A Comparison of ARIMA and GVM(1,1) models for Forecasting Rice Production in Iraq

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Abstract

Time series forecasting is a statistical method, involves analyzing past data patterns to predict future values. It is widely applied in various fields. This research compared the forecasting performance between ARIMA model and the Grey Verhulst Model GVM(1,1) model to determine the best method to forecast the rice production in Iraq. The data was obtained from the "International Production Assessment Division (IPAD)" website. The performance of the two models will be evaluated using various metrics, such as root mean square error (RMSE) and mean absolute percentage error (MAPE). From the result of the forecasting accuracy based on RMSE and MAPE showed that the values of RMSE and MAPE of ARIMA (1,1,2) model is smaller than the values of GVM(1,1). it can be concluded that the performance of ARIMA is better than GVM (1,1) to forecast the rice production in Iraq.

Keyword: Time series, ARIMA Model, Grey Verhulst Model.

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1. Introduction

Data classification methods are one of the most widely used in statistical methods and forecasting agricultural production is critical for ensuring food security [10], optimizing resource allocation, and stabilizing markets. Rice, as a staple food crop, plays a significant role in the diets of millions of people worldwide, including Iraq. Accurate forecasting models for rice production can help policymakers, farmers, and stakeholders make informed decisions to improve crop management, enhance supply chain efficiency, and respond effectively to climatic and economic changes. In the realm of forecasting, several statistical and mathematical models are employed to predict agricultural outputs. Among these, the Auto Regressive Integrated Moving Average (ARIMA) model and the Grey Verhulst Model (VGM(1,1)) are widely recognized for their robustness and applicability. This introduction delves into the fundamental principles of these models, their respective strengths and weaknesses, and their relevance in the context of rice production forecasting in Iraq.[6]

The ARIMA model, introduced by Box and Jenkins in the 1970s, is a versatile tool for analyzing and forecasting time series data. ARIMA integrates three key components: auto regression (AR), differencing (I), and moving average (MA)[2]. The autoregressive component captures the relationship between an observation and a number of lagged observations. The integrated component involves differencing the observations to make the time series stationary, which means its statistical properties like mean and variance are constant over time. The moving average component models the relationship between an observation and a residual error from a moving average model applied to lagged observations. The ARIMA model is particularly effective for linear time series data and can accommodate various data patterns and trends through appropriate selection of its parameters (p, d, q). These parameters denote the order of the autoregressive part, the degree of differencing, and the order of the moving average part, respectively. The model's flexibility makes it suitable for diverse applications, from economic forecasting to environmental data analysis[3].

The ARIMA model stands out for its versatility, capable of modeling a wide range of time series patterns, including trends and seasonality. This adaptability makes it a robust tool for various applications. Furthermore, ARIMA benefits from extensive literature and software support, with abundant resources and packages available, making it highly accessible for practitioners. Its proven accuracy is widely validated across different fields, underscoring its effectiveness in producing reliable forecasts. However, ARIMA does have some drawbacks. One significant challenge is the complexity in model selection; choosing the right parameters (p, d, q) can be time-consuming and requires a certain level of expertise. Additionally, ARIMA performs best with extensive historical data, which may not always be available, posing a limitation for datasets with fewer observations. Another challenge is the requirement for stationarity in the data, necessitating transformations to make the series stationary, which can complicate the modeling process.[11]

The Grey Verhulst Model (VGM(1,1)), part of the Grey Systems Theory, was developed by Julong Deng in the 1982s [3]. Grey Models are designed to handle systems with partially known information, making them highly suitable for small datasets and situations with uncertainty [1]. The VGM(1,1) model is a specific type of Grey Model tailored for forecasting nonlinear time series data that exhibit exponential growth or saturation trends. The Verhulst model is a differential equation-based model that describes the growth process in a constrained environment. It captures the S-shaped logistic growth curve, which is characterized by an initial slow growth phase, followed by a rapid growth phase, and finally a saturation phase where growth slows down as it approaches a maximum limit [4].

