

System Dynamics Modelling of Long-term Effects of Agricultural Mechanisation on Wheat Cultivated Area and Yield

A. Keshvari¹, A. Marzban^{1*}, M. A. Asoodar¹, A. Abdeslahi², M. S. Pishvaei³

1- Department of Agricultural Machinery and Mechanization, Faculty of Agricultural Engineering and Rural Development, Agricultural Sciences and Natural Resources University of Khuzestan, Mollasani, Iran

2- Department of Agricultural Economics, Faculty of Agricultural Engineering and Rural Development, Agricultural Sciences and Natural Resources University of Khuzestan, Mollasani, Iran

3- Department of Intelligent Systems Engineering, Faculty of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran

(*- Corresponding Author Email: Afshinmarzban@asnrukh.ac.ir)

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Abstract

Amid escalating pressures on global food systems, driven by resource constraints, climatic variability, and rural labour shortages, agricultural mechanisation has become a strategic lever for enhancing productivity and sustainability. This study develops and applies a system dynamics model to examine the long-term effects of mechanisation on wheat cultivated area and yield in fragmented farming systems. The research begins by constructing a causal loop diagram (CLD) to conceptualise the key feedback structures governing mechanisation dynamics. Building on this framework, a stock-and-flow simulation model is formulated and empirically validated using provincial-level data from Khuzestan, Iran (2011-2022). Validation results demonstrate strong alignment between simulated and observed trends across major indicators, including power availability, mechanisation level, cultivated area, and yield. The model is subsequently used to simulate alternative policy scenarios targeting machinery fleet modernisation, water availability, and precipitation variability. In Scenario 3, a 30% increase in the machinery replacement rate leads to a 7% rise in yield and a 1% expansion in the cultivated area, relative to baseline projections. When mechanisation improvements coincide with enhanced water availability, the marginal impact of mechanisation on land expansion becomes negligible (less than 1% increase), indicating a behavioural shift among farmers toward higher-value crops under favourable hydrological conditions. In contrast, under water-scarce scenarios, wheat area expands by approximately 1-1.5%, while yield improvements remain below 3%, reflecting both the crop's adaptability and the compensating efficiency gains enabled by mechanisation. These findings underscore the importance of accounting for water-mechanisation interactions in policy design, particularly in arid and semi-arid regions. The model offers a flexible and empirically grounded decision-support tool for policymakers seeking to improve climate resilience, optimise resource use, and foster sustainable intensification in agricultural ecosystems facing structural and environmental challenges.

Keywords: Agricultural mechanisation, Cultivated area, System dynamics, Yield

Introduction

The fundamental human need for food, as a cornerstone of survival, has consistently driven global efforts to enhance agricultural production. Despite more than a twofold increase in global food output over the past six decades (Wittwer *et al.*, 2021) and the implementation of numerous international initiatives aimed at reducing hunger, food insecurity, and malnutrition, these challenges remain persistent in many parts of the world (Sibhatu & Qaim, 2017). These

challenges are now exacerbated by increasing constraints such as limited availability of arable land and water, adverse impacts of climate change (Araújo, Chavez-Santoscoy, Parra-Saldívar, Melchor-Martínez, & Iqbal, 2023; Khatri, Kumar, Shakya, Kirlas, & Tiwari, 2024), ageing rural populations, and acute labour shortages (Bissadu, Sonko, & Hossain, 2024). In this context, enhancing agricultural productivity is not merely an option but a necessary strategy to ensure food security and support sustainable development (Smith *et al.*, 2020).

Among the many drivers of productivity growth, agricultural mechanisation has emerged as a transformative force (Chisadza *et al.*, 2025; Zhu, Zhang, & Piao, 2022). The evolution from traditional hand tools to modern machinery, digital technologies, automation, and artificial intelligence has generated tangible benefits, including increased crop yields (Van den Berg *et al.*, 2007; Yang, Huang, Zhang, & Reardon, 2013), improved labour efficiency (Paudel, Kc, Khanal, Justice, & McDonald, 2019), higher economic returns (Peng, Zhao, & Liu, 2022), and reductions in production costs (Chaudhary, Pandit, & Burton, 2022; Hamilton, Richards, Shafran, & Vasilaky, 2022; Rahman *et al.*, 2021; Sarkar, 2020). Furthermore, mechanisation optimises input use, reduces post-harvest losses (Yan, Sun, Chen, & Dai, 2024), and contributes to environmental sustainability through better resource management and reduced greenhouse gas emissions (Belton, Win, Zhang, & Filipski, 2021; Emami, Almassi, Bakhoda, & Kalantari, 2018; Manida, 2022).

