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RESEARCH ARTICLE

Predicting the Value of Agricultural GDP in Iraq for the Period 2019—2030 by Applying the Markov Transition Matrix

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Abstract: This research aims to predict the values of agricultural GDP in Iraq for the period 2019–2030 using the Markov Transition Matrix, whereby the fifth state was chosen due to the convergence of the predicted values with the most recent real values in the original time series. In addition, the predictive error or predictive accuracy of the selected state was better compared to other states. The reason for choosing this methodology in forecasting is that it is based on probabilities derived from old historical data, but this methodology does not need old historical data for the purpose of extracting predictive values, even if the time series includes long-time series data. The predicted values follow the same path as the original time series and are not affected by the general trend of the original data, which gives us an indication that there is a problem of stagnation of agricultural GDP. Therefore, a recommendation that can be given to economic policymakers, in particular the agricultural ones, is the existent need to address the problems that the agricultural sector has always suffered from in order to break this stagnation.

Keywords: Markov chains; Finite state machines; Predictive accuracy

1. Introduction

The agricultural sector is the second sector after the oil sector, based on GDP in Iraq. However, although Iraq has been an agricultural country since ancient times and agriculture was the driving force of the economy, the last five decades have revealed a great weakness in the agricultural sector due to many reasons, including the political, social and economic conditions, as well as wars and the migration of farmers from their lands towards cities due to the decline in agricultural income, another reason for the decline in agricultural GDP is the war conditions that Iraq suffered from, which led

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to the use of all working hands, including the peasants who engaged in the war, which caused a decline in the value of the gross product. The decline in the value of agricultural GDP further to the inability of agricultural commodities to compete with foreign agricultural commodities in terms of price and quality. This is why the Iraqi government has recently reduced the exchange rate of the Iraqi currency to compete with foreign goods. However, it remains a main question whether this policy will be a success and enable the required modernization of agriculture.

In order to present policymakers with reliable figures about the future development of agriculture predicting the value of the agricultural domestic product is important, because knowing the future values of agricultural production will give us the ability to know how the agriculture sector is evolving without intervention so that, the decision can be made to strengthen the factors that contribute to its increase, including the measures taken by the Iraqi government to reduce the value of the currency so that local agricultural commodities can compete with other foreign commodities.

Markov chains are a fairly common way and relatively simple to method model random operations statistically, and they are very concept intuitive, and easily accessible as they can be implemented without using any advanced statistical concepts as well as it is a great way to start learning about probability modeling techniques and data science. Markov chains are one of the most important methods to model stochastic processes, enabling to description of the current state of a system or process while capturing all the information that can influence the future development of the process [1]. Markov chains have been modeled for many real-world models processes and can be extended to other fields, including search algorithms and mapping of animal life groups, as well as the fields of music composition and speech recognition. In addition to the above, Markov chains are commonly used in fields such as data science, economics, and finance, in order to predict market collapses and economic cycles between recession and expansion. The Markov chain is generally classified into two, namely the Markov chain with a discrete parameter index and the Markov chain with a continuous parameter index. The Markov chain is said to be a discrete parameter index if the shift state occurs with a fixed discrete time interval [2]. The applications of this method did not stop at the above fields but were rather extended to predicting the prices of capital assets, as well as game theory, genetics, credit risk calculation, and communications, which gives great importance to Markov chains in covering many fields, making their way of predicting a safe way to reach accurate predictions [3].

It is worth noting that Markov chains are named after the Russian scientist Andrei Markov, and are in themselves a mathematical system that tests the transition from one state to another according to a set of probabilistic rules. However, the characteristic that distinguishes Markov chains from other methods is that the possible future states are fixed, meaning that going to any particular state depends only on the current state and the elapsed time.

This manuscript aims to predict the value of the Iraqi agricultural GDP for the period 2019–2030 by testing different states of the Markov Transition Matrix to reach the future agricultural GDP values in Iraq as close as possible to the actual values for the most recent years.

We have mentioned that the use of Markov chains is common in various fields. Among the many applications, we find applications of Markov chains in geology [4], in bridge deterioration models for different types of superstructures [5], in random environments (the state of Marcovic environments) [6], to model the state of underground pipelines [7]. In the field of crime science, analysis of the Markov series was used to predict specialization in criminal professions [8]. In geophysics, Godfrey [9] wrote about seismic impedance modeling with Markov chains, while in the field of health, Jain [10] used the Markov chain model to study the case of asthma with regard to seasonal variations.