The Grey Verhulst Model (VGM(1,1)) is highly effective with small datasets, making it particularly valuable for agricultural studies where data is often limited. Its design is tailored for handling nonlinear growth patterns, which makes it suitable for biological and ecological data[14].

Additionally, VGM(1,1) demonstrates robustness to incomplete information, performing well in scenarios characterized by uncertainty and partial data. However, the model has its limitations; it is best suited for data exhibiting logistic growth and may not perform well with purely linear data[15].

Furthermore, compared to ARIMA, there is less familiarity and support for VGM(1,1), with fewer available literature and software tools. In the context of rice production forecasting in Iraq, these strengths and weaknesses play a significant role. Rice production in Iraq is influenced by a variety of factors including climatic conditions, water availability, agricultural practices, and socio-economic dynamics. Given the country's diverse agro-ecological zones, accurate forecasting models like VGM(1,1) are essential for effective agricultural planning and policy-making, helping stakeholders navigate the complexities of rice production and ensure food security[9].

Both ARIMA and VGM(1,1) models have unique strengths and limitations that make them suitable for different aspects of rice production forecasting in Iraq[7]. While ARIMA excels in linear and seasonal trend analysis with extensive data, VGM(1,1) is advantageous in situations with nonlinear growth patterns and limited information. By leveraging the strengths of these models, stakeholders can enhance their forecasting accuracy, leading to better agricultural planning and decision-making [8].

GVM(1,1) was selected for its suitability in handling small-sample, non-linear data, making it ideal for capturing rice production trends in limited datasets. Using only ARIMA and GVM(1,1) allows for an insightful comparison of benchmark models, highlighting the performance differences between linear and non-linear forecasting. This choice contrasts ARIMA's linear approach with the grey system framework of GVM(1,1), providing valuable insights for forecasting rice production in Iraq

2. Objective of the research

This study aims to identify the most appropriate model between two models, ARIMA and GVM(1,1) models, for forecasting rice production in Iraq. The selected model will then be used to project rice production from 2025 to 2029. The performance of the models will be evaluated using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) metrics. The model that performs the best will be chosen to forecast rice production in Iraq for the 2025-2036 period.

3. Materials and Methods

Statistical methods often utilize data classification techniques, where forecasting plays a vital role in predicting future values based on pertinent historical and current data. Data on rice production in Iraq spanning from 2014 to 2024 was gathered from the International Production Assessment Division (IPAD) website. This information can be accessed through the following link: (https://shorturl.at/6bu7P). For forecasting rice production in Iraq from 2025 to 2036, both the ARIMA and GVM(1,1) models were applied.

4. Forecasting Models

Forecasting rice production is essential for agricultural planning and food security in Iraq. Among the various statistical methods available, the Auto Regressive Integrated Moving Average (ARIMA) and the Grey Verhulst Model (VGM(1,1)) are prominent choices for forecasting time series data, particularly in agricultural contexts[12][14]. This study introduces the concepts of the ARIMA model and the GVM (1,1) model, providing more detailed information as follows:

4.1 Auto Regressive Integrated Moving Average ARIMA Model

The ARIMA (Auto Regressive Integrated Moving Average) model integrates three fundamental time series processes: Auto Regressive (AR), Moving Average (MA), and differencing processes [2][3]. These components, widely utilized across diverse applications, are foundational in statistical literature as primary univariate time series models [7][8]. Mathematically, the equations for AR, MA, and ARMA processes are represented as follows:

Auto Regressive (AR) process :

$$X_t = c + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \emptyset_3 X_{t-3} + \cdots + \emptyset_p X_{t-p} + \varepsilon_t \quad t = 1,2,\ldots T \qquad (1)$$

Moving Average (MA) process:

$$X_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \theta_3 \varepsilon_{t-3} - \cdots - \theta_q \varepsilon_{t-q} \qquad (2)$$

Auto Regressive Moving Average (ARMA) process combines AR and MA:

$$X_t = c + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \emptyset_3 X_{t-3} + \cdots + \emptyset_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \theta_3 \varepsilon_{t-3} - \cdots - \theta_q \varepsilon_{t-q}$$

