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SPECIAL SECTION: MACHINE LEARNING IN AGRICULTURE

Markov model planning on the adoption of an enhanced wheat cultivar

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Abstract

Predictions on the time needed to adopt new technologies can be used for planning purposes. These predictions should be calculated using a Markov planning model, which is a probabilistic approach to estimating the speed of adoption. In a research project, a data-driven model was developed to simulate the adoption rate of an enhanced, drought-resistant rain-fed hard wheat (*Triticum aestivum* L.) cultivar in Kurdistan, Iran. The growers' decision-making on cultivar replacement was mapped onto the transition matrix, state probability, transition diagram, and tree of the states of the Markov process to compute the limiting probability of the stochastic model, thereby simulating the adoption rate of the wheat cultivar. The mathematical model, which achieves a convergence of 82% adoption for the enhanced wheat cultivar within 5 years, simulates farmers' behavior and knowledge to enhance food security. Simulating the future of new technology in food and agricultural systems using the proposed methodology can assist policymakers in making informed decisions.

1 | INTRODUCTION

Because wheat (*Triticum aestivum* L.) production is limited by abiotic and/or biotic stress, stress-resistant cultivars are needed to improve food security. However, to improve food security, cultivars with enhanced drought tolerance need to be planted (Clay et al., 2017). To effectively implement an enhanced drought-resistant cultivar, it is important to analyze farmers' decision-making regarding adoption.

The mathematical models can analyze the interactions between different factors that influence food and agricultural systems (Golpira et al., 2021). For example, a Markov process-based model was employed to simulate grain harvesting efficiency (Golpira & Sola-Guirado, 2022). The Markov process has also been applied to soil erosion (Liu et al., 2016), farm profitability (Stabel et al., 2018), hydrology (Tan et al., 2019), land-use changes (Khwarahm et al., 2021), and livestock farm sizing (Saint-Cyr, 2022). A Markov process can calculate the probability of a system reaching a limiting state after an infinite number of transitions, given its initial state.

This study analyzes the probability of transitioning from seeding the most sown wheat cultivars to planting an enhanced drought-resistant wheat cultivar. A data-driven model was developed to map farmers' willingness on planting the enhanced wheat cultivar onto the Markov process and simulate the adoption of the new technology over time.

2 | MATERIALS AND METHODS

2.1 | Markov chain

A Markov process is a mathematical model with n states: S_1, $S_2, S_3, S_4 \ldots S_n$, and a transition matrix **P**. The matrix **P** is the description of the Markov process, described as:

$$\mathbf{P} = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{12} \\ P_{21} & P_{22} & \dots & P_{2n} \\ . & . & \dots & . \\ P_{n1} & P_{n2} & \dots & P_{nn} \end{bmatrix} \quad (1)$$

The conditional probability, P_{ij}, describes the probability of occupying state S_j, if the system currently settles in state S_i after its next transition. If $\alpha = (\alpha_1, \ \alpha_2, \cdots \alpha_n)$ is a probability vector with n components, then $\alpha\mathbf{P}$ is a probability vector (Bharucha-Reid, 1997). The probability vector can be calculated as:

$$\alpha\mathbf{P} = \sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i P_{ij} = \sum_{i=1}^{n} \alpha_i \sum_{i=1}^{n} P_{ij} = \sum_{i=1}^{n} \alpha_i = 1 \quad (2)$$

The quadratic matrix in form (2) is a stochastic matrix with nonnegative elements that are not greater than 1. However, a problem of interest is to calculate the probability that the system will be in state j after n years, given that the system was initially in state i at the beginning of the n-year period.

The state probability $\alpha(0) = \alpha_j(0) = [\alpha_1(0) \ \alpha_2(0)]$ describes the initial state probability vector. The state probabilities $\alpha_1(1)$ and $\alpha_2(1)$ are calculated by

$$\alpha_1(1) = \left[\alpha_1(0) \ P_{11} \quad \alpha_2(0) \ P_{21}\right] \quad (3)$$

$$\alpha_2(1) = \left[\alpha_1(0) \ P_{12} \ \ \alpha_2(0) \ P_{22}\right] \quad (4)$$

where $\alpha_j(k)$ is the probability that the system will occupy state j after k transitions if its state at $n = 0$ is known. Accordingly, (3) and (4) could be expanded to the general form of

$$\alpha_j(1) = \left[\alpha(0) \ P_j\right] \quad (5)$$

where P_j is the jth column of $\mathbf{P}$. For the state j, the state probability is (Howard, 1960)

$$\alpha_j(K) = \sum\nolimits_i \alpha_i(0) \, P_{ij}^k \quad (6)$$

The probability matrix $\mathbf{P}^k$ estimates the state of matrix $\mathbf{P}$ after k years. The limiting or steady-state probability of the Markov process α_j is calculated as:

$$\alpha_j = \lim_{k\to\infty} \alpha_j(k) = \lim_{K\to\infty} P_{ij}^k \quad (7)$$

