



## Dynamics of Stabilization and Structural Transformation of Wheat Productivity in Iraq: A Markov Switching Modeling Approach

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### Abstract

The study aimed to conduct a dynamic analysis to explain the behavior of wheat production in Iraq using a Markov-switching autoregressive model (MS-AR), covering an annual time series from 1990 to 2023. Using data from the Iraqi Central Bureau of Agricultural Statistics, it assumed that there are underlying systems linked to a historical record of state policies and climate factors. The results revealed two distinct systems governing the behavior of the wheat production sector in Iraq. The first is characterized by its flexibility and continuity, which exceeds five years, and its ability to absorb shocks and return to its long-term average of 611.5 kg/dunum, indicating the high potential for cultivating this strategic crop. The second system is unstable and vulnerable to the shocks it is exposed to, which constantly affect it. However, it tends to recover from them within about a year, indicating an internal dynamic that drives it to return to its stable and flexible state. The research found that the dynamic behavior of productivity is what specifically distinguishes these two systems, not the average productivity itself. The distinctive feature is how they behave over time and respond to shocks. The research recommended adopting proactive risk management policies, not just those related to increasing production, such as developing drought-resistant seed varieties and investing in water infrastructure. It also recommended adopting such analytical models as a diagnostic tool to monitor the resilience of the wheat production sector and anchor it in its stable system.

**Keywords:** Structural resilience, Agricultural risk management, Exogenous shocks, Agricultural productivity, Transitional possibilities

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### Introduction

The Markov switching model is an advanced model for detecting and distinguishing transitions in agricultural production systems without prior knowledge, and then analyzing the probability of transitions between them over time. Irregular production behavior appears due to multiple factors, which requires dynamic analysis tools that can provide a deep explanation and realistic analysis of the change occurring in the time series. By Middle Eastern standards, Iraq has considerable agricultural resources and extensive irrigation potential, but its agricultural sector suffered

significant damage during the 1991 Gulf War, beginning in the first year following the implementation of UN economic sanctions against it in August 1990.

The central government took several measures to increase production and control domestic food, which resulted in a distorted system of incentives that included subsidized agricultural inputs, mandatory production quotas, and an implicit tax on the sale of that production. By the mid-1990s, irrigation infrastructure and agricultural productivity were severely hampered by over-exploitation of resources and the deterioration of essential inputs, and their subsidies were gradually reduced under severe macroeconomic pressure. By 1998,

the government's distribution of high-yield seeds and subsidized credit ended. This cessation allowed the entry of inferior agricultural commodities, which directly harmed farmers[15].

Wheat is the leading strategic crop in Iraq, representing about 70% of the total grains in the country. The government invests significant resources in its local production in the form of subsidized inputs and direct crop purchases. It is grown in both irrigated and rain-fed lands, and the price at which that the Ministry of Agriculture purchases it is usually announced before harvest. It is sold to the Ministry of Trade and Industry for milling and distribution through the public distribution system (PDS), and the bulk of consumption is for food, as its grains are not processed in any industrial establishment[12]. In 2008, the government launched an agricultural initiative to support agricultural projects represented by financial loans, which were provided to farmers in an easy and interest-free manner that amounted to trillions of dinars. It also offered limited support for some production inputs in addition to subsidizing the prices of the final output of the wheat crop, in particular at rewarding and above international prices[7].

Agricultural policies in Iraq since 2010 have reflected a traditional approach. They prioritize immediate production and job creation over sustainability, including purchase guarantees for strategic crops (wheat and barley), equipment subsidies and infrastructure support, seasonal import restrictions to protect local farmers, and basic maintenance of the irrigation system [14]. Iraq was exposed to successive droughts in 1999-2001 and 2008-2009, the latter causing severe losses to rainfed crops in the north, damaging about 50% of the productivity of agricultural lands. 2021 was also considered a dry year, as the agricultural sector consumes about 85% of the water and uses open and old irrigation channels, traditional irrigation techniques and old agricultural patterns. As this resource is affected by climate changes such as high temperatures and drought, the policies of neighboring countries also had a bearing, resulting in a reduction in the area of agricultural land and increased water scarcity [11].