Further, prediction of Markov chains was used to study dehydration phenomena using the Markov series model in combination with artificial nerve networks [11]. We also found a study that dealt with the prediction of travel behavior [12], as well as a study [13] that used the Markov series for predicting future crop patterns. Further, the study of Khiatani [14] predicted the future weather conditions using a hidden Markov model, while Zakaria [15] developed a Markov chain model to predict the air pollution index in Miri, Sarawak. Wilinski [16] used time series modeling and prediction based on Markov chains with variable transition matrices, and Yapo [17] introduced a new Markov chain flow model approach for flood forecasting. Finally, Alevizos [18] introduced a probabilistic event prediction system via the Internet.

As for research that dealt with forecasting using Markov chains in the agricultural sector, reference can be made to Alani's research [19], which predicted wheat crop productivity in Iraq for the period 2019–2025.

The research recommended adopting the Markov chain method in forecasting because it requires less stringent assumptions than other methods require a series of past historical observations and more complex statistical tests.

Bosabt [20] predicted wheat productivity in Algeria using Markov chains. The research concluded that wheat productivity in Algeria in the next three years would not differ much from its present values, as the relative error in 2013 did not exceed 11.64%, while in 2014 and 2015, this error did not even reach the level of 4%, which means that the estimated value is close to 88% of the value of wheat productivity in Algeria in 2013 and 96% in 2014 and 2015. Jain and Agrawal [21] adopted the Markov chain method to predict sugarcane yield. They used two years' data (1977–1978 and 1978–1979) collected from biometric and yield traits collected by IASRI, New Delhi under an experimental study on pre-harvest forecasting of sugarcane yield in Meerut (UP) district. Their yield predictions 7–8 months after planting (about 2–3 months before harvest) were very close to those observed, with percent deviations from observation between 4% in 1978–1979 and 2% in 1977–1978. Hence, this study reveals that the Markov chain method can be successfully used in crop productivity forecasting.

Buongiorno and Zhou [22] used Markov optimization models in the economic and environmental management of vulnerable forest landscapes. Their results showed that natural disasters enhance landscape diversity, but weaken tree diversity. Current management would generate higher natural diversity, but lower timber productivity.

2. Materials and Methods

For this study, agricultural GDP data were collected from the Agricultural Economics Department of the Iraqi Ministry of Agriculture for the period 1980–2019, and used to predict the agriculture GDP for the period 2019–2030, after testing multiple states of the transition matrix to identify the best states that achieved logical future values and closest to the values of the most recent period used in the research.

Theoretical Framework

Markov Chain's Transition Probability Matrix

The state transition probability matrix in Markov chains predicts the probabilities of transitioning from one state of the system under investigation to another in one unit of time, but this concept can be more useful if it covers longer periods.

A square random matrix is mathematically generated from the basic data to describe transitions in Markov chains. All numbers in the square matrix are non-negative real numbers and represent a probability of passing from one to another. The square matrix is called a probability matrix, substitution matrix or Markov matrix as a reference to the inventor of the method.

State Transition Matrix and Diagram

The transition probabilities are included in the matrix. We call this matrix the state transition matrix and mostly displayed with the symbol , Assuming that the states are 1, 2, …. r, the transition matrix can be represented as follows [23]:

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{1r} \\ p_{21} & p_{22} & p_{2r} \\ . & . & . \\ . & . & . \\ . & . & . \\ p_{r1} & p_{r2} & p_{rr} \end{bmatrix} \tag{1}$$

Note that $p_{ij} \geq 0$, and for all i we have:

$$\sum_{k=1}^{r} p_{ik} = \sum_{k=1}^{r} P\left(X_{m+1} = \frac{k}{X_m} = i\right) \rightarrow= 1 \tag{2}$$

This is because, when we are in state i, the next state must be one of all possible states. Thus, when we add all possible values of k, we should get 1. In other words, the sum of each row should be equal to 1.