While the benefits of mechanisation are well documented, the underlying dynamics governing its interaction with other agricultural inputs and constraints remain insufficiently understood, particularly in systems characterised by fragmented landholdings, resource scarcity, and climatic variability. Most previous studies in this domain have relied on static, linear, or simplified analytical frameworks, which often fail to capture the complex feedback structures, time delays, and non-linear relationships inherent in agricultural systems. This modelling gap hinders our ability to effectively evaluate long-term impacts and policy trade-offs. In response to this deficiency, the present study employs a system dynamics modelling approach to explore the feedback-rich, time-dependent interactions among mechanisation, cultivated area, yield, and key resource constraints. Using wheat production in Khuzestan Province (Iran) as a case study, the research integrates empirical data and policy scenarios to simulate system

behaviour under different conditions. The model aims to provide both conceptual insights and practical guidance for policymakers and stakeholders operating in arid and semi-arid agro ecosystems, where mechanisation and resource limitations are critical factors shaping agricultural performance.

Literature review

Mechanisation is widely recognised as a pivotal lever in transforming agricultural systems and an effective catalyst for sustainable rural development. Amid growing food demand driven by population growth and economic expansion, mechanisation plays a vital role in enhancing production efficiency and reducing operational costs. It also facilitates the scalability of farming operations and the optimal utilisation of agricultural resources. Empirical evidence highlights the significant impact of mechanisation on agricultural productivity and rural economic development (Chaudhary *et al.*, 2022; Hamilton *et al.*, 2022). In response, many countries, including Bangladesh, Nepal, India, and China, have prioritised mechanisation as a key strategy to increase agricultural output (Daum *et al.*, 2020; Daum & Birner, 2020; Qiao, 2017; Rahman *et al.*, 2021). In China, the rising share of machinery in agricultural inputs is considered a major structural shift in the national food production system. Several studies (Dedewanou & Kpekou Tossou, 2022; Wu, Dang, Pang, & Xu, 2021) have demonstrated the positive impact of mechanisation on crop yields. Recent policy initiatives, such as government subsidies for the acquisition of agricultural machinery, have aimed to promote modernisation, boost farmers' income, and foster rural development (Sun, Liu, Yao, Shen, & Bian, 2023; Zhou, Li, Lin, & Cheng, 2022; Zhou & Ma, 2022). In Pakistan, evidence suggests that complete mechanisation across all production stages can increase farm income by up to 55% (Yasar *et al.*, 2024). In Malaysia, Isaak, Yahya, Razif, and Mat (2020) used indices of machinery and labour use to assess the mechanisation status,

concluding that productivity gains are strongly linked to mechanisation advancement. In India, despite notable progress in recent years, the national mechanisation rate remains low (45%) compared to China (57%), Brazil (75%), and the United States (95%) (Anonymous, 2018; Round & Conference, 2017). Mechanisation patterns in India are influenced by factors such as landholding size and topographical diversity. Reports indicate that small and fragmented landholdings, particularly among smallholder farmers, constitute a major barrier to mechanisation. This challenge is further exacerbated by increasing land fragmentation due to urbanisation and land-use change (Rath *et al.*, 2024).

Iran exhibits comparable conditions. Studies have shown that both net return indices and benefit–cost ratios for fully mechanised wheat production surpass those of semi-mechanised systems (Amoozad-Khalili, Rostamian, Esmailpour-Troujeni, & Kosari-Moghaddam, 2020). Furthermore, analyses of rice production data reveal a significant positive correlation between mechanisation indices and technical efficiency (Hormozi, Asoodar, & Abdeslahi, 2012). Another study on post-harvest losses reports that the alignment of mechanisation with regional cropping patterns can substantially reduce losses, especially for staple crops such as wheat, rice, and maize (Emami *et al.*, 2018). These findings underscore the need for targeted investments to upgrade mechanisation levels and modernise agricultural machinery fleets in countries like Iran.

