IRAQI Academic Scientific Journals

University of Kirkuk Journal For Administrative and Economic Science (2023) 13 (3): 261-271

UKJAES

University of Kirkuk Journal For Administrative and Economic Science

ISSN 2222-2995
University of Kirkuk Journal For Administrative and Economic Science

Karim Rezan Hama Rashid, Mohamad Soran Husen & Ahmed Dara Hassan. Using Single Exponential Smoothing Model and Grey Model to Forecast Corn Production in Iraq during the period (2022-2030). *University of Kirkuk Journal For Administrative and Economic Science* (2023) 13 (3):261-271.

Using Single Exponential Smoothing Model and Grey Model to Forecast Corn Production in Iraq during the period (2022-2030)

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Abstract: Time series forecasting involves analyzing historical data to make predictions about future values, thereby assisting in decision-making and resource allocation across various domains. Forecasting is a technique that involves anticipating future values by considering relevant past and current data. The primary aim of this research is to compare the effectiveness of Single Exponential Smoothing (SES) and Grey Model (1,1) (GM (1,1)) in predicting corn production. The data for this analysis was obtained from the "index mundi-Iraq Corn Production" website, covering the time span from 2003 to 2021, totalling nineteen time periods. The analysis revealed a discernible trend in the data, making the application of both the SES and GM (1,1) models suitable. To conduct the forecasting, tools such as Stratigraphic, Minitab, and Excel were utilized. The forecasting process involved applying the SES and GM (1,1) models to predict corn production. To determine the most suitable model, the researchers employed the mean absolute percentage error (MAPE and MSE) for both models, Finally, according to their results the parameter optimization are the optimum value of α in (SES) is (0.04) and the optimum MAPE and MSE of (27.78216464% and 226507.9193) by respectively and MAPE and MSE of the GM (1,1) is (26.43480046% and 141381.9409) by respectively. Then, the GM (1,1) was found to be the best method to forecast the corn production in Iraq since it produces the lowest MAPE and MSE value compared to SES.

Keywords: Grey Model, Single Exponential Smoothing, Mean Absolute Percentage Error, Parameter Optimization.

استخدام نموذج التمهيد الاسي المفرد والنموذج الرمادي للتنبؤ بإنتاج الذرة في العراق خلال الفترة (٢٠٢٢-٢٠٣٠)

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المستخلص: يتضمن التنبؤ بالسلاسل الزمنية تحليل البيانات التاريخية للتنبؤ بالقيم المستقبلية، وبالتالي المساعدة في اتخاذ القرار وتخصيص الموارد عبر المجالات المختلفة. التنبؤ هو أسلوب يتضمن توقع القيم المستقبلية من خلال النظر في البيانات السابقة والحالية ذات الصلة. الهدف الأساسي من هذا البحث هو مقارنة فعالية التمهيد الاسي المفرد (SES) والنموذج الرمادي GM(1,1) في التنبؤ بإنتاج الذرة. تم الحصول على بيانات هذا التحليل من موقع "index mundi-Iraq Corn Production"، الذي يغطي الفترة الزمنية من ٢٠٠٣ إلى ٢٠٢١، بمجموع تسع عشرة فترة زمنية. كشف التحليل عن اتجاه واضح في البيانات، مما يجعل تطبيق نموذجي SES وGM(1,1) مناسبًا. لإجراء التنبؤ، تم استخدام أدوات مثل Stratigraphic وMinitab وExcel. تضمنت عملية التنبؤ تطبيق نموذجي SES وGM(1,1) للتنبؤ بإنتاج الذرة. ولتحديد النموذج الأنسب استخدم الباحثون متوسط نسبة الخطأ المطلق (MAPE وMSE) لكلا النموذجين، وأخيراً ووفقاً لنتائجهم فإن القيمة المثلى لـ α في (SES) هي (٠,٠٤) والقيمة المثلى لـ α في (SES) هي (٠,٠٤). MAPE وMSE بنسبة (٢٧,٧٨٢١٦٤٦٤٪ و٢٢٦٥٠٧,٩١٩٣) على التوالي، وMAPE وMSE من GM(1,1) هي (٢٦,٤٣٤٨٠٠٤٦٪ و١٤١٣٨١,٩٤٠٩) على التوالي. بعد ذلك، وجد أن GM(1,1) هي أفضل طريقة للتنبؤ بإنتاج الذرة في العراق لأنها تنتج أقل قيمة MAPE وMSE مقارنة بـ SES.