(3)

By enabling the statistics that produce ARIMA models to change, the ARIMA can be further extended to non-stationary sequence. ARIMA (p, d, q) is the name of the general non-seasonal model, which has three parameter. The first one "p" is auto regressive order, "d" is the level of differencing, and "q" is the moving-average. If the " X_t " is a non-stationary series, for instance, we will apply first-differencing of "X_t" to make "X_t" stationary, and then the ARIMA ($p, 1, q$) model is:

$$\Delta X_t = c + \emptyset_1 \Delta X_{t-1} + \cdots + \emptyset_p \Delta X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q}$$

In the equation four $\Delta X_t = X_t - X_{t-1}$. But if $p = q = 0$, then the model become a random walk form and classified as ARIMA (0, 1, 0).(Jenkins & P, 1976)

4.2 Grey Verhulst Model GVM (1,1)

Combining Grey System Theory with the Verhulst model, the GVM forecasts using first-order discrete equations for small-sample data [5][9][14]. The GVM formulation is as follows:

Step 1: Given the non-negative original sequence data $\mathrm{X}^{(0)}$

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}, \quad n \geq 4 \qquad (4)$$

Step 2: Utilizing the non-negative original sequence data $X^{(0)}$, $X^{(1)}$ is constructed through the 1-AGO process, represented as

$$X^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \ldots, x^{(1)}(n)\right) \qquad (5)$$

$$x^{(1)} = \sum_{i=1}^{k} x^{(0)}(1) \quad k = 1,2,3,\ldots,n$$

Where: $X^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(1) \quad k = 1,2,3,\ldots,n$

Step 3: Calculating a background value z by MGO:

$$z^{(1)}(k) = 0.5x^{(1)}(k+1) + 0.5x^{(1)}(k) \quad k = 2,3,\ldots \qquad (6)$$

The form of the GVM is as follows:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = bx^{(1)^2}$$

where a is the development coefficient and b is the grey action.

Step 4 : The parameter $\hat{a} = [a, b]^T$ can be handled using the least squares method, employing the function as follows: $\hat{a} = [a, b]^T$ of the GM (1,1) power model is

$$\binom{a}{b} = (\beta^T \beta)^{-1} \beta^T Y_n \tag{7}$$

where B and Y_n are defined as follows:

$$\beta = \begin{bmatrix} -z^{(1)}(2) & (z^{(1)}(2))^2 \\ -z^{(1)}(3) & (z^{(1)}(3))^2 \\ \vdots & \cdots \\ -z^{(1)}(n) & (z^{(1)}(n))^2 \end{bmatrix} \text{ and } Y_n = [x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n)]^T$$

The value taken is $x^{(1)}(0)$, and after solving the mentioned differential equation, the time response equation of the GVM is as follows:

$$\hat{x}^{(1)}(k+1) = \frac{ax^{(1)}(0)}{bx^{(1)}(0) + \left(a - bx^{(1)}(0)\right)e^{ak}} \qquad k = 0,1,2, \dots n \tag{8}$$

Step 5 : The resulting grey Verhulst prediction model of $X(0)$) is as follows

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \qquad k = 1,2,3, \dots \tag{9}$$

6.Testing for stationary using the Dickey-Fuller Test:

The Dickey-Fuller test assesses stationary in time series data, identifying whether a unit root is present [2][3][13]. Stationary is essential for reliable forecasting with models like ARIMA. The test's formula is:

$$\Delta Y_t = \propto + \beta Y_{t-1} + \delta t + \epsilon_t \tag{10}$$

Where : $\Delta Y_t = Y_t - Y_{t-1}$ and

$\propto$: The intercept or constant term, representing a fixed value that affects all observations in the time series. Including α\alpha$\alpha$ allows the test to account for a non-zero mean in the series.

β:: The coefficient of Y_{t-1} , representing the effect of the previous time period's value on the current change.

δt represents a deterministic trend component ϵ_t is white noise

The following presumptions guide the test's execution:

H0 :The unit root is present and is non-stationary. vs H1:The unit root is not exist and is stationary.