A study by Stabel et al. (2017) comparing the characteristics of farms that remained in the most profitable and least profitable categories in Kansas noted that these farms shifted from the highest to the lowest profitability categories between 5% and 20% of the time within a year. It found that while some farmers were

more than half as likely to remain in the highest profitability category, others remained in the lowest profitability category 42% of the time [17]. Tyubee and Iwan (2019) examined dry and rainy spells in Nigeria's Middle Belt, advising agricultural preparations during weeks 20 to 22 [19]. Yogesh and Srivastava (2020) examined the trade trajectories of Indian flue-cured Virginia tobacco through Markov chains, identifying Western Europe, Africa, and the Americas as principal markets [22]. Al-Ani and Alhiyali (2021) projected maize productivity in Iraq utilizing Markov chains, revealing a decrease in future productivity and a lateral expansion instead of an augmentation in yield per unit area[2].

Wahid et al. (2022) investigated generational transitions among agricultural laborers in Pasuruan to propose policy solutions for youth engagement [21]. Chavan (2023) examined basmati rice export trends from 2009-10 to 2021-22, forecasting a constant market share for the UAE and Saudi Arabia while anticipating a decrease for Iraq and Iran [3]. Stokes (2024) found that crop yields can be predicted by leveraging their information status during the season. His statistical evidence, through an experimental application of the presented methods to corn production in Nebraska, indicated that the Markov chains for crop conditions were time-homogeneous, and that both approaches to estimating transition probabilities produced similar predictions [18].

Adekunle and Aregbeshola (2025) used the Markov model to explore some of the determinants affecting the effectiveness of agricultural policies and analyzed the gap between them and agricultural productivity by evaluating the various incentives of these policies and the imbalances that occur in them. The results indicated that agricultural credit consistently enhances various agricultural productivity systems [1]. Gaffney (1997) [5], Piet (2011) [18], Jahangir Alam et al. (2014) [8], Voinalovych et al. (2019) [20], and Fadhil and Unami (2021)[4], also studied the use of Markov models in the agricultural sector.

The study of ( Le Quoc, D & et.al, 2026) seeks to determine the impact of financial development—measured by domestic credit extended to the private sector—on agricultural performance in Bangladesh from 1980 to 2023. To account for the potential for non-linear relationships, the analysis employs a Markov switching systems (MRS) model, which distinguishes between two unobserved phases of the agricultural cycle: a crop loss

phase and a boom phase. The empirical results indicate that during periods of crop loss, financial development contributes positively to the recovery of the agricultural sector by easing liquidity constraints and mitigating financial shocks to the incomes of farming households. Conversely, during boom periods, the effect of finance becomes negative, highlighting the shortcomings and risks of debt accumulation associated with excessive credit expansion. The findings also suggest that the relationship between finance and agriculture is system-dependent and not uniform, underscoring the need for policy interventions that adapt to market volatility. Accordingly, the study advocates for a countercyclical credit strategy—expanding credit during recessions while improving its quality and efficiency during booms—to support agricultural growth and enhance its resilience in Bangladesh [10].

A study by Kim, S., Hwang, S., Choi, W., & Lee, S. (2026) developed a probabilistic risk management framework using a Markov chain approach to analyze snow load dynamics under varying climatic conditions, considering the effects of snow density variations due to temperature fluctuations. Time-sequential meteorological data from 99 weather stations across South Korea over the past 20 years were used to calculate hourly snow loads. Cluster analysis was used to classify snow load states, and transition probabilities between states were derived to construct Markov transition matrices. The framework assesses the failure probabilities of different greenhouse specifications, highlighting the impact of structural thresholds and regional snowfall patterns. Areas exposed to heavy snowfall showed significantly higher failure probabilities compared to areas with moderate conditions. National-level failure probability maps were developed to provide practical insights for disaster mitigation, emphasizing the importance of region-specific risk management strategies. The results demonstrated the crucial role of snow density in the development of snow loads and their impact on structural integrity. This study underscores the need to integrate probabilistic models with structural integrity assessments to enhance the resilience of agricultural structures to heavy snowfall, thus providing an effective tool for sustainable agricultural practices [9].