الكلمات المفتاحية: النموذج الرمادي، التمهيد الاسي المفرد، متوسط النسبة المئوية للخطأ المطلق، تحسين المعلمة.

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1. Introduction

Botanically recognized as Zea mays, corn is a versatile and crucial cereal grain cultivated on a global scale. Its historical roots extend to ancient civilizations in the Americas, and in contemporary times, it occupies a pivotal position in modern agriculture and food supply networks. The domain of corn production encompasses an extensive array of varieties, each meticulously crafted to cater to distinct needs such as food consumption, animal feed, and utilization in industrial contexts. Moreover, Corn stands as a prominent essential dietary staple, furnishing crucial calories and nourishment to countless individuals on a global scale. The extensive cultivation of corn can be attributed to its remarkable ability to thrive in a multitude of climatic and soil settings. From the temperate zones of North America to the tropical expanses of Africa and Asia, corn has evolved into a foundational crop in numerous agricultural terrains. Furthermore, Corn production in Iraq assumes a crucial role in satisfying the demands for both food and animal feed. The favorable warm climate and fertile soils create a propitious setting for its growth. Farmers employ modern approaches to land preparation, planting, and cultivation, resulting in improved crop yields. The versatile nature of corn contributes substantially to the country's advancement in both agricultural and economic domains. Moreover, the significance of corn production in Iraq extends to being a pivotal facet of the nation's agricultural and economic realms. The prevailing warm and arid climate, particularly pronounced in the southern territories, provides an advantageous backdrop for the growth of corn crops. Iraqi farmers adopt advanced agricultural practices encompassing hybrid seed usage, sophisticated irrigation systems, and effective pest control strategies to optimize crop output. Corn plays a dual role as a primary dietary staple for the populace and a vital feed resource for livestock. Furthermore, the byproducts derived from corn contribute substantively to diverse industries, encompassing ethanol manufacturing and the processing of food items. Despite challenges arising from water scarcity and political instability, the ongoing prioritization of corn cultivation remains indispensable to guaranteeing both food security and the sustainability of Iraq's economic trajectory. In summary, the significance of corn production reverberates throughout contemporary agriculture and food networks. Its multifaceted nature and capacity to thrive underscore its pivotal status as a fundamental crop for human nourishment, animal sustenance, and industrial utilization. As the demand for corn escalates, the imperative of implementing sustainable agricultural methodologies becomes paramount. Such practices are instrumental in safeguarding the sustained success of corn cultivation, upholding its role in bolstering worldwide food security and catalyzing economic advancement.

2. Objective of the research

The first objective of this research is twofold: firstly, it aims to contrast the predictive capabilities of the Single Exponential Smoothing model with those of the GM(1,1) model concerning the estimation of corn production levels in Iraq. Secondly, it seeks to prognosticate the corn production within Iraq for the period spanning from 2022 to 2030, with the aim of facilitating strategic planning for the forthcoming year.

3. Materials and methods

Data classification methods are one of the most widely used in statistical methods. Forecasting is a tool or technique used to predict or predict a value in the future by paying attention to relevant data or information, both past data or information or current data or information. In forecasting, there are 2 general methods, namely qualitative and quantitative. The qualitative method is intuitive and is usually done when there is no past data / history, which results in the inability of mathematical calculations. While quantitative methods can be done based on previous data/history so that calculations can be done mathematically. This study employed time series data from 2003 to 2021 to analyze corn production in Iraq. The data, sourced from the (index mundi-Iraq Corn Production) website, specifically the section on corn production in Iraq (https://www.indexmundi.com/agriculture/?country=iq&commodity=corn&graph=production) were utilized for analysis. The (SES) model and grey GM(1,1) model were employed to forecast corn production in Iraq for the years 2022 to 2030.

A. Exponential Smoothing model

Exponential smoothing is a technique employed within the forecasting process. This method involves a continuous calculation process that incorporates the most recent data. Each individual data point is attributed a weight, denoted by the term "alpha.". The selection of alpha symbols is flexible, leading to a decrease in prediction inaccuracies. The smoothing constant, denoted as α, can be chosen from a range of values between 0 and 1, as it is applicable in this context: $0 < \alpha < 1$. Exponential smoothing encompasses three method variations: single exponential smoothing, double exponential smoothing, and triple exponential smoothing.