7. Measuring Forecast Accuracy

The Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) can be used to analyze the results of forecasting. RMSE is used to search for the accuracy of forecasting results with historical data [1]. The smaller the value, the better the results of forecasting. MAPE is used to calculate the accuracy of forecasting methods, evaluate the accuracy of forecasts, compare the accuracy of forecasting techniques, and help o find an optimal method in the form of a percentage. The way it works is that forecasting results are calculated by using equation (11) (12), later the error value of each data is known. The smallest error value is the model with the best performance [8][9].

Here is the formula of RMSE and MAPE

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=2}^{n}(x^{(0)}(k) - \hat{x}^{(0)}(k))^2} \qquad (11)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x^{(0)}(k)-\hat{x}^{(0)}(k)}{x^{(0)}(k)}\right| * 100\% \qquad (12)$$

Where: $x^{(0)}(k)$: Actual demand $\hat{x}^{(0)}(k)$: Forecast demand n: Time period count,

Table (1) A forecasting can be categorized in several levels depending on the value of MAPE which is generated

MAPE (%)	$\leq 10\%$	(10%- 20%)	(20%- 50%)	$> 50\%$
Preference	High	Good	Ration	Not Good

8. Application

8.1 Introduction

This study evaluates ARIMA and GVM(1,1) models for forecasting Iraq's rice production from 2025 to 2029 using data spanning 2014 to 2024, sourced from the "International Production Assessment Division (IPAD)" website. The models are then applied to forecast rice production in Iraq from 2025 to 2029.

8.2 Variable of this Study

The data utilized for both the ARIMA and GVM(1,1) models consists of rice production records spanning from 2014 to 2024.

Table (2) shows the rice production in Iraq, from 2014 to 2024

Years	Yield (T/Ha)	Years	Yield (T/Ha)
2014	4.2	2020	4.5
2015	3.4	2021	4.4
2016	3.3	2022	2.8
2017	3.4	2023	3.8
2018	3.3	2024	4.2
2019	4.5	2025	?
Yield (T/Ha) : Yield (Tons/hectare)			

8.3 Results and Discussions

To determine the best forecasting model for projecting rice production in Iraq from 2025 to 2029, this study analyzed forecast results to assess their consistency. EViews 10, Statgraphics, and Microsoft Excel programs were used to calculate model parameters.

8.3.1 Testing for stationary using the Dickey-Fuller Test:

The following presumptions guide the test's execution:

H0 :The unit root is present and is non-stationary. vs H1:The unit root is not exist and is stationary.

Table (3) Present Dickey-Fuller Test for stationary

Time series variable	T-Statistics	P-Value
Y= rice production	-2.516755	0.1398

From the table, we notice that the p-value of the test is (0.1398) and is greater than the level of significance ($\propto=$ 0.05), meaning we accept the null hypothesis. We say there exists a unit root in the time series, and it is non-stationary. We take the first difference for the purpose of obtaining stationary, then we test again to obtain stationary.

Table (4) Present Dickey-Fuller Test for stationary

Time series variable	T-Statistics	P-Value
Y= rice production	-3.368881	0.0428

From the table, we notice that the p-value of the test is (0.0258) and is less than the level of significance ($\propto=$ 0.05), meaning we accept alternative hypotheses, which means the time series is stationary.

8.3.2 Estimated Model forecasting of ARIMA model

As the previous process, the data of rice production will be processed by using ARIMA models. First, predetermine that the data used have been already qualified. This study is using the model of equation (3) for forecasting. The table (5) displays the root mean square error (RMSE) and mean absolute percentage error (MAPE) for various ARIMA models tested for forecasting rice production. The objective is to determine which ARIMA model provides the highest forecasting accuracy.