State Transition Diagram

A state transition diagram is a display of a Markov chain. Assuming we have a Markov chain consisting of three possible states: 1, 2, 3, the transition probabilities could be as follows (numerical example):

$$P = \begin{bmatrix} \frac{1}{4} & \frac{1}{2} & \frac{1}{4} \\ \frac{1}{3} & 0 & \frac{2}{3} \\ \frac{1}{2} & 0 & \frac{1}{2} \end{bmatrix} \tag{3}$$

Figure 1 shows the state transition diagram for the above Markov chain. The diagram represents that we have three possible states 1, 2, 3, the arrows from each state to the next indicate the transition probabilities p_{ij}. We note that if there is no arrow from state i to state j, this indicates that the value of $p_{ij} = 0$.

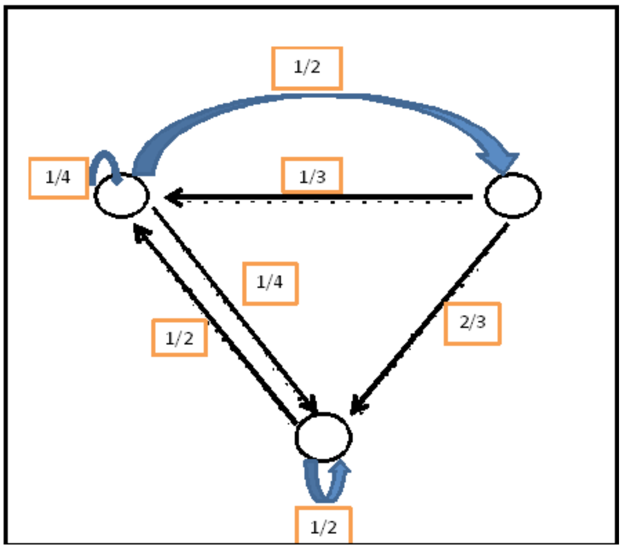

Figure 1. A state transition diagram.

How do Phase Transition Matrices Work?

The state transition matrix is essential for determining the complete solution, stability, controllability and observability of linear time-varying systems [24]. The success of the state transition matrix depends on the use of probabilities as it is about the future based on what happened in the past. Therefore, the state transition matrix provides us with the probabilities for each possible transformation, which enables us to determine the probability of each outcome that can be expected. This may then allow making sound decisions in the future to be used for judging the success of the administration and improving its performance.

Types of State Transition Matrices

a. Finite State Machines

Today this type is used in a variety of fields in pattern recognition, or in fields to which pattern recognition is related such as computational linguistics, machine learning, time series analysis, circuit testing, computational biology, speech recognition, as well as machine translation [25]. A finite state machine is a mathematical abstraction used to design algorithms:

Definition finite-state machine: $M = [S, I, O, f_s, f_o]$ is a finite-state machine if S is a finite set of states, I is a finite set of input symbols (the input alphabet), O is a finite set of output symbols (the output alphabet), and f_s and f_o are functions for $f_s: S \times I \rightarrow$ and $f_o: S \rightarrow O$). The machine is always initialized to begin in a fixed starting state S_0 [26].

b. Markov Chains

Markov chains indicate that the probability of moving from one state to another depends on the current state and not on previous states. Therefore, they are used to model systems that contain a large number of states. They allow us to have a broad and long-term understanding of the behavior of any system.

c. Hidden Markov Models

It is a more complex type of state transition matrix as it is used in broader applications, including the field of speech and pattern recognition as well as DNA analysis [27].

How the Markov Method Works

The mechanism of Markov chains can be explained in the following steps:

A—After preparing the data for the phenomenon whose future path we want to predict, we first divide it into certain levels, after we subtract the smallest value of the phenomenon from its largest value (range), then divide the result of the subtraction process by the number of levels previously specified.

Note: All possible cases are calculated and then the case is selected based on whether the particular case passes the approved statistical tests [19].

$$Output = \frac{R_{Max} - R_{Min}}{Number\ of\ possible\ states}$$

Then we configure the levels according to the number of specific cases. For example, if the states are (4), as shown in Table 1:

Table 1. Composition of levels according to the number of specific states.