This research stemmed from the exposure of the wheat crop in Iraq to extreme fluctuations due to the country's exposure to several shocks represented by the economic blockade and climate challenges such as drought and water scarcity during the study period.

Those factors required a search for a dynamic analysis that went beyond the superficial analysis which considered these fluctuations as mere random deviations. In other words, trying to better explain the behavior of the productivity of the crop under study by assuming the existence of several latent systems and not one fixed system that can link to historical periods such as those experienced by the country. Accordingly, the hypothesis of this study is that the productivity of the wheat crop operates within two distinct dynamic systems: A resilient and stable system (stationary) capable of returning to a high average productivity, and a fragile and unstable system (non-stationary) where shocks have permanent effects. It aims to identify these two regimes and relate their dominance to historical policy and climate events.

## Materials and Methods

The Markov-switching autoregressive (MS-AR) model allows parameters (mean, continuity) to be changed between separate systems, enabling these changes to be captured internally without specifying change dates in advance. This justifies its selection.

Markov switching models are a set of models that can introduce temporal variations in the values of the model coefficients so that they have different values depending on the regime in which the time series is operating. Each system will have a different equation that provides the model with greater flexibility in explaining the behavior of the data, whereby this temporal variation is governed by a discrete-value and a latent stochastic process with limited memory, which is incorporated as regime-specific values [16]. The general mathematical function of the Markov switching model is:

It is a first-order autoregressive model in which both the constant term and the autoregressive coefficient vary across subsamples, where  $\epsilon_t \sim \text{i.i.d. } N(0, \sigma^2)$  is the modeling of system  $s_t$  as the outcome of an unobserved Markov chain with  $N$  states, with  $\epsilon_t$  independent of  $s_\tau$  for all values of  $t$  and  $\tau$ . This process allows the generation of future predictions that take into account the probability of changing from system 1 to system 2.

Calculating smoothed probabilities: smoothed inferences can be calculated using an algorithm developed by Kim (1993). In its vector form, it is written as follows:

where  $\hat{\xi}_t(t|\tau)$  is found by inversely iterating the above equation starting from  $t=T-1, T-2, \dots, 1$

This algorithm is valid only when  $s_t$  follows a first order Markov chain and when the conditional density depends on  $s_t, s_{t-1}$ , only by the current state  $s_t$ , and when  $x_t$  (the vector of explanatory variables other than the previous values of  $y$  is completely exogenous), meaning that  $x_t$  is independent of  $s_t$  for all values of  $t$  and  $\tau$ .

Calculating transition probabilities: The maximum likelihood estimates of transition probabilities satisfy the following equation:

$$y_t = c_{s_t} + \phi_{s_t} y_{t-1} + \epsilon_t$$

Thus, the estimated transition probability  $\hat{p}_{ij}$  is essentially the number of times that state  $i$  appears to have been followed by state  $j$ , divided by the number of times the process was in state  $i$ . These numbers are estimated based on smoothed probabilities [6].

## Results and Discussion

An annual time series was used for the wheat crop productivity variable in Iraq that covered the period from 1990 to 2023, with 34 observations obtained from the

Iraqi Central Bureau of Statistics, according to the study model.

where  $y_t$  represents wheat productivity in the current year  $t$  kg/dunum, represents wheat productivity in the previous year, is the state variable that determines whether the economy is in regime 1 or regime 2, and  $\phi_{s_t}$  are the mean and autoregressive parameters whose values change based on the dominant regime and finally represents the random error.