Despite this substantial body of literature on the impacts of mechanisation on agricultural productivity, most existing studies are confined to static, sectoral, and short-term analyses. These approaches often fail to capture causal relationships, dynamic interactions, and feedback mechanisms that characterise agricultural production systems. For example, Kienzle, Ashburner, and Sims (2013), in an FAO report, emphasised that most prevailing analyses are descriptive and lack feedback-based modelling. Biggs and

Justice (2015) highlighted the limited attention to mechanisation dynamics in South Asia. Similarly, Diao, Silver, and Takeshima (2016) argued that partial equilibrium models used in African mechanisation studies are insufficient for representing feedback structures and long-term effects. Turner, Menendez, Gates, Tedeschi, and Atzori (2016), in a systematic review of natural resource modelling, pointed out that many agricultural studies neglect system feedbacks and dynamic features, which are integral to understanding complex systems. A study by the Conforti (2001) also demonstrated the limitations of partial equilibrium models in evaluating long-term impacts of policy on agricultural pricing and producer behaviour. Additionally, studies by Takeshima, Edeh, Lawal, and Isiaka (2015); Peng *et al.* (2022); Wang, Liu, and Wang (2025), while affirming the positive influence of mechanisation on output, rely primarily on statistical or cross-sectional data analysis and do not incorporate structural feedback modelling or dynamic simulation. Accordingly, there is a clear research gap calling for analytical approaches that can systematically capture time delays, nonlinear relationships, and endogenous feedback interactions. In this context, system dynamics modelling serves as a powerful tool to analyse complex structures and support evidence-based policymaking. A synthesis of the reviewed studies, their methodological approaches, key limitations, and the specific contribution of the present research is summarised in Table 1.

Methodology

General framework of the study

In this study, a causal model was first created by examining the influencing factors in a production system. Then, its flow-stock model was developed to quantify the causal relationships drawn. To validate the model's accuracy, historical data from a case study of wheat production in Khuzestan province from 2011 to 2031 were used. Khuzestan province is the hub of wheat production in Iran, and changes in its production process have a

significant impact on the production of the entire country. Finally, using different policies and scenarios, the conditions of important

variables in the future were predicted in the horizon of 2031.

Table 1- Summary of reviewed studies, research gaps, and the contribution of the present study

Author(s) / Year	Focus of Study	Method / Approach	Main Gap or Limitation	This Study's Contribution
Kienzle <i>et al.</i> (2013, FAO Report)	Overview of agricultural mechanisation in developing countries	Descriptive analysis	Lacked dynamic and feedback-based modelling	Provides a dynamic modelling framework integrating mechanisation and resource flows
Biggs & Justice (2015)	Mechanisation trends in South Asia	Policy and economic review	Ignored dynamic interactions and systemic feedbacks	Highlights mechanisation feedbacks within agricultural systems
Diao <i>et al.</i> (2016)	Mechanisation in African agriculture	Partial equilibrium modelling	Static representation; no feedback or long-term dynamics	Introduces long-term system dynamics approach
Turner <i>et al.</i> (2016)	Review of natural resource modelling	Systematic literature review	Identified lack of feedback representation in agricultural models	Applies system dynamics (SD) to capture feedback and time-delay effects
Amoozad-Khalili <i>et al.</i> (2020)	Economic performance of mechanised wheat systems in Iran	Empirical cost–benefit analysis	No system-level interaction with water or land	Extends mechanisation modelling to include resource interactions
Hormozi <i>et al.</i> (2012)	Mechanisation index and technical efficiency (Iranian rice)	Statistical correlation	Focused on technical efficiency, not dynamic relationships	Incorporates mechanisation efficiency in dynamic structure
Emami <i>et al.</i> (2018)	Post-harvest loss reduction via mechanisation	Descriptive analysis	Ignored causal and feedback mechanisms	Models mechanisation as an endogenous driver in the system
Takeshima <i>et al.</i> (2015); Peng <i>et al.</i> (2022); Wang <i>et al.</i> (2025)	Effects of mechanisation on productivity	Cross-sectional and regression models	Static analysis without feedback or adaptive behaviour	Integrates behavioural adaptation and feedback processes
Daum <i>et al.</i> (2020); Wu <i>et al.</i> (2021); Sun <i>et al.</i> (2023)	Policy measures for mechanisation promotion	Policy analysis and field data	Limited quantitative modelling of systemic impacts	Embeds policy levers into a feedback-based SD framework
This Study (2025)	Mechanisation–water–land dynamics in wheat production (Khuzestan, Iran)	System Dynamics modelling and sensitivity analysis	—	Develops an integrated SD model capturing mechanisation, water, and farmer adaptation feedbacks