Second term	First term	States
State1	R_{Min}	$Y1 = (R_{Min} + \frac{Range}{4})$
State2	$Y1$	$Y2 = (Y1 + \frac{Range}{4})$
State3	$Y2$	$Y3 = (Y2 + \frac{Range}{4})$
State4	$Y3$	$R_{Max} = (Y3 + \frac{Range}{4})$

The first term for the first state represents the lowest value of the productivity values R_{Min}. When we add the quotient of dividing the range/4 (number of selected states) to the first term) (R_{Min}), we get the value of Y_1, i.e., the second term of the first state, and so on for the other states: The first terms for the second, third, and fourth states represent the value of the second term for the immediately preceding state. As for the second terms for the states: the first, Y_1, the second, Y_2, the third, Y_3, and the fourth R_{Max} is obtained by adding the quotient of the range/number of specified states, for example (4), to the first limit of the specified state.

B—We define the transition matrix, as each element in this matrix expresses the probability of the phenomenon moving from one level to another, provided that the sum of each row of the transition matrix is equal to the correct one (for example, if the levels are 4), as shown in Table 2:

Table 2. Transition matrix.

	S1	S2	S3	S4	Total
S1	P_{11}	P_{12}	P_{13}	P_{14}	1
S2	P_{21}	P_{22}	P_{23}	P_{24}	1
S3	P_{31}	P_{32}	P_{33}	P_{34}	1
S4	P_{41}	P_{41}	P_{43}	P_{44}	1

C—We take the average values of the phenomenon (the phenomenon under analysis) at each of the four levels, shown in Table 3.

Table 3. The average values of the phenomenon at each of the four levels.

State1	State2	State3	State4
$\Sigma Y1$/N1 The number of values for the first state	$\Sigma Y2$/N2 The number of values for the second state	$\Sigma Y3$/N3 The number of values for the third state	$\Sigma Y4$/N4 The number of values for the fourth state

D—We form a line vector whose elements are the number of levels specified by (A), all of which are equal to zero except for an element that is equal to one and whose location in the line corresponds to the level in which the last value of the phenomenon falls. For example, if the last value is in the fourth level, the vector is written as follows in Table 4:

Table 4. Linear vector if the last value in the data falls at the fourth level.

State1	State2	State3	State4
0	0	0	1

E—By multiplying this line vector by the transition matrix, we get a new line vector and by multiplying this in turn by the transition matrix, we get a new line vector with new probabilities.

F—We multiply the new line vector by the averages calculated in step (C), and we obtain the expected value of the phenomenon in the coming year.

G—By repeating the last two steps on the last line vector, we obtain the values of the phenomenon in subsequent years.

In section 3, we will based on what was presented for forecasting using Markov chains, present forecasting results for the value of agricultural GDP in Iraq providing detailed information on the different steps in the calculation.

3. Results and Discussions

In several trials, multiple results have been obtained for predicting the value of the agricultural GDP in Iraq using different numbers of states, including using three, four, five and six states, the best results were obtained when we divided the observed time series into 5 states because the predictive values that were generated by using 5 states were very close to the real values of the most recent years from the time series used what we consider as an important condition for selecting number of the states.

For determining the number of states, a time series was used for the period 1980–2019, and the highest and lowest values from this series were taken. The difference between this highest and lowest value was divided by the chosen number of states (in the final case 5) which provides the minimum and maximum value of each state after which we could calculate the number of yearly values falling within each state (Table 5).

Table 5. Distribution of the five states of the value of agricultural GDP during the period 1980–2019.

States	Min value	Max value	No of values in each state
State1	288661	339307	9
State2	339307	389953	6
State3	389953	440599	15
State4	440599	491245	7
State 5	491245	541891	3
Total			40

Table 6 indicates the distribution of the selected states for the value of agricultural domestic product during the studied period, showing that 9 years fall under State 1, 6 under State 2, 15 under State 3, 7 under State 4 and 3 under State 5 adding up to 40, which is the number years in the studied period.

After calculating the number of years falling under each state, the transitional matrix can be generated, the first step of the methodology. Hereby it is calculated how many times we pass from one state to another when we go from one year to another. For example, in 6 of 9 cases we observed state 1 also the next year is in state 1 other words we obtained a probability of 6 divided by 9 or 0.66667, the same for the other observed transition. As can be noted, the sum of the probabilities in each row of the transition matrix is equal to 1, as shown in Table 7.