Core Ideas

- The adoption of an enhanced drought-resistant wheat cultivar was mathematically modeled.
- A data-driven simulator was developed to analyze the adoption of the wheat cultivar over time.
- The seeding adoption rate of the enhanced wheat cultivar was predicted.
- The stochastic analysis of farmers' decision-making to improve food security was conducted.

where one could approximate k by applying the boundary condition

$$\left|\alpha_j(k+1) - \alpha_j(k)\right| < \varepsilon \quad (8)$$

In (8), ε is a small value that would be set by the policymaker.

2.2 | Study area

The highland between Dehgolan, Bijar, and Divandara in Kurdistan province (34°–36° N latitude and 45°–48° E longitude) is typically farmed with a popular rotation of rain-fed winter wheat and spring chickpeas, as shown in Figure 1. While the economy of this area is dependent on agricultural products, with a particular focus on rain-fed hard wheat, the sustainability of agriculture and overall development of the province have been hindered by the low attainable yield and farmers' income in previous years. Drought, which refers to the lack of precipitation causing a prolonged shortage of water supply, reduces harvested yield to ≤1 ton per hectare. During severe droughts, unharvested plants are often transformed into cover crops or used as animal feed.

An enhanced drought-resistant wheat cultivar was introduced to the farmers after grain harvesting in the summer of 2015. The established or commonly sown cultivars in that region are Sardary, Azar, and Sabalan. The seed distribution centers provided growers with seed originality (subsidized, breeding purpose, producer, etc.) and field evaluation results (plant height, 1000-kernel weight, harvestable yield, protein content, etc.). While the price of the enhanced and established seeds was the same, the growers were free to choose between the enhanced drought-resistant wheat cultivar and the established and well-known cultivars.

A survey was conducted in the fall of 2017 and the identical forms for 2016 and 2017 were provided to each grower, as