Model development

Problem definition

In the face of accelerating population growth, mounting constraints on essential production resources, namely water and arable land, and the escalating impacts of climate change, the imperative to maximise input efficiency and enhance agricultural productivity has intensified markedly. Within

this context, agricultural mechanisation is increasingly acknowledged as a major contributor to productivity gains and a cornerstone of sustainable agricultural development (Winarno, Sustiyono, Aziz, & Permani, 2025). Nevertheless, the advancement of mechanisation remains hindered by a range of structural and institutional barriers, including the prevalence

of fragmented landholdings, the obsolescence of existing machinery fleets, deficiencies in farmer training and technical capacity, and misalignments across institutional frameworks (Huo, Ye, Wu, Zhang, & Mi, 2022; Ravikishore, Supriya, & Subbaiah, 2022; Sanaullah & Ullah, 2021). Furthermore, the interplay among mechanisation levels, crop yields, and cultivated area is characterised by inherently complex and dynamic relationships. On the one hand, increased mechanisation may lead to productivity improvements that reduce reliance on extensive land use; on the other hand, it may lower production costs, thereby incentivising the expansion of cultivated areas. These dualistic outcomes are often mediated by time lags, nonlinearities, and interdependent feedback mechanisms, rendering them resistant to analysis through conventional static or linear models. As such, there is a critical need to adopt a more integrated and dynamic systems-based approach to holistically examine and simulate these multifaceted interactions over time.

Dynamic hypothesis and conceptual model

Within an agricultural production system, the disparity between the actual and the desired level of mechanization, commonly referred to as the "mechanisation gap", is fundamentally shaped by the availability and growth rate of tractor power. This gap exerts complex, nonlinear, and indirect influences on both cultivated area and crop yield. An increase in available tractor and combine power toward the desired threshold facilitates higher mechanisation levels, thereby enhancing the efficiency of input and contributing to yield improvements. In contrast, insufficient tractor and combine power relative to agronomic requirements constrains the timely execution of critical field operations, such as sowing, crop management, and harvesting, resulting in diminished input productivity, intensified land-use pressure, and reduced yields. Figure 1 presents the conceptual model outlining these interrelationships.

In response to the research problem and grounded in the formulated dynamic hypothesis, a causal loop diagram (CLD) was developed and is presented in Figure 2.