Table 6. Ranking of the selected states of the value of the gross domestic product in Iraq during the period (1980–2019).

Year	AGGDP	States	Year	AGGDP	States
1980	322252	1	2000	408581	3
1981	319761	1	2001	469865	4
1982	326978	1	2002	526290	5
1983	334196	1	2003	417657	3
1984	355501	2	2004	405069	3
1985	386397	2	2005	437218	3
1986	417293	3	2006	438557	3
1987	384484	2	2007	424374	3
1988	403577	3	2008	382613	2
1989	430652	3	2009	386894	2
1990	473304	4	2010	446892	4
1991	324624	1	2011	480196	4
1992	354600	2	2012	488140	4
1993	416388	3	2013	541891	5
1994	407297	3	2014	508775	5
1995	417109	3	2015	302328	1
1996	420756	3	2016	303401	1
1997	412750	3	2017	293428	1
1998	443159	4	2018	288661	1
1999	418185	3	2019	446218	4
MAX	541891				
MIN	288661				
Range	253230				
Range/5	50646				

Source: Ministry of Agriculture. Department of Agricultural Economics.

Table 7. Transition matrix (5 states).

	State1	State2	State3	State4	State5	Total
State1	0.666667	0.2222	0	0.111111	0	1
State2	0	0.333333	0.5	0.166667	0	1
State3	0	0.133333	0.666667	0.2	0	1
State4	0.142857	0.142857	0.142857	0.285714	0.285714	1
State5	0.333333	0	0.333333	0	0.333333	1

Vector Extraction

The next step includes extracting the vector which is calculated based on the last observed value in the time series, which is 446218 in the year 2019 this value is located in the fourth state, so the vector is as follows in Table 8.

Table 8. Extract the vector when the value of the last observation in the data falls into the fourth state.

State1	State2	State3	State4	State5
0	0	0	1	0

The calculations are successive to extract the predictive values for the subsequent years, starting from 2019 to 2030. Hereby we can observe that the reason for choosing the fifth state is because of the predictive accuracy, which is represented by dividing the predicted value in 2019 of 440790.4, with the real value for 2019 that was equal to 446218 or, predictive accuracy of 0.98, which is a reliable accuracy. The steps calculating the predictive values for the period 2019–2030 are clarified in Table 9.

Table 10 and Figure 2 indicate the predictive values of agricultural GDP for the period 2019–2030.

The results of the predictive values using the fifth Markovian state are only affected by the probabilities obtained and the values of the last years before the prediction because the prediction of the Markov chains method does not take into account the historical path of the data over a long period of time. Therefore, the selection of the method (Markovian state) relied upon the predictive accuracy of the last year of the data. It was calculated as follows:

$$\text{Predictive accuracy} = \frac{\textit{the real value in } 2019}{\textit{the predictive value in } 2019} = \frac{446218}{440790.4} = 0.9878$$

Table 9. Extract predictive values according to the Markov method for the period 2019–2030.