(1) single Exponential Smoothing model theory

The Exponential Smoothing model, often referred to as the Single Exponential Smoothing model, stands as a frequently employed technique for time series forecasting. This method, known for its simplicity and efficacy, allocates diminishing exponential weights to historical data points. Within this model, the prediction for time t+1 is derived through a weighted blend of the actual value at time t and the forecasted value at time t. These weights gradually diminish in an exponential manner as we extend farther into the past. The emphasis of the model is on recent observations, presupposing that more recent data holds greater relevance in forecasting future values. The Single Exponential Smoothing model is especially apt for time series data lacking distinct trends or seasonal patterns. Its implementation is relatively straightforward and does not necessitate intricate parameter adjustment. This model's widespread adoption in diverse forecasting scenarios is attributed to its simplicity and adaptability.

(2) Advantage of Single Exponential Smoothing model

The Single Exponential Smoothing model presents numerous benefits within the realm of time series forecasting. Its implementation is straightforward, demanding only minimal parameter adjustment, and it is capable of delivering precise predictions for data lacking evident trends or seasonal patterns.

(3) Time series Data by using Single Exponential Smoothing model

Time series data comprises consecutive observations documented over a duration. The Single Exponential Smoothing model is a well-liked method applied to predict such data. It allocates decreasing exponential weights to previous observations, rendering it apt for both time series analysis and prediction endeavors, especially in scenarios lacking evident trends or seasonal patterns.

(4) The Single Exponential Smoothing model

The method referred to as single exponential smoothing, also recognized as simple exponential smoothing, represents a short-term predictive model. Among all forecasting techniques, this prediction method is the most extensively employed. It necessitates minimal computational efforts. (Himawan, Hidayatullah; Silitonga, Parasian DP, 2020) .This approach is employed when the data pattern appears predominantly horizontal, meaning that neither cyclic variations nor distinct trends are evident in the historical data. In simpler terms, this model presupposes that the data oscillates around a consistent mean value, without displaying consistent growth trends or recognizable patterns. The general equation for single exponential smoothed statistics is given as:

$$F_{t+1} = \propto X_t + (1+\propto)F_t \qquad (1)$$

Where:

F_{t+1} : Forecasting at time - (t+1), F_t : Forecasting at time – t

$X_t + (1+\propto)$: Actual time series value, $\propto$:Constants between 0 to 1

(5) Parameter Optimization of Single Exponential Smoothing

Parameter fine-tuning was executed utilizing the golden section method with the aim of minimizing the MAPE (Mean Absolute Percentage Error). This MAPE was derived from the forecast generated by the Single Exponential Smoothing model and was then juxtaposed with the actual values. The optimization of the Single Exponential Smoothing's parameter (α) was carried out employing the golden section technique.

B. Grey system theory

The inception and development of Grey System theory are attributed to Ju Long in 1982. In the realm of information, systems lacking comprehensive data, such as structural information, operational mechanisms, and documented behaviors, are categorized as Grey Systems. Instances of Grey Systems encompass entities like the human body, agriculture, and the economy. By leveraging existing grey relationships, grey elements, and grey numbers (symbolized by $\emptyset$), one can identify the nature of a Grey System; here, "grey" signifies attributes like incompleteness, uncertainty, or inadequacy. The central objective of Grey System theory and its applications is to bridge the gap between social sciences and natural sciences. This interdisciplinary theory spans various specialized domains and has endured since its inception in 1982. The notion of the Grey System, both in theory and its effective implementation, has gained substantial recognition in China. The application arenas of the Grey System encompass diverse fields like agriculture, ecology, economics, meteorology, medicine, geography, and industry.

(1) GM (1, 1) Model

The prevalent grey prediction model is typically the GM (1, 1), which implies that a single variable is utilized within the model. The initial-order differential equation is employed to align with the data produced through the Accumulated Generating Operation (AGO).