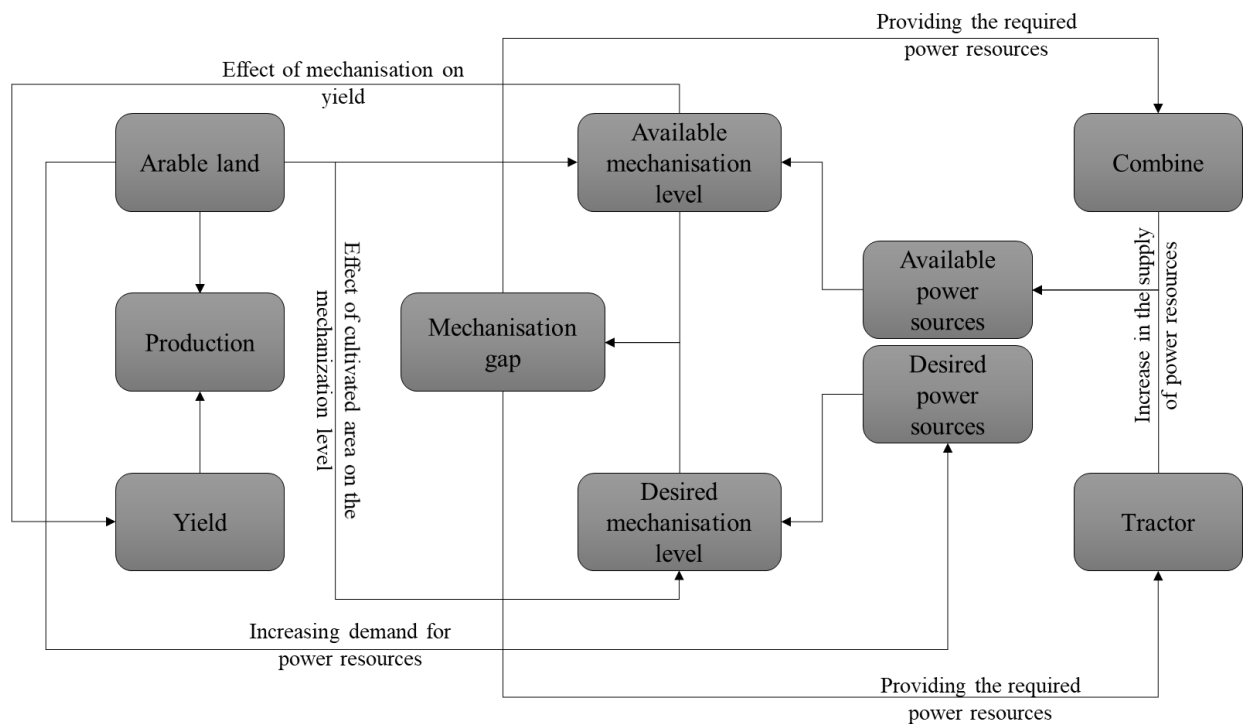


Fig. 1. Conceptual model of the effects of mechanisation on cultivated area and yield

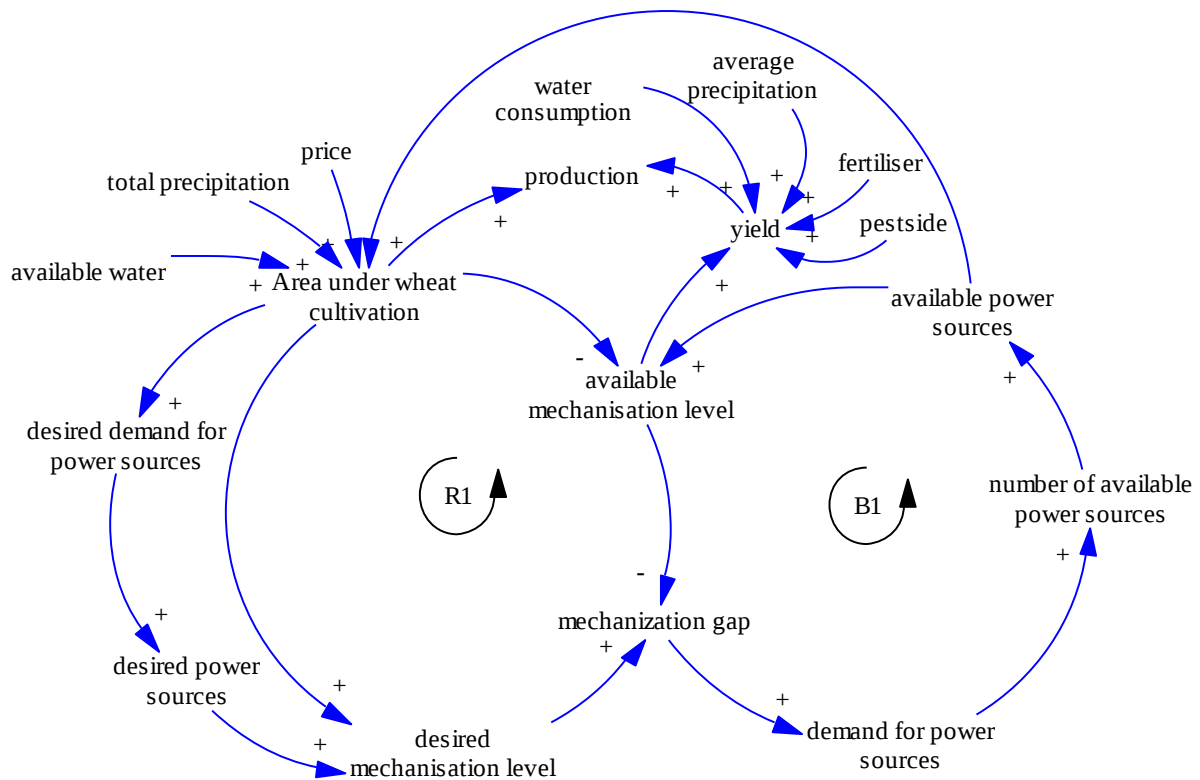


Fig. 2. CLD model of the effects of mechanisation on cultivated area and yield

This diagram highlights two principal feedback loops, each representing a distinct dynamic mechanism influencing agricultural mechanisation and its systemic interactions. The first loop is detailed as follows:

Loop 1: Reinforcing Loop (R1) – Cultivated Area Expansion Induced by Mechanization

In many agricultural systems where landholding structures are characterised by small-scale and fragmented plots, such as those commonly found in developing countries or regions with unequal distribution of land and resources, an increase in cultivated area introduces complex dynamics in the demand for and access to mechanisation power. In such contexts, expanding the cultivated area often entails a rise in the number of land parcels, greater physical distances between them, and consequently, more complex machine operations within limited agricultural time windows. This situation directly leads to an

increased demand for desirable tractor power, as timely operations across small and scattered plots require higher operational capacity per unit area.