	Predictive values					
Vector 2019	0.142857	0.142857	0.142857	0.285714	0.285714	
Average	312847.7	375081.5	418364.2	463967.7	525652	
AGGDP 2019	44692.52	53583.07	59766.31	132562.2	150186.3	440790.4
Vector 2020	0.231293	0.139226	0.302721	0.149887	0.176871	
Average	312847.7	375081.5	418364.2	463967.7	525652	
AGGDP 2020	72359.32	52221.04	126647.7	69542.55	92972.46	413743
Vector 2021	0.234564	0.159577	0.351796	0.152272	0.101782	
Average	312847.7	375081.5	418364.2	463967.7	525652	
AGGDP 2021	73382.89	59854.38	147179	70649.5	53501.74	404567.5
Vector 2022	0.212057	0.173972	0.37	0.166525	0.077434	
Average	312847.7	375081.5	418364.2	463967.7	525652	
AGGDP 2022	66341.42	65253.64	154794.7	77262.01	40703.14	404354.9
Vector 2023	0.190972	0.178232	0.383253	0.174136	0.07339	
Average	312847.7	375081.5	418364.2	463967.7	525652	
AGGDP 2023	59744.99	66851.58	160339.3	80793.28	38577.42	406306.6
Vector 2024	0.176654	0.177821	0.393958	0.177328	0.074216	
Average	312847.7	375081.5	418364.2	463967.7	525652	
AGGDP 2024	55265.81	66697.55	164817.8	82274.47	39011.91	408067.6
Vector 2025	0.167841	0.176387	0.401621	0.178722	0.075404	
Average	312847.7	375081.5	418364.2	463967.7	525652	
AGGDP 2025	52508.57	66159.36	168023.7	82921.16	39636.21	409249
Vector 2026	0.16256	0.175171	0.406607	0.179434	0.076198	
Average	312847.7	375081.5	418364.2	463967.7	525652	
AGGDP 2026	50856.55	65703.34	170109.7	83251.69	40053.64	409974.9
Vector 2027	0.159406	0.174359	0.409689	0.179846	0.076666	
Average	312847.7	375081.5	418364.2	463967.7	525652	
AGGDP 2027	49869.86	65398.77	171399.3	83442.57	40299.77	410410.3
Vector 2028	0.157518	0.173857	0.411553	0.180094	0.07694	
Average	312847.7	375081.5	418364.2	463967.7	525652	
AGGDP 2028	49279.28	65210.6	172179.2	83557.77	40443.6	410670.4
Vector 2029	0.156387	0.173554	0.412672	0.180244	0.077102	
Average	312847.7	375081.5	418364.2	463967.7	525652	
AGGDP 2029	48925.2	65097.07	172647.1	83627.54	40528.84	410825.7
Vector 2030	0.155708	0.173373	0.413342	0.180335	0.077199	
Average	312847.7	375081.5	418364.2	463967.7	525652	
AGGDP 2030	48712.77	65028.89	172927.3	83669.51	40579.84	410918.3

Table 10. Predictive values of AGGDP for the period (2019–2030).

Year	Predictive values
2019	440790.4
2020	413743
2021	404567.5
2022	404354.9
2023	406306.6
2024	408067.6
2025	409249
2026	409974.9
2027	410410.3
2028	410670.4
2029	410825.7
2030	410918.3

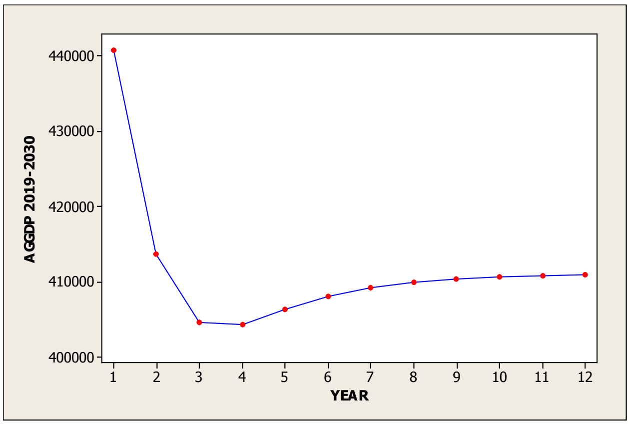

Figure 2. Predictive values of AGGDP for the period (2019–2030).

Depending on the predictive accuracy that we extract in each state, the fifth state was chosen to predict the value of the Iraqi agricultural GDP for the period 2019–2030, and because the fifth state outperformed all other state numbers tested by the research, as shown in Table 11.

It should be noted that the predicted values in the Markov chains methods do not depend on old historical data, that are only to calculate the transition matrix, but only on the recent close values of the time series that we need to predict, while most other prediction methods are affected by the general trend of the time series. The ARIMA method, e.g., reads the entire time series, including a general trend, seasonality, and occasional changes making the prediction results maybe more logical. However, because of the occasional changes that occur in global economies affected by local economies, including the Iraqi economy, predicting the future will be risky because of the possibility that predictive errors will be high due to the fact that historical data are influenced by rather temporary phenomena in such ARIMA method. Hence, the predictive error using the fifth Markovian state was less than the others, reason why it has been chosen. In addition, the predictive values were logical and consistent with the shape of the original time series in terms of the presence of fluctuations, although they were lower compared to the original series, as shown in Figure 3.