The AGO reveal the hidden regular pattern in the system development. Before the algorithm of GM (1, 1) is described, the raw data series is assumed to be

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

Where n is the total number of modeling data. The AGO formation of $X^{(1)}$ is defined as:

$$x^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)\} \ , n \geq 4 \qquad (3)$$

Where:

$$x^{(1)}(1) = x^{(0)}(1)$$

$$x^{(1)}(k) = \sum_{j=1}^{k} x^{(0)} \ (k = 1,2, \ldots, n). \qquad (4)$$

The GM(1,1) model is created by formulating a first-order differential equation for $x^{(1)}$ (k) as::

$$\frac{dx^{(1)}}{dt} + aX^{(1)} = u \qquad (5)$$

The terms "developing coefficient" and "grey input" refer to the parameters a and u, respectively. When applied in practical situations, parameters a and u are not typically determined directly from Equation (5). Consequently, solving Equation (5) is accomplished by employing the least squares method. That is,

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{u}{a}\right] e^{-ak} + \frac{u}{a} \qquad (6)$$

Where

Where, $\hat{x}^{(1)}(k+1)$ denotes the prediction x at time point k+1 and the coefficients [a,u]T can be obtained by the Ordinary Least Squares (OLS) method:

$$\hat{a} = [a, u]^T = (B^T B)^{-1} B^T Y \qquad (7)$$

In that:

$$Y_N = [X^{(0)}(2), X^{(0)}(3), \ldots, X^{(0)}(n)]^T$$

And

$$B = \begin{bmatrix} -\frac{1}{2}(x^{(1)}(1) + x^{(1)}(2)) & 1 \\ -\frac{1}{2}(x^{(1)}(2) + x^{(1)}(3)) & 1 \\ -\frac{1}{2}(x^{(1)}(n-1) + x^{(1)}(n)) & 1 \end{bmatrix} \qquad (8)$$

The Inverse AGO (IAGO) method is utilized for forecasting values in the initial sequence. This is accomplished by employing IAGO:

$$\hat{x}^{(0)}(k+1) = [x^{(0)}(1) - \frac{u}{a}](1 - e^{a})e^{-ak} \qquad (9)$$

Therefore, the fitted and predicted sequence $\hat{x}^{(0)}$ is given as:

$$\hat{x}^{(0)} = \left(\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(n), ..\right) \qquad (10)$$

and

$$\hat{x}^{(0)}(1) = x^{(0)}(1) \ , (k = 2,3, \ldots, n).$$

Where

$$\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(n)$$

are called the GM (1, 1) fitted sequence while:

$\hat{x}^{(0)}(n+1), \hat{x}^{(0)}(n+2), \ldots,$ are called the GM (1, 1) forecast values

(2) Advantage of Grey models

The Grey Model GM(1,1) presents multiple benefits in the realm of forecasting. Firstly, it exhibits strong performance even with limited data, rendering it well-suited for scenarios involving a small quantity of observations. Additionally, Grey models remain applicable even when only four observations are available. Secondly, through the Accumulated Generating Operation (AGO), it captures underlying patterns and trends, allowing for accurate predictions in the presence of nonlinearities or evident trends. Thirdly, its implementation is relatively uncomplicated, demanding minimal computational resources and parameter adjustment. Fourthly, the outcomes of GM(1,1) are easily understandable, offering insights into the interplay between input data and forecasted values. Finally, it excels particularly in short-term forecasting, making it highly valuable for swift decision-making. In general, the Grey Model (1,1) provides simplicity, effectiveness in data-constrained scenarios, and the capacity to capture underlying trends. This renders it a valuable asset for forecasting across a range of fields and applications.

(3) Time series Data by using Grey Model

Time series data comprises a set of observations documented across a span of time. The Grey Model GM(1,1) is a particular methodology employed for the examination and prediction of such data. Through its ability to apprehend latent trends and patterns, GM(1,1) enables precise forecasts, thereby serving as a crucial asset for decision-making in a variety of fields that heavily depend on time-related data.

(4) Grey Theory Steps

The term "grey" signifies a deficiency in information, and the Grey system yields satisfactory outcomes even in scenarios characterized by incomplete data or limited study samples. This efficacy is attributed to the cumulative generate operator, which assigns greater importance to each observation within the sample.

(5) Grey Model

In the theory of grey systems, the GM (m, n) formulation is utilized to address situations with limited information, where m signifies the order of the difference formula and n indicates the number of factors involved. Grey models demonstrate the ability to forecast future system outputs with notable accuracy, even when an exact mathematical model of the real system is absent. Many perceptive researchers have chosen to concentrate on the GM (1, 1) model when making predictions, largely owing to its computational efficiency.