At a broader scale, this increased demand translates into a rise in total desirable power. In other words, to complete timely, mechanised field operations across all cultivated land, the system as a whole must operate at a higher power level. This requirement is typically represented by the index of desirable mechanisation level (horsepower per hectare), which follows an upward trend under such conditions. Meanwhile, the availability of mechanical power (i.e., total tractor horsepower) typically does not change significantly in the short term, as scaling up mechanisation requires time, capital investment, and infrastructure support. Consequently, when the cultivated area expands, the existing mechanisation level (i.e., horsepower per hectare) tends to decline

because the same amount of available power is now distributed over a larger area of land. The simultaneous decrease in existing mechanisation and increase in desirable mechanisation results in a growing mechanisation gap, that is, the difference between required and available power per hectare. This widening gap imposes increasing pressure on the agricultural system and intensifies demand for mechanised resources, such as tractors. If this demand is met, fully or partially, by public or private investment, the number of tractors and total available power in the system will rise. However, it is important to note that if the cultivated area continues to expand faster than power availability, the ratio of power to land area (i.e., the existing mechanisation level) may continue to decline. In other words, an increase in total available power does not necessarily translate into higher mechanisation levels, since the power requirements generated by land expansion may outpace the system's capacity to respond.

Nevertheless, in cases where a relative balance is achieved between the rate of land expansion and the provision of mechanised power, increased availability of tractors and power can enhance the existing mechanisation level and, in turn, enable or incentivise further land cultivation. Farmers with improved access to mechanised services are more likely to bring idle land into production or expand their cropping activities. This chain of relationships forms a reinforcing feedback loop, in which an initial increase in cultivated area activates a set of systemic dynamics that ultimately leads to further expansion. A crucial insight in this context is that, in smallholder-based systems, unlike consolidated large-scale farms, an increase in desirable mechanisation level is not necessarily associated with economies of scale. On the contrary, fragmented landholdings typically reduce machine efficiency, increasing the power requirement per unit area to maintain timeliness and quality of operations. Therefore, in the absence of policy intervention and resource management, this reinforcing loop may intensify demand,

destabilise mechanisation supply chains, and exert pressure on both technical and financial infrastructure within the agricultural system. Although this structure describes a reinforcing dynamic capable of driving continual growth in cultivated area and mechanisation demand, it must be recognised that land expansion is constrained by physical, economic, and ecological limitations. Accordingly, the present model defines an exogenous upper threshold for cultivated area to prevent infinite growth and to ensure a more realistic system behaviour. While this cap is not part of the internal feedback loop, it plays a critical role in curbing endogenous dynamics and ensuring the long-term stability of the system.

Loop 2: Balancing Loop (B₁)– Mechanization Gap Adjustment through Power Supply Expansion

Alongside the primary reinforcing feedback loop that links the expansion of cultivated area, the mechanisation gap, and rising demand for tractor power in a growth-oriented trajectory, the model also incorporates a balancing feedback loop, designated as Loop B₁, that emerges from the corrective mechanisms addressing mechanisation imbalances. In this loop, the existing mechanisation level (measured as horsepower per hectare) serves as the initial trigger. A decline in this index widens the mechanisation gap, thereby increasing demand for additional power resources (e.g., tractors). If this demand is met, total available power in the system increases, subsequently improving the existing mechanisation level. This adjustment process can potentially reduce the gap and steer the system toward rebalancing the power-to-land ratio. Thus, this loop operates with a corrective logic and offers a stabilising mechanism in response to negative fluctuations in mechanisation capacity. Although it shares several variables with the main reinforcing loop and interacts with similar components of the system, its feedback direction is distinct. Loop B₁ functions as a balancing feedback structure, helping the system resist destabilising trends and supporting temporary recovery, especially in the face of short-term

shocks or partial policy interventions aimed at mechanisation support. However, while Loop B1 introduces a corrective mechanism, its balancing effect alone may not be sufficient to counteract the reinforcing momentum generated by Loop R1. Thus, external constraints and systemic interventions remain crucial to ensure sustainable long-term behaviour.