The Markov switching model was estimated in its simple form, and **Table 1** shows the results.

**Table 1.** Results of the Markov switching model in its simple form

| Regime                   | Variable    | Coefficient | Std. Error | z-Statistic | prob.  |
|--------------------------|-------------|-------------|------------|-------------|--------|
| Regime 1                 | C           | 611.1211    | 35.62518   | 17.15419    | 0.0000 |
| Regime 2                 | C           | 281.8625    | 25.62255   | 11.00056    | 0.0000 |
| Common                   | LOG (SIGMA) | 4.534204    | 0.153596   | 29.52032    | 0.0000 |
| Probabilities Parameters | P1-C        | -0.599202   | 0.439252   | -1.364142   | 0.1725 |

Dependent Variable: WHEAT\_PRODUCTIVITY

Method: Simple Switching Regression (BFGS/ Marquardt steps)

Date: 08/03/25 Time: 11:30 Sample: 1990 2023

Included observations: 34

Number of states: 2

Standard errors & covariance computed using observed Hessian

Random search: 25 starting values with 10 iterations using 1 standard deviation (rng=kn, seed=2044713076)

Convergence achieved after 4 iterations

Mean dependent var 398.5912, S.D. dependent var 185.7394, S.E. of regression 191.6373, Sum squared resid 1138471, Durbin-Watson stat 0.221248, Log likelihood -220.8905, Akaike inf criterion 13.22885, Schwarz criterion 13.40842, Hannan-Quinn criter. 13.29009

Source: Prepared by the researcher using EViews 13.

**Table 1** shows that there are two distinct average productivity regimes, a high productivity regime (with an average of 611 kg/ dunum) and a low productivity regime (with an average of 282 kg/ dunum). However, the model has an autocorrelation issue which is indicated by the low Durbin-Watson statistic (DW = 0. 22), which

means that it fails to capture the temporal nature of productivity. In order to ensure the reliability of the results and to address this issue, the model was developed to include an autoregressive term (AR(1)), as seen in **Table 2**.

**Table 2.** Results of model development and autocorrelation treatment

| Regime                   | Variable   | Coefficient | Std. Error | z-Statistic | Prob.  |
|--------------------------|------------|-------------|------------|-------------|--------|
| Regime 1                 | C          | 286.6675    | 59.06701   | 4.853260    | 0.0000 |
|                          | AR(1)      | 0.531309    | 0.139330   | 3.813320    | 0.0000 |
| Regime 2                 | C          | 411.6548    | 76.46020   | 5.383909    | 0.0000 |
|                          | AR(1)      | 1.031219    | 0.065854   | 15.65912    | 0.0000 |
| Common                   | LOG(SIGMA) | 3.863317    | 0.181761   | 21.25491    | 0.0000 |
| Probabilities Parameters | P1-C       | -1.475550   | 0.601349   | -2.453733   | 0.0141 |

Date: 08/03/25 Time: 11:31

Sample (adjusted): 1991 2023

Included observations: 33 after adjustments

Number of states: 2

Initial probabilities obtained from ergodic solution

Standard errors &amp; covariance computed using observed Hessian

Random search: 25 starting values with 10 iterations using 1 standard deviation (rng=kn, seed=2044713076)

Convergence achieved after 12 iterations

1: Inverted AR Roots .53 ; 2: Inverted AR Roots 1.03 ; Estimated AR process is nonstationary

Mean dependent var 402.9727, S.D. dependent var 186.8264, S.E. of regression 87.22342, Sum squared resid 213021.9, Durbin-Watson stat 2.039914, Log likelihood -186.8679, Akaike inf criterion 11.68896, Schwarz criterion 11.96105, Hannan-Quinn criter. 11.78051