4. Evaluate Precision of forecasting Models

A. Mean Absolute Percentage Error

Several statistical tests and metrics are applied to assess the precision and effectiveness of the suggested model. The study utilized the Mean Absolute Percentage Error (MAPE) as a measure to assess the predictive accuracy of the forecasting model. The performance and reliability of the forecasting technique were evaluated using the Means Absolute Percentage Error (MAPE) index.
It is defined as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{z_t}\right| * 100 = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{z_t-\hat{z}_t}{z_t}\right| * 100 \qquad (11)$$

Where:
z_t: Actual demand for time period t, $\hat{z}_t$: Forecast demand for time period t
n: Specified number of time period, e_t: $z_t - \hat{z}_t$
And

$$MAPE = \frac{1}{n}\sum_{i=2}^{n} APE(k) * 100\% = \frac{1}{n}\sum_{i=2}^{n}\frac{|x^{(0)}(k)-\hat{x}^{(0)}(k)|}{x^{(0)}(k)} * 100\% \qquad (12)$$

The forecasting accuracy level can be classified into four grades based on the MAPE of each model as indicated in Table 1.

Table (1) Categorizing the grade of predicting accuracy.

Level	Highly accurate prediction	Good prediction	Reasonable prediction	Inaccurate prediction
MAPE	<10%	10% - 20%	20% - 50%	>50%

B. Mean Absolute Percentage Error

Another approach to assess forecasting methods is the Mean Square Error (MSE). MSE is computed by adding up the squares of forecast errors for each time period and then dividing it by the number of forecast periods. Evaluation of a forecasting method involves considering the following criteria

$$MSE = \frac{1}{n}\sum_{t=1}^{n} {e_t}^2 = \sum_{t=1}^{n}(z_t - \hat{z}_t)^2 \qquad (13)$$

Where:

z_t: Actual demand for time period t, $\hat{z}_t$: Forecast demand for time period t

n: Specified number of time period, e_t: $z_t - \hat{z}_t$

And

$$MSE = \frac{1}{n}\sum_{i=2}^{n} {e_t}^2 = \frac{1}{n}\sum_{i=2}^{n}\left(x^{(0)}(k) - \hat{x}^{(0)}(k)\right)^2 \qquad (14)$$

5. Application

A. Introduction:

In this study, used the time series data of the corn production in Iraq during the year (2003–2021).The data were obtained from the website (index mundi-Iraq corn Production).(https://www.indexmundi.com/agriculture/?country=iq&commodity=corn&graph=production) (Agriculture, 2023). In this section we use the two models disculled earlier to analyze the time series to the corn production using Single Exponential Smoothing (SES) model and grey model (GM (1,1)) for forecasting applied corn production in Iraq for (19) years from 2003 to 2021.

B. Variable of this Study

The data used for the Single Exponential Smoothing (SES) and Grey Model GM (1.1) is corn production data from 2003 to 2021. Data can be seen in the table below.

Table (2) Corn production -Iraq- Data from 2003 - 2021

Year	Corn production (1000 MT)	Year	Corn production (1000 MT)	Year	Corn production (1000 MT)
2003	233	2010	267	2017	185
2004	416	2011	336	2018	225
2005	401	2012	503	2019	350
2006	399	2013	831	2020	365
2007	384	2014	289	2021	360
2008	288	2015	182	2022	?
2009	238	2016	300	2023	?