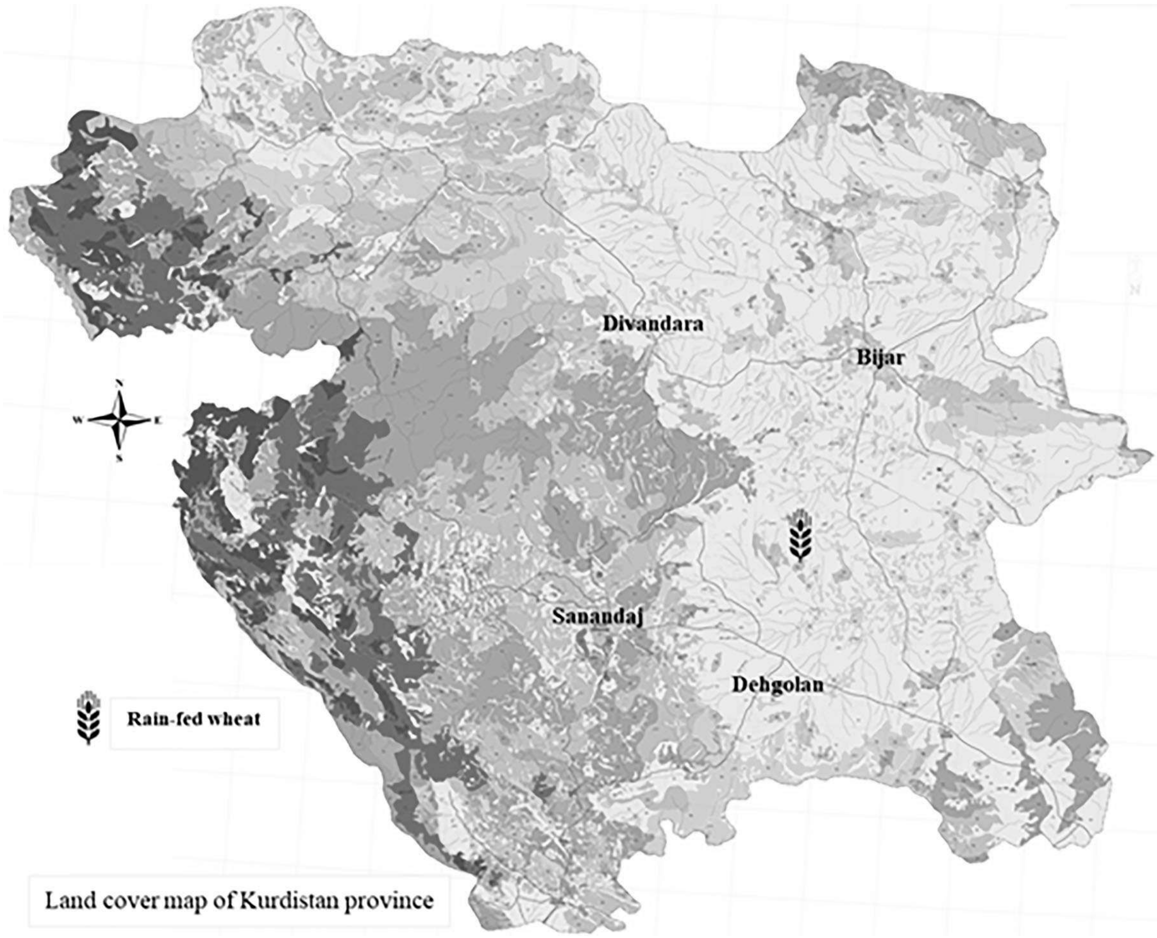

FIGURE 1 The surveyed area between Dehgolan, Bijar, and Divandara is located on the west side of the Kurdistan province.

shown in Figure 2. Trained research assistants guided growers to fill out the 10-item paper-and-pencil questionnaires. They helped illiterate growers to fill them out. No incentives were offered to complete the survey. With a response rate of 91%, approximately 1000 filled surveys were collected and analyzed. The study was conducted under the Declaration of Helsinki, and approved by the Ethics Committee of the University of Kurdistan (date of approval: 3/7/2016).

2.3 | Data retrieval from the survey

According to the on-farm participatory data, 83% of farmers who seeded the enhanced cultivar in 2016 remained planting the enhanced cultivar in 2017, while 17% of the farmers returned to the established cultivars. Additionally, 23% of the farmers, who cultivated the established cultivars in 2016 continued to seed the established cultivars in 2017. Therefore, 77% of the farmers switched to planting the enhanced cultivar in 2017. Additionally, Table 1 gives some agronomic, biotic, and/or abiotic characterizations of the rain-fed wheat cultivars in 2016 and 2017. However, this rough data was not used in the development of the data-driven model.

TABLE 1 Some agronomic, biotic, and/or abiotic characterizations of the rain-fed wheat in Kurdistan province in the successive years, 2016 and 2017.

Characteristics	2016	2017
Average yield irrigated (kg/ha)	3200	3700
Average yield rain-fed (kg/ha)	840	950
Phosphate consumed (kg/ha)	50	55
Urea fertilizer (kg/ha)	40	45
Farm infected by disease (%)	18	6
Crop damaged by pests (%)	56	15
Farms infested with weeds (%)	85	85
Autumn rainfall (times)	2	3
Spring rainfall (times)	3	4
Cold and chill weather (%)	80	80

3 | RESULTS AND DISCUSSION

3.1 | Data-driven model

The model maps the wheat cultivar perception by farmers onto the transition matrix and diagram of the Markov process. The