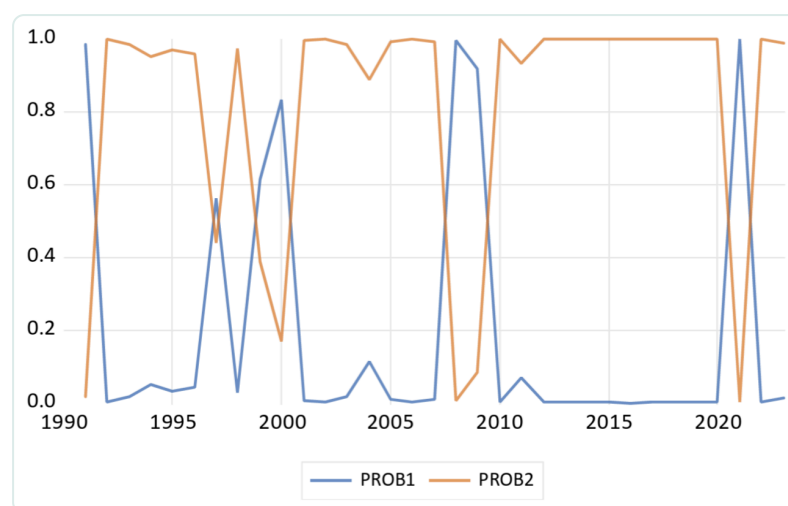
Source: Prepared by the researcher using EViews 13.

**Table 2** shows that the dynamic model was successfully modified to correct for autocorrelation (with a Durbin-Watson value of 2.04). This is the final model adopted in the research, which differentiates between regimes not based on their mean, but on their dynamic behavior. Based on the AR (1) coefficients in **Table 2**, we can clearly identify the nature of the two systems: The first regime (Regime 1) is the "Stable Regime" which is characterized by an autoregressive coefficient of 0.53 ( $AR < 1$ ). This indicates a stable system capable of returning to its mean after a shock. The shocks here are temporary. Although the constant (C) appears lower (286.67), the Long-Term Mean for this stable regime is

calculated as  $286.67 / (1 - 0.5313) = 611.5\$ \text{ kg/dunum}$ . This reveals that under stable conditions, there is a very high potential for wheat cultivation in Iraq.

The second regime (Regime 2) is the "Unstable Regime" and is characterized by an autoregressive coefficient of 1.03 ( $AR > 1$ ). This unit-root behavior confirms that it is an unstable and fragile system. In this regime, shocks (such as political crises or drought waves) have a cumulative and permanent effect, meaning the system cannot self-recover.

To discuss the periods in which productivity is likely to follow the flexible versus the fragile regime, the regime diagram in **Figure 1** was produced to describe the historical record narrated by the study's model.



**Figure 1.** Smoothed probabilities for the study period

Source: Prepared by the researcher using EViews 13.

In the smoothed probabilities analysis for the study period depicted in the graph, the dominance of each system as a historical record is shown by the blue line (PROB1) which represents the resilient and stable system, while the orange line (PROB2) represents the fragile and unstable system. For the 1991-1996 period, a clear dominance of the unstable or fragile regime (orange line) can be seen, which can be attributed to the pressures of the economic sanctions imposed on the country. The 1997-2002 period showed a slight improvement consistent with the implementation of the oil-for-food agreement. A sudden shift towards the flexible system occurs in 1997; however, it soon reverts to the fragile regime from 1999 onward. This may indicate the political and economic uncertainty that preceded the events of 2003 or could also be due to the fact that the UN program mentioned above was not sufficient to resolve all structural issues.

The 2003-2009 period was characterized by high volatility, showing a big spike in 2008 and 2009, as indicated by the orange line of the unstable system

peaking to 1.0, due possibly to the drought that hit the country during this period. The period 2010-2020 refers to recovery and state support for policies, as the flexible system prevails (the blue line), making it a period of relative stability, and despite some sharp declines, the system was in good shape for most of the decade. Historically, this may be attributed to the improved security situation and high oil revenues, enabling the governments to expand their support for the agricultural sector. After 2020 the model picked up another challenge, the most notable perhaps being the water crisis and climate change, suggesting that the state of stability achieved is not guaranteed, and the system under such shocks can revert to one of instability.