Stock-Flow Model and Parameterisation

After identifying the key feedback loops and influential variables, the stock–flow (SF) model was developed based on the conceptual framework derived from the causal loop diagram (CLD) (Figure 3). This model not only enables the quantification of feedback relationships among mechanisation, inputs, price, and yield, but also facilitates the transformation of conceptual structures into accumulative variables and functional flows, thereby allowing for the analysis of dynamic

system behaviour over time. In contrast to static or partial equilibrium approaches, which are often incapable of capturing endogenous dynamics, time delays, and nonlinear interactions, the SF model provides a robust analytical foundation for simulating scenarios, evaluating policy impacts, and systematically understanding the long-term behaviour of agricultural production systems. Some of the variables used in the stock-flow model are explained in Table 2. All variables were parameterised using empirical data from Khuzestan Province (2011-2022). Technical coefficients, such as field and irrigation efficiencies, were adapted from national studies ([Keshvari & Marzban, 2018](#); [Jalalzadeh, Borghei, & Almassi, 2016](#)), while crop-water parameters followed FAO guidelines ([Allen, Pereira, Raes, & Smith, 1998](#)).

Table 2- Summary of model variables

Variable	Description	Unit	Source/reference	Data origin/applicability
Mechanisation level index (MLI)	Ratio of mechanical power to cultivated area	hp ha ⁻¹	Keshvari & Marzban (2018); Jalalzadeh <i>et al.</i> (2016)	Calculated from Khuzestan mechanisation statistics (2011–2022)
Desired mechanisation level	Required power per hectare for timely field operations	hp ha ⁻¹	Keshvari & Marzban (2019); FAO (Allen <i>et al.</i> , 1998)	Derived from local operation time and crop calendar (Khuzestan)
Mechanisation gap	Difference between desired and actual mechanisation level	hp ha ⁻¹	Jalalzadeh <i>et al.</i> (2016); Sterman (2000)	Computed endogenously in model (calibrated with local data)
Available power resources (P _{av})	Total usable power from tractors and combines	hp	Ministry of Agriculture Jihad (2011–2022); Amoozad-Khalili <i>et al.</i> (2020)	Empirical (Khuzestan Province)
Desired power resources (P _{des})	Required power to meet field operation demand	hp	Keshvari & Marzban (2018); Jalalzadeh <i>et al.</i> (2016)	Derived from cultivated area and machine efficiency
Number of tractors and combines	Stock of power units available	number	Statistical Center of Iran (2011–2022)	Empirical (Khuzestan)
Add (inflow)	Annual addition rate of tractors/combines	number year ⁻¹	Ministry of Agriculture Jihad (2011–2022)	Provincial purchase records
Retire (outflow)	Annual retirement rate of tractors/combines	number year ⁻¹	Emami <i>et al.</i> (2018); Amoozad-Khalili <i>et al.</i> (2020)	Based on the local age structure of machinery
Field efficiency (ηf)	Efficiency of field operations	–	Keshvari & Marzban (2018); Jalalzadeh <i>et al.</i> (2016)	Calibrated for Iranian wheat farms
Irrigation efficiency (IE)	Fraction of applied water used by crop	–	FAO (Allen <i>et al.</i> , 1998); Keshvari & Marzban (2019)	Calibrated for Khuzestan irrigation systems
Feasible working days (FWD)	Days suitable for field work per season	days	FAO (Allen <i>et al.</i> , 1998); Jalalzadeh <i>et al.</i> (2016)	Estimated from Khuzestan meteorological data
Field capacity (FC)	Area covered by a machine per hour	ha h ⁻¹	Jalalzadeh <i>et al.</i> (2016); Keshvari & Marzban (2019)	Derived from machine specifications in Iran
Average machine lifetime (L)	Expected service life of agricultural machinery	year	Emami <i>et al.</i> (2018); Amoozad-Khalili <i>et al.</i> (2020)	Based on Iranian mechanisation reports
Area under wheat cultivation (A _{wheat})	Total cultivated wheat area	ha	Ministry of Agriculture Jihad (2011–2022); Hormozi <i>et al.</i> (2012)	Provincial statistics
Wheat yield (Y _{wheat})	Wheat yield per hectare	ton ha ⁻¹	Statistical Center of Iran (2011–2022); Amoozad-Khalili <i>et al.</i> (2020)	Empirical (Khuzestan data)
Water requirement (WR)	Total water needed for crop growth	m ³	FAO (Allen <i>et al.</i> , 1998); Hoekstra, Chapagain, Martinez-Aldaya, & Mekonnen (2009)	Calculated by Eqs. (11–15) using local climate data
Available water for planning (AWP)	Water available for agriculture	m ³	Khuzestan Water Authority (2020); Araijo <i>et al.</i> (2023)	Provincial hydrological data
Water consumption (WC)	Actual crop water consumption	m ³	FAO (Allen <i>et al.</i> , 1998)	Computed within model (validated with FAO-56)
Price change (PΔ)	Relative change in wheat price	%	Agricultural Statistical Yearbook (2011–2022)	National economic data
Price change rate (dP/dt)	Flow of price change over time	%	Derived from Eq. (9–10) in this study	Simulated stock variable