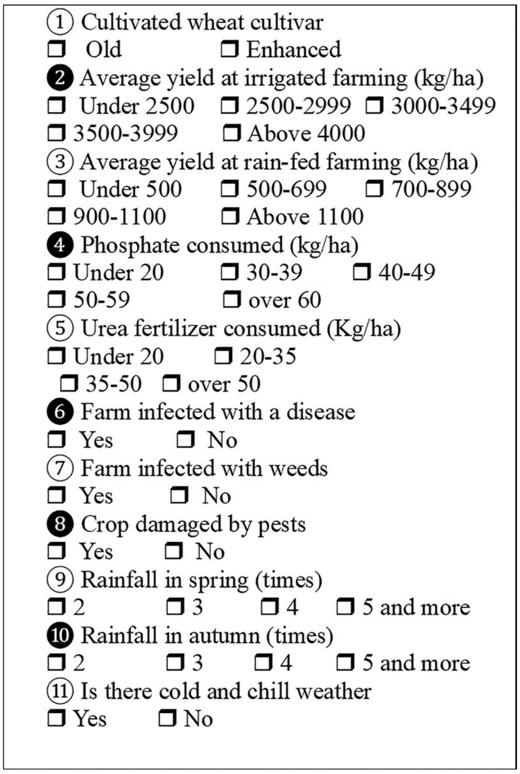
① Cultivated wheat cultivar
❒ Old ❒ Enhanced
❷ Average yield at irrigated farming (kg/ha)
❒ Under 2500 ❒ 2500-2999 ❒ 3000-3499
❒ 3500-3999 ❒ Above 4000
③ Average yield at rain-fed farming (kg/ha)
❒ Under 500 ❒ 500-699 ❒ 700-899
❒ 900-1100 ❒ Above 1100
❹ Phosphate consumed (kg/ha)
❒ Under 20 ❒ 30-39 ❒ 40-49
❒ 50-59 ❒ over 60
⑤ Urea fertilizer consumed (Kg/ha)
❒ Under 20 ❒ 20-35
❒ 35-50 ❒ over 50
❻ Farm infected with a disease
❒ Yes ❒ No
⑦ Farm infected with weeds
❒ Yes ❒ No
❽ Crop damaged by pests
❒ Yes ❒ No
⑨ Rainfall in spring (times)
❒ 2 ❒ 3 ❒ 4 ❒ 5 and more
❿ Rainfall in autumn (times)
❒ 2 ❒ 3 ❒ 4 ❒ 5 and more
⑪ Is there cold and chill weather
❒ Yes ❒ No

FIGURE 2 Questionnaires delivered to growers on the interest in the enhanced drought-resistant wheat cultivar in Kurdistan province in 2017.

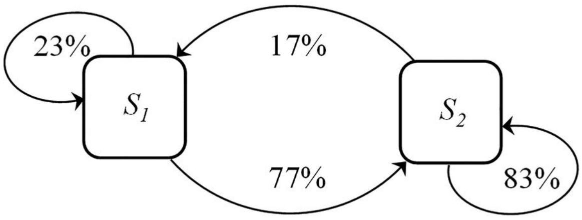

FIGURE 3 Transition diagram of state S_1 (seeding of the established cultivars) and state S_2 (planting the enhanced drought-resistant wheat cultivar) for the cultivar adoption problem. The values shown on the arrows are the conditional probabilities of the states.

conditional probability, P_{12}, shows that 77% of farmers who cultivated the established cultivars (state S_1) in 2016, changed to seeding the drought-resistant cultivar (state S_2) in 2017. The transition matrix **P** for the wheat varietal replacement is

$$\mathbf{P} = \begin{array}{cc} & \begin{array}{cc} S_1 & S_2 \end{array} \\ & \begin{bmatrix} 0.23 & 0.77 \\ 0.17 & 0.83 \end{bmatrix} \begin{array}{c} S_1 \\ S_2 \end{array} \end{array} \tag{9}$$

Accordingly, the graphical form of the transition diagram is shown in Figure 3.

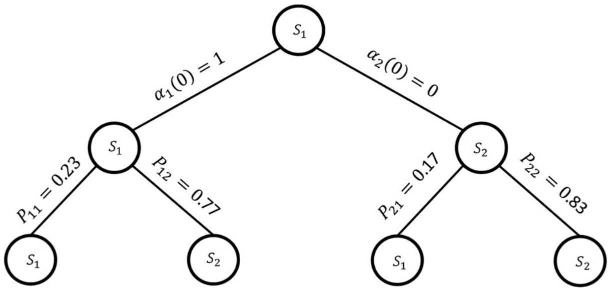

FIGURE 4 The tree of the states for the probability of planting the established cultivars (S_1) or the enhanced drought-resistant cultivar (S_2) by farmers in the Kurdistan province in the years 2016 and 2017.