To illustrate the probability of remaining in the flexible system for another successive year or moving to the unstable system and vice versa, the transition probability matrix was extracted, as shown in **Table 3**.

**Table 3.** Results of the transition probability matrix

| State | 1        | 2        | Expected Duration |
|-------|----------|----------|-------------------|
| 1     | 0.813898 | 0.186102 | 5.373385          |
| 2     | 0.813898 | 0.186102 | 1.228656          |

Equation: UNTITLED; Date: 08/03/25 Time: 12:52; Transition summary: Constant simple switching; Transition probabilities and expected durations; Sample (adjusted):1991 2023; Included observations: 33 after adjustments; Constant transition probabilities:  $P(i,k) = P(s(t) = k/s(t-1) = i)$  (row=i/column=k>). Constant expected duration.

Source: Prepared by the researcher using EViews 13.



The results reveal that the expected survival time (which is the important point) in the stable system is approximately 5.4 years, meaning that the wheat production sector can remain stable for more than five years on average before it is exposed to an external shock. This reinforces the idea that stability is normal and continuous for a relatively long period. The unstable system averaging 1.2 years is revealing as it shows that the sector recovers fairly quickly, in about a year, from

shocks, indicating an internal dynamic reverting it towards stability, and that the state of instability is a short-term phenomenon. To confirm the reliability of the different characteristics of the two systems (flexible and unstable) and to show that it was not a statistical coincidence, confidence intervals were extracted providing statistical evidence validating this finding (Table 4).

**Table 4.** Reliability results, confidence intervals

| Variable                 | Coefficient | Low (90% CI) | High (90% CI) | Low (95% CI) | High (95% CI) | Low (99% CI) | High (99% CI) |
|--------------------------|-------------|--------------|---------------|--------------|---------------|--------------|---------------|
| Regime 1                 |             |              |               |              |               |              |               |
| C                        | 411.6600    | 281.4257     | 541.8942      | 254.7760     | 568.5439      | 199.8122     | 623.5077      |
| AR(1)                    | 1.031239    | 0.919062     | 1.143399      | 0.896109     | 1.166352      | 0.84769      | 1.213691      |
| Regime 2                 |             |              |               |              |               |              |               |
| C                        | 286.6705    | 186.0611     | 387.2800      | 165.4735     | 407.8676      | 123.0125     | 450.3286      |
| AR(1)                    | 0.531321    | 0.294004     | 0.768638      | 0.245442     | 0.817200      | 0.145286     | 0.917357      |
| Common                   |             |              |               |              |               |              |               |
| LOG(SIGMA)               | 3.863313    | 3.553727     | 4.172899      | 3.490377     | 4.236249      | 3.359720     | 4.366906      |
| Probabilities Parameters |             |              |               |              |               |              |               |
| P1-C                     | 1.475537    | 0.451284     | 2.499790      | 0.2416092    | 2.709382      | -0.190581    | 3.141656      |

Source: Prepared by the researcher using EViews 13.

At the 95% confidence level, the autoregressive coefficient AR(1) in the first system (unstable or fragile) is between 0.896, 1.166 while in the second (flexible) it is between 0.245, 0.817. The highest possible value that appears in the flexible system (0.817) is still less than the lowest possible value in the fragile system (0.896). This statistically proves that the system is stable and able to absorb shocks and return to its average, unlike the first system, which has a value of 1, which confirms that the shocks are permanent. This accurately illustrates that the two systems have fundamentally different dynamic behaviors and that their ranges do not overlap at all.

Another important observation relates to the confidence intervals of the average coefficient C which, by overlapping slightly, indicates that it is the dynamic behavior of productivity that accurately distinguishes the two systems and not average productivity. In other words, the key distinguishing feature separating the two cases is not just whether productivity is high or low, but how the system behaves over time and how it responds to shocks.