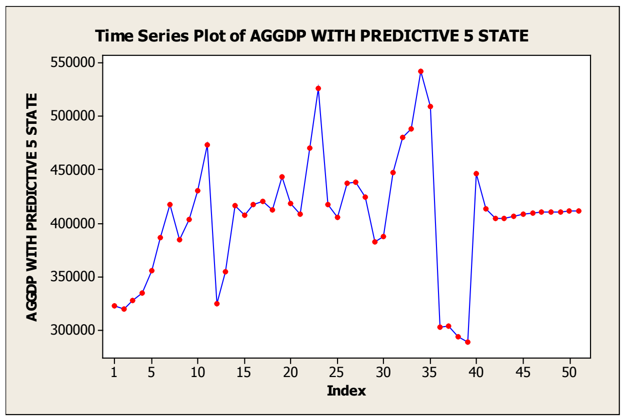

Figure 3. Time series plot of AGGGDP with predictive values by using Markovian state 5.

It is for the above reason that predictive methods such as Markov chains do not take into account too

Table 11. Estimated value for 2019 compared to its real value in all states.

Period	Used state	The real value of agricultural GDP in 2019	Estimated value of agricultural GDP in 2019	Predictive accuracy = real value/estimated value
2000–2019	4	446218	424664.6	0.9517
1980–2019	6	446218	412785.8	0.9250
1980–2019	4	446218	400411.2	0.8973
1980–2019	5	446218	440790.4	0.9878
2000–2019	6	446218	409435.3	0.9175

much old historical data. We argue that future estimates based on recent data are more logical and closer to the reality of the original time series data. This is one of the purposes of using this method, because logical predictive values will contribute to prospecting the future more properly.

With regard to the research variable, which is the value of the agricultural domestic product, predicting its value for a future period of time more accurately may contribute to drawing up a correct future plan for the reality of the agricultural sector in Iraq, which suffers from difficult conditions that extended for decades. In order to make correct decisions and future policies, it is of great importance to use a method that provides a realistic estimate of the value of the agricultural domestic product. Although the contribution of the agricultural domestic product to the gross domestic product in Iraq has always been weak and does not exceed 10% at best, it remains an important sector that deserves correct forecasts and policy-making.

4. Conclusions

Because of the deficiencies in data that researchers in Iraq suffer when making time series the use of accurate forecasting methods, can help those interested in setting agricultural policies to formulate correct decisions about the future related to imports and exports and to determine agricultural plans based on the vision of the future that predictive methods draw for us. In addition, the GDP data although less precise as separated data, such as prices and quantities of agricultural products, may provide a more accurate picture of the future, especially for agriculture in Iraq accurate accountancy records are lacking because workers in the agricultural sector may not provide the state with correct data.

The results of the research proved that the predicted values of the research variable follow the same path as the original time series in terms of the presence of fluctuations, although the fluctuations of the predicted values were less pronounced because of the short predicted period. In addition, the selected Markovian state (the fifth state) confirmed the presence of a decrease and a rise in the predicted values.

The research results also confirm that Markov chains based on older data for calculating the probabilities can then predict the future values based on the most recent data which means that there are no major obstacles in interpreting the prediction results, as the future values are affected by recent values providing logical explanations. On the basis of the results obtained the recommendation that can be given to economic policy makers, in particular the agricultural ones, is the existent need to address the problems that the agricultural sector has always suffered from in order to break this stagnation. A further and next step of analysis would be to try to estimate how policies such as the recent measures taken by the Iraqi government to reduce the value of the currency or other changing external conditions would affect the calculated probability values so that it becomes possible to predict the possible change on agricultural GDP of applying these policies. However, this is a topic for further research. With this article, we have put the methodological foundation.

Author Contributions

Study conception and design: A.D.K AL-Hiyali, Hayder Hameed Blaw; data collection: Najlaa Salah Madlul; analysis and interpretation of results: A.D.K AL-Hiyali, Hayder Hameed Blaw; draft manuscript preparation: Hayder Hameed Blaw, Najlaa Salah Madlul; manuscript revision: A.D.K AL-Hiyali. All authors reviewed the results and approved the final version of the manuscript.

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Data Availability

Data on the value of the Iraqi agricultural GDP for the period under study can be found in the Agricultural Economics Department of the Iraqi Ministry of Agriculture.

Conflict of Interest

The authors declare no conflict of interest.

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