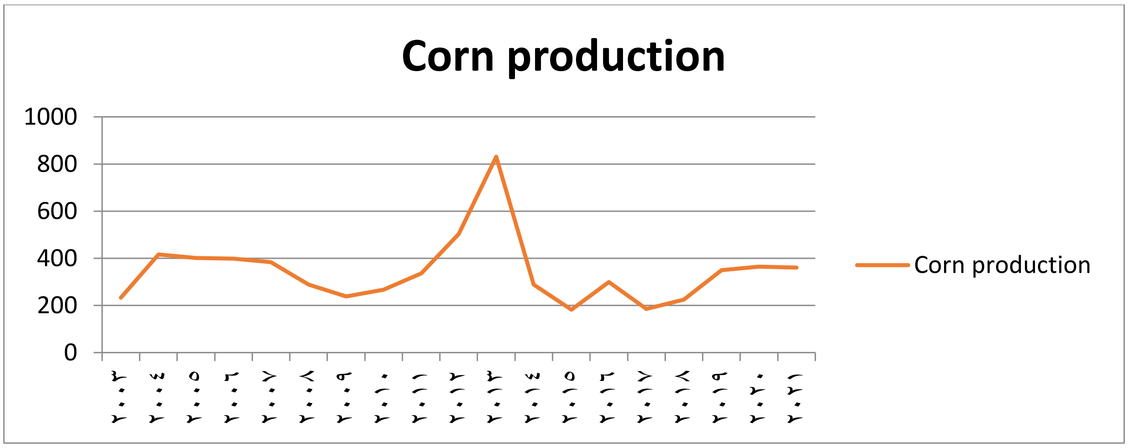

Fig.(1): Plot the data corn production from (19) years

Based on Figure 1 of the corn production Chart, it can be seen that the data shows obedience in the 2003 period to the 2021 period.

C. Results of Single Exponential Smoothing (SES) model

(1) Applied Single Exponential Smoothing (SES) model

Following the conducted data analysis, it has been determined that the data displays a discernible trend pattern. The chosen approach for time series analysis is exponential smoothing. Within the framework of exponential smoothing, there are three method variations: single exponential smoothing, double exponential smoothing, and triple exponential smoothing. However, in this context, a singular approach is utilized, namely the one-parameter linear exponential smoothing derived from single exponential smoothing. Test scenarios are then executed using randomly assigned parameter values. For the Single Exponential Smoothing testing, smoothing parameters (α) are selected from the set (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9). The calculation of Mean Absolute Percentage Error (MAPE) results is presented in Table (3). The outcomes of these test runs reveal that the value α=0.1 yields the smallest error, denoted by a MAPE of 30.72082236%. This makes α=0.1 the parameter that generates the least error for forecasting within the Single Exponential Smoothing model, rendering it the optimal parameter choice.

Table (3) MAPE value for Single Exponential Smoothing (SES) model

α	MAPE (%)	α	MAPE (%)	α	MAPE (%)
0.1	30.72082236	0.4	36.46023141	0.7	33.67812919
0.2	35.08007742	0.5	35.17904243	0.8	33.40021294
0.3	36.63565722	0.6	33.9351293	0.9	32.89806476

(2): Parameter optimization results for Single Exponential Smoothing

he optimization of the parameter α in the Single Exponential Smoothing method was conducted using the golden section technique, and the outcomes are available in Table 4. From the conclusions drawn through this optimization process, it has been determined that α=0.04 results in the optimal MAPE value of 27.78216464%. Consequently, when α is set to 0.04, it can be affirmed that the Single Exponential Smoothing approach is effective for prediction. The optimization process has effectively identified the optimal MAPE value.

Table (4) Parameter optimization results for Single Exponential Smoothing

α	MAPE (%)	α	MAPE (%)	α	MAPE (%)
0.01	28.81149985	0.06	28.45878989	0.11	31.33111909
0.02	28.36480051	0.07	29.07662564	0.12	31.89676333
0.03	27.9646513	0.08	29.64570479	0.13	32.42018701
0.04	27.78216464	0.09	30.16867801	0.14	32.9036997
0.05	27.92755579	0.1	30.72082236	0.15	33.34948456

D. Applied Grey Model GM (1,1)

The Grey forecasting model is employed to acquire the projected value for the upcoming period. Utilizing Equation (7) and employing the OLS method, the parameters of the GM(1,1) model have been calculated. These parameters encompass the model's intercept and slope, with respective values of (398.3463613) and (0.013432874).

Table (5) Results of the GM(1.1) prediction model

Year	Original data	Predicted values	Percentage Error (PE)
2003	233	233	0
2004	416	392.5739007	5.631273864
2005	401	387.3357654	3.407539802
2006	399	382.1675228	4.218665968
2007	384	377.0682403	1.805145747
2008	288	372.0369979	29.17951315
2009	238	367.0728876	54.23230571

2010	267	362.1750137	35.64607254
2011	336	357.3424924	6.351932258
2012	503	352.5744517	29.90567561
2013	831	347.8700312	58.13838373
2014	289	343.2283821	18.76414606
2015	182	338.6486668	86.07069602
2016	300	334.1300588	11.37668627
2017	185	329.6717429	78.20094211
2018	225	325.2729146	44.5657398
2019	350	320.93278	8.304919998
2020	365	316.6505561	13.24642298
2021	360	312.4254702	13.21514717