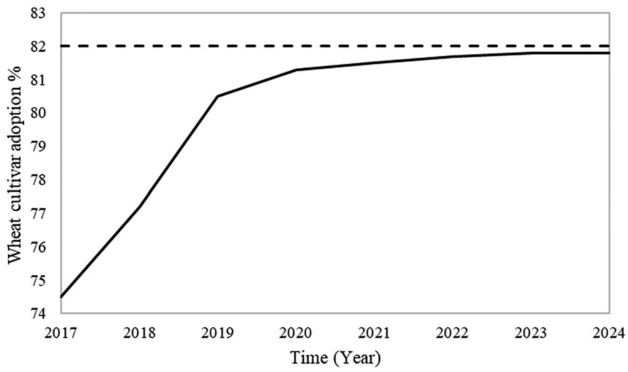

FIGURE 5 Simulated adoption of seeding the enhanced drought-resistant wheat cultivar by the farmers in the Kurdistan province from 2017 to 2024.

Figure 4 depicts the tree of the states along with the corresponding state probabilities and conditional probabilities of cultivar adoption. In the initial year t_0, all farmers seeded the established cultivars, $\alpha_1(0) = 1$ and $\alpha_2(0) = 0$. The probabilities of being in the states in 2016, calculated from Equations (3) and (4), are $\alpha_1(1) = 0.23$ and $\alpha_2(1) = 0.77$, respectively.

3.2 | Adoption rate

The limiting probability, α_j, was computed for different values of k in FORTRAN. Figure 5 shows the probabilities, predicted by the data-driven model, of seeding the enhanced drought-resistant wheat cultivar from the years 2017 to 2024. By increasing k and setting ε to 0.1% in Equation (8), the rows of $\mathbf{P}^k$ converged to a probability of 82% for farmers who are planting the enhanced cultivar. One can conclude that it takes 5 years (iterations), starting from the release year of 2016, to achieve adoption of the enhanced wheat cultivar among farmers. However, the probability of the adoption of the enhanced cultivar increased by only 8% (with an average adoption rate of 2.7%) during the 3 years from 2017 to 2020. 74% of farmers adopted within 2 years from the release year 2016, resulting in an adoption rate of 37% for seeding the enhanced cultivar in Kurdistan province.

Although knowledge of society about technological innovations and their impacts on agriculture affects the adoption time (Kassie et al., 2017), those who faced food insecurity were willing to opt for enhanced cultivars (Krishna & Veettil, 2022). Moreover, the cultivation of old wheat cultivars, addressed as a problem for Pakistanis farmers (Joshi et al., 2017), may be another reason for the high adoption of 74% in 2 years. For comparison, the adoption time for cultivar replacement in most developing countries (Fischer et al., 2022; Pavithra et al., 2017) and in the United Kingdom (Singh et al., 2020) is 10 years and 3 years, respectively. This high adoption rate of planting the enhanced drought-resistant wheat cultivar in Kurdistan province may be linked to increasing harvestable yield by 13% in successive years of 2016 and 2017. The reader must notice that while some drought-resistant cultivars perform well in drought conditions, their yield may be below average when sufficient water is available. Additionally, the low protein content poses a challenge for rain-fed wheat, especially in years with higher grain yields (Ghimire et al., 2021). In addition to gluten proteins, starch has an impact on the quality of baked breed (van Rooyen et al., 2023).

4 | CONCLUSION

In this study, a data-driven model was developed to plan adoption of an enhanced wheat cultivar over time. The farmers' willingness on transitioning from seeding the established wheat cultivars to the enhanced drought-resistant cultivar was mapped onto the Markov process to simulate the adoption rate. Therefore, this research focused on:

1. Applying a mathematical modeling approach to analyze on-farm participatory data, and
2. Simulating the adoption rate of a wheat cultivar.

For the specific case of Kurdistan, where the adoption of drought-resistance cultivars was valued by farmers, the simulator predicts a high adoption rate of 74% within 2 years from the seed release year. While farmers' decision-making may contribute to sustaining the profitability and productivity of the enhanced cultivar, it could potentially have implications for food security in vulnerable communities. Going forward, it is recommended that the simulator be utilized for planning the introduction and adoption of new technologies in agriculture.

AUTHOR CONTRIBUTIONS

Hiwa Golpira: Conceptualization; formal analysis; funding acquisition; investigation; methodology; software; validation; visualization; writing—original draft, writing—review and editing. **Parviz Rashidian**: Data curation; investigation; visualization. **Markus Demmel**: Validation, writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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