Table (5): Measures table used to compare different model of ARIMA Model

ARIMA (p , d , q)	RMSE	MAPE
ARIMA(1,1,1)	0.596326	9.61253
ARIMA(2,1,1)	0.698418	13.3625
ARIMA(1,1,2)	0.560232	9.31376
ARIMA(1,2,1)	0.760558	12.0453
ARIMA(1,2,2)	0.803542	11.5677
ARIMA(2,2,1)	0.835642	12.1033
ARIMA(2,2,2)	0.967127	13.1904

Based on the experimental results, the ARIMA (1,1,2) model was selected as the most accurate model. This model achieved the lowest RMSE of 0.560232 and the lowest MAPE of 9.31376%, indicating that it provides the best fit for the data among all the models tested.

8.3.3: Estimated Model forecasting of ARIMA (1, 1, 2) and GVM (1,1) models

The analysis reveals that the ARIMA (1,1,2) model demonstrates better predictive performance than the GVM (1,1) model, as indicated by the RMSE and MAPE values shown in Table 6. The parameters for the GVM (1,1) model were obtained using the least squares method and are as follows: a=−0.35180626 and b=−0.006831. These results are detailed in the table below.

Table (6) : Actual and forecasting value of ARIMA (1,1,2) and GVM (1,1) model

Years	**Actual value**	**Forecast Value**	
		ARIMA (1,1,2)	GVM(1,1)
2014	4.2		4.2
2015	3.4	3.46293	1.5724
2016	3.3	3.33935	2.0635
2017	3.4	3.52249	2.6323
2018	3.3	3.64738	3.2389

2019	4.5	3.82845	3.8131
2020	4.5	4.00762	4.2625
2021	4.4	3.83581	4.4974
2022	2.8	3.78667	4.4652
2023	3.8	3.79923	4.17336
2024	4.2	4.28481	3.68604

The table presents the actual values and forecasted values of the ARIMA (1,1,2) and GVM (1,1) models. Based on experimentation, the ARIMA (1,1,2) model was selected due to its superior accuracy.

Table (7) Represents the accuracy of models

Criteria	ARIMA (1,1,2)	GVM(1,1)
RMSE	0.560232	0.913362246
MAPE (%)	9.31376	19.9950

In Table 7, the root mean square error (RMSE) and mean absolute percentage error (MAPE) for both the ARIMA (1,1,2) and GVM (1,1) models are reported. Specifically, the ARIMA (1,1,2) model shows an RMSE of 0.560232 and a MAPE of 0.913362246%. In contrast, the GVM (1,1) model has an RMSE of 9.31376 and a MAPE of 19.9950%. These metrics indicate that the ARIMA (1,1,2) model exhibits higher accuracy compared to the GVM (1,1) model, as its RMSE and MAPE values are significantly lower. Therefore, based on these results, the study recommends using the ARIMA (1,1,2) model for future estimations of rice production in Iraq. The forecasted values for 2025 to 2029 can be found in Table 8.