The table presented above displays the model value and MPAE achieved through the GM (1,1) model based on Equation (11). The MAPE value can be calculated by dividing the total PE by the entire dataset. It is evident that the MAPE value for the GM (1,1) model stands at 26.43480046%, signifying an accuracy and efficiency measure of (100 - MAPE = 100 - 26.43480046 = 73.56519954%). This indicates that the forecasting value is a commendable prediction, as the MAPE falls within the range of 10% to 20%.

Table (6) Represents the accuracy of models

Criteria	SES ($\alpha = 0.04$)	GM(1,1)
MAPE (%)	27.78216464	26.43480046
MSE	226507.9193	141381.9409

The table presented provides a distinct depiction of the MPAE and MSE values for the SES (α=0.04) model, which amounts to 27.78216464% and 226507.9193 by respectively, in accordance with Equation (11,13). Conversely, the MAPE and MSE values attributed to the GM(1,1) model for the period 2003-2021 stands at 26.43480046% and 141381.9409 by respectively, as based on Equation (12-14) and further illustrated in Table (5). It's apparent that the MAPE values associated with the GM (1,1) model are lower than those of the SES model, indicating that the forecasted values from the GM (1,1) model are more accurate compared to the SES model. Consequently, GM(1,1) is recommended over the SES model for predicting corn production in Iraq from 2022 to 2030. The forecasted values for the years 2022-2030 are detailed in Table (7).

Table (7) The forecasted the corn production in Iraq during the period (2022-20230)

Years	SES ($\alpha = 0.04$) forecasting value	GM(1,1) forecasting value
2022	**280.0728121**	**308.26**
2023	**268.8698996**	**304.14**
2024	258.1151036	300.09
2025	247.7904995	296.08
2026	237.8788795	292.13
2027	228.3637243	288.23
2028	219.2291754	284.39
2029	210.4600084	280.59
2030	202.041608	276.85

6. Discussion

The comparison between the forecasting performances of the SES and GM(1,1) models for corn production, as applied in this research, is evident in Table (7). This methodology allows for the prediction of forthcoming corn production values in Iraq based on data spanning a period of 19 years. Furthermore, relying on the optimization results from the SES model with an optimal α=0.04, the associated MAPE and MSE reaches its optimum value at 27.78216464% and 226507.9193 by respectably. In contrast, the MAPE and MSE for the GM(1,1) model is recorded at 26.43480046%

and 141381.9409 by respectively . Consequently, the observation can be drawn that GM(1,1) serves as the more suitable technique for forecasting corn production compared to the SES model, as the GM(1,1) model's MAPE value is lower than that of the SES model.

$$(MAPE\%)_{GM(1,1)} = 26.43480046\% < (MAPE\%)_{(SES)} = 27.78216464\%$$
$$(MSE)_{GM(1,1)} = 141381.9409 < (MSE)_{(SES)} = 226507.9193$$

7. Conclusion and Recommendation

The assessment between Single Exponential Smoothing (SES) and the Grey model (GM (1,1)) is drawn to a conclusion by utilizing the Mean Absolute Percentage Error (MAPE) criterion to determine the superior method for forecasting corn production in Iraq. Furthermore, the optimization process for the (α) parameter in the SES model led to the identification of an optimal value of (α=0.04) along with an associated MAPE and MSE of (27.78216464% and 226507.9193) respectively, which surpasses the MAPE and MSE recorded for the GM (1,1) model, at (26.43480046% and 141381.9409) respectively. Utilizing MAPE as the performance measure, the inference is drawn that the GM (1, 1) model is the most effective technique, as it exhibits a lower MAPE compared to the (SES) model. This study's outcomes advocate for the adoption of the GM (1, 1) model to predict corn production, providing a more accurate forecast compared to the (SES) model in representing the patterns within corn production data in Iraq. Future research could involve the exploration of Brown’s and Holt’s Double Exponential Smoothing for identifying the optimal model, as well as a comprehensive comparison of the GM (1,1) model. Furthermore, it is recommended that future studies incorporate additional statistical methodologies for forecasting corn production to attain more precise and dependable results.

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