## Conclusion

This research confirmed the existence of two distinct and completely different systems governing the behavior of the wheat production sector in Iraq. The sector does not move between high and low production levels but rather alternates between these two systems in nature and behavior. The first system is characterized by the ability to absorb shocks and return to its average and high potential in production, is flexible, and with a continuity that exceeds five years on average. The second is fragile and unstable, unable to absorb the impact of the shocks to which it is exposed, which are permanent and cumulative. It has the ability to absorb the impact of the shocks, so it is permanent and cumulative, meaning that if exposed to another setback, it loses its flexibility and ability to return to the right path despite its short-expected duration (one year), causing a structural risk to production and its sustainability.

The historical record showed that the shift towards it was not a statistical coincidence, but was associated with shocks to which the country was exposed, such as

economic sanctions and waves of water scarcity that led to drought.

## Recommendation

The research recommends that decision makers adopt proactive policies in risk management and not only those related to increasing production such as developing drought-resistant seed varieties and investing in water infrastructure. Analytical models should be adopted as diagnostic tools to monitor the resilience of the wheat production sector and to prioritize maintaining it in its stable system as any absence of stability will force it into its fragile state.

## Supplementary Materials

None.

## Author Contributions

Rafid Fattah Muhammed methodology, writing - original draft preparation; Ali Darub Kassar and Najlaa Salah Madlul - review and editing. All authors have read and agreed to the published version of the manuscript.

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## Data availability statement

None.

## Conflicts of Interest

The authors declare no conflicts of Interest

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## مقالة أصيلة

## ديناميكيات الاستقرار والتحول الهيكلي في إنتاجية القمح في العراق: منهج نمذجة التحول ماركوف

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## الخلاصة

هدفت الدراسة إلى إجراء تحليل ديناميكي لتفسير سلوك إنتاج القمح في العراق باستخدام نموذج الانحدار الذاتي لماركوف (MS-AR)، والذي يغطي سلسلة زمنية سنوية من عام 1990 إلى عام 2023. بافتراض وجود أنظمة أساسية مرتبطة بسجل تاريخي لسياسات الدولة والمناخ. كشفت النتائج عن وجود نظامين متميزين يحكمان سلوك قطاع إنتاج القمح في العراق. يتميز النظام الأول بمرونته واستمراريته التي تتجاوز خمس سنوات، وقدرته على امتصاص الصدمات والعودة إلى متوسطه طويل الأجل البالغ 611.5 كجم/دونم، مما يدل على الإمكانيات العالية لزراعة هذا المحصول الاستراتيجي. أما النظام الثاني فهو غير مستقر وعرضة للصدمات التي يتعرض لها، والتي تؤثر عليه باستمرار. ومع ذلك، فإنه يميل إلى التعافي منها في غضون عام واحد تقريباً، مما يدل على ديناميكية داخلية تدفعه للعودة إلى حالته المستقرة والمرونة. ووجد البحث أن السلوك الديناميكي للإنتاجية هو ما يميز هذين النظامين بدقة، وليس متوسط الإنتاجية نفسه. والسمة المميزة هي كيفية سلوكها مع مرور الوقت واستجابتها للصدمات. أوصى البحث باعتماد سياسات استباقية لإدارة المخاطر، لا تقتصر على سياسات زيادة الإنتاج، مثل تطوير أصناف بذور مقاومة للجفاف والاستثمار في البنية التحتية للمياه. كما أوصى باعتماد هذه النماذج التحليلية كأداة تشخيصية لمراقبة مرونة قطاع إنتاج القمح وترسيخه في نظامه المستقر.

**الكلمات المفتاحية:** المرونة الهيكلية، إدارة المخاطر الزراعية، الصدمات الخارجية، الإنتاجية الزراعية، احتمالات الانتقال