Table (8) The forecasted Rice Production in Iraq by ARIMA (1,1,2) model

Years	2025	2026	2027	2028
Forecasting value	4.33779	4.4939	4.60098	4.71697

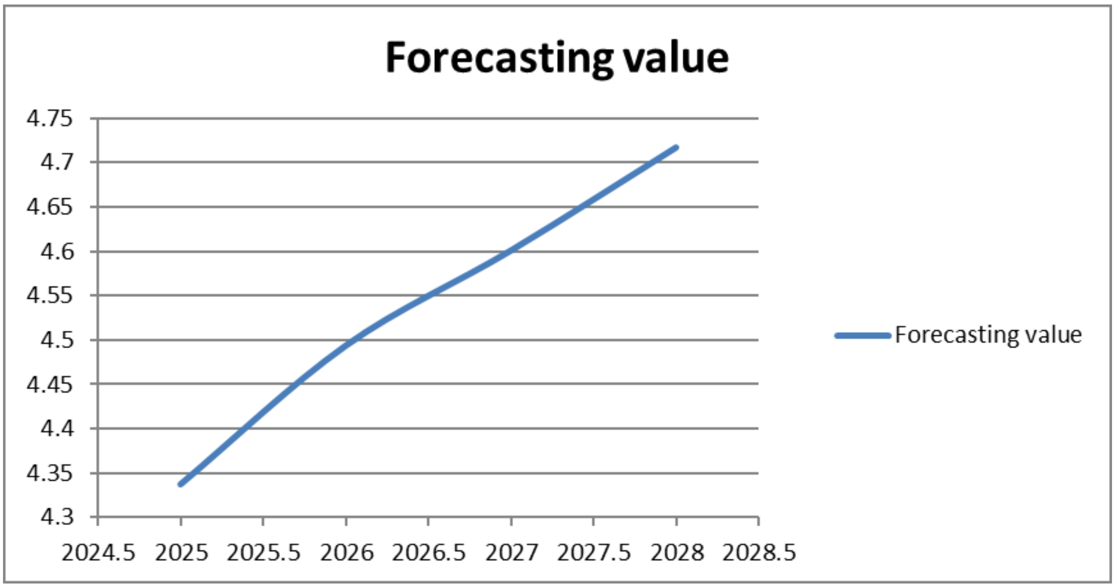

Fig.(1): Plot the forecasting rice production in Iraq

9. Discussion

This study evaluates the performance of ARIMA and GVM(1,1) models in forecasting rice production in Iraq for the period 2025 to 2029. The comparison is based on root mean square error (RMSE) and mean absolute percentage error (MAPE), aiming to identify the most accurate method for forecasting future production levels. Lower RMSE and MAPE values are indicators of higher predictive accuracy. Among the tested models, ARIMA(1,1,2) outperforms other ARIMA configurations, achieving the lowest RMSE and MAPE, thus establishing itself as the most accurate model for forecasting rice production in Iraq. Comparing the best-performing ARIMA(1,1,2) model with GVM(1,1), the ARIMA model demonstrates superior forecasting performance. Specifically, ARIMA(1,1,2) achieves an RMSE of 0.560232 and a MAPE of 9.31376%, in contrast to the GVM(1,1) model's RMSE of 0.913362246 and MAPE of 19.9950%. Consequently, based on the RMSE and MAPE metrics, the ARIMA(1,1,2) model is the most effective technique for accurately predicting rice production in Iraq

10. Conclusion and Recommendation

Two models were utilized to determine the most suitable fit: the Box-Jenkins ARIMA model and the Grey Verhulst Model (GVM (1,1)). The results indicate that the ARIMA (1,1,2) model demonstrates superior forecasting ability based on RMSE and MAPE criteria. The analysis shows that the ARIMA (1,1,2) model provides better prediction results than the GVM (1,1) model according to these metrics. Future studies are recommended to apply and compare the Grey model with other models, such as the Artificial Neural Network and Hybrid ARIMA-GVM (1,1), to further improve forecasting accuracy.

مقارنة بين نماذج ARIMA و GVM(١،١) لتوقع إنتاج الأرز في العراق

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المستخلص

التنبؤ بالسلاسل الزمنية هو طريقة إحصائية تتضمن تحليل أنماط البيانات السابقة للتنبؤ بالقيم المستقبلية. يُستخدم على نطاق واسع في مجالات متعددة. تهدف هذه الدراسة إلى مقارنة أداء التنبؤ بين نموذج ARIMA ونموذج Grey Verhulst Model GVM(١،١) لتحديد أفضل طريقة للتنبؤ بإنتاج الأرز في العراق. تم الحصول على البيانات من موقع «قسم التقييم الدولي للإنتاج (IPAD)». سيتم تقييم أداء النموذجين باستخدام مقاييس مختلفة، مثل متوسط الجذر التربيعي للخطأ (RMSE) ومتوسط النسبة المئوية المطلقة للخطأ (MAPE). من نتائج دقة التنبؤ بناءً على RMSE و MAPE، تبيّن أن قيم RMSE و MAPE لنموذج ARIMA (١،١،٢) أصغر من قيم نموذج GVM(١،١)، مما يُشير إلى أن أداء ARIMA أفضل من GVM (١،١) للتنبؤ بإنتاج الأرز في العراق.

كلمات مفتاحية: السلاسل الزمنية، نموذج Grey، نموذج Grey Verhulst

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