISBN 0691042896.
20. Brockwell, P.J.; Davis, R.A. Introduction to Time Series and Forecasting - Second Edition; 2002; ISBN 9780387781884.
21. Makridakis S, Wheelwright SC, H.R. Forecasting Methods and Applications; Third.; Jhon Wiley and Sons,INC., 1997;
22. Enders, W. Applied Econometric Time Series (PDFDrive); Fourth.; John Wiley & Sons, Inc, 2015; ISBN 978-1-118-80856-6 (pbk.).
23. Nourani, V.; Alami, M.T.; Aminfar, M.H. A Combined Neural-Wavelet Model for Prediction of Ligvanchai Watershed Precipitation. Eng. Appl. Artif. Intell. **2009**, 22, 466–472, doi:10.1016/j.engappai.2008.09.003.
24. Pal, S.; Devara, P.C.S. A Wavelet-Based Spectral Analysis of Long-Term Time Series of Optical Properties of Aerosols Obtained by Lidar and Radiometer Measurements over an Urban Station in Western India. J. Atmos. Sol. Terr. Phys. **2012**, 84–85, 75–87, doi:10.1016/j.jastp.2012.05.014.
25. Dong, Z.; Guo, X.; Zheng, J.; Xu, L. Calculation of Noise Resistance by Use of the Discrete Wavelets Transform. Electrochem. commun. **2001**, 3, 561–565.
26. Percival, D.B.; Walden, A.T. Wavelet Methods for Time SeriesAnalysis. Wavelet Methods for Time SeriesAnalysis 2000.
27. Shan, R.; Shi, S.; Liu, W. Forecasting Model for Stock Data Based on New Wavelet and Conjugated-ARIMA Combination Model. Journal of Computer Information System **2014**, 10, 3023–3030.
28. Wang, W.; Ding, S. Wavelet Network Model and Its Application to the Prediction of Hydrology. Nat. Sci. (East Lansing). **2003**, 1, 67–71.
29. Burrus, C.S.; Gopinath, R.A.; Guo, H. Introduction to Wavelets and Wavelet Transforms: A Primer; 1998; ISBN 0134896009.
30. Wavelet Threshold Estimators for Data with Correlated Noise (PDFDrive).
31. Cascio, I. Lo Wavelet Analysis and Denoising: New Tools for Economists; Queen Marry Press, Ed.; London, 2007;
32. Misiti, M.; Misiti, Y.; Oppenheim, G.; Poggi, J. Wavelet Toolbox For Use with M ATLAB; Wellesley Cambridge Press, 1996;
33. Bruce, A.G.; Gao, H.Y.E. Understanding WaveShrink: Variance and Bias Estimation. Biometrika **1996**, 83, 727–745, doi:10.1093/biomet/83.4.727.
34. Daubechies, Ingrid. Ten Lectures on Wavelets; Society for Industrial and Applied Mathematics, 1999; ISBN 0898712742.
35. Mohamed, J. Time Series Modeling and Forecasting of Somaliland Consumer Price Index: A Comparison of ARIMA and Regression with ARIMA Errors. American Journal of Theoretical and Applied Statistics **2020**, 9, 143, doi: 10.11648/j.ajtas.20200904.18.