Initialisation of Power Resource Stocks

The foundational step in model formulation involved estimating the number of agricultural power resources, specifically disaggregated into tractors and combines. These were represented as stock variables within the system dynamics framework (Eqs. 1 and 2).

$$N_{trac}(t) = \int_{t_0}^t [Add_{trac}(s) - Retire_{trac}(s)] ds + N_{trac}(t_0) \quad (1)$$

$$N_{comb}(t) = \int_{t_0}^t [Add_{comb}(s) - Retire_{comb}(s)] ds + N_{comb}(t_0) \quad (2)$$

where N_{trac} and N_{comb} are the number of available tractors and combines, respectively, Add_{trac} and Add_{comb} denote the rates of addition (e.g., purchases), and $Retire_{trac}$ and $Retire_{comb}$ represent the rates of retirement (e.g., decommissioning) for tractors and combines, respectively.

To allocate these power resources to wheat cultivation, the current mechanisation level was calculated as the ratio of total available tractor power (including tractors and combines) to the cultivated area. This required an initial estimation of the province's autumn-sown crop area. By dividing the aggregate tractor power by this area, the mechanisation level (expressed as power per hectare) was derived, facilitating the estimation of the number of power sources (primarily tractors) assigned to wheat production as the initial stock.

Estimation of Desired Mechanisation Level

To estimate the desired level of mechanisation, a multi-step approach integrating climatic, agronomic, and operational parameters was employed. Meteorological data were first obtained from the Iranian National Meteorological Organisation. The number of feasible working days (D) for field operations was then estimated using Equation (3), as recommended

by the Food and Agriculture Organisation (FAO) (Keshvari & Marzban, 2018; Rabet, Bahrami, & Sheikhdavoodi, 2014):

$$D = d_s + \frac{1}{8}d_n + \frac{1}{2}d_t \quad (3)$$

where D represents the number of workable days in a given period, d_s denotes the number of sunny days, d_n shows the number of partially sunny days, and d_t is the number of overcast days.

Subsequently, drawing on the operational calendar of major field crops, specifically the work conducted by Keshvari and Marzban (2018), the type and frequency of mechanised field operations per hectare were identified. These data, coupled with the estimated number of workable days during peak agricultural periods, enabled the determination of the minimum field capacity required to ensure the timely completion of farm tasks. This was calculated using Equation (4), adapted from (Jalalzadeh et al., 2016; Keshvari & Marzban, 2019; Mitiku Degu, Nageswara, Moges Ketsela, & Workneh Fanta, 2025):

$$C_a = \frac{A}{t_{ad} \times T \times p_{wd}} \quad (4)$$

where C_a denotes the effective required field capacity (hectares per hour), A is the target operational area (hectares), t_a is the number of workable days available within the specified time window, T is the number of working hours per day (assumed to be 10), and p_{wd} is the probability of a workable day (calculated as the ratio of feasible working days to the total days in the target month).

This procedure enables a realistic estimate of mechanisation demand under region-specific climatic constraints and agronomic calendars, thereby informing investment decisions in machinery planning and mechanisation policy.

Determination of implementation requirements and power resources demand

To estimate the peak operational demand for each type of agricultural implement, the monthly distribution of field operations was analysed, and the month with the highest operational density for each implement type

was identified. It was assumed that meeting the operational capacity required during the peak month would ensure sufficient machinery availability throughout the rest of the agricultural calendar, thereby preventing delays in critical field activities and minimising the economic losses associated with untimely interventions.

The required working width for each implement was calculated using Equation (5), adapted from (Jalalzadeh *et al.*, 2016; Keshvari & Marzban, 2019):

$$W = \frac{C_a \times 10}{V \times \eta_f} \quad (5)$$

where:

W = required working width (m),

C_a = effective field capacity (ha h^{-1}),

V = operational speed (km h^{-1}), and

η_f = field efficiency (dimensionless).

Field efficiency values were adjusted based on the average parcel size and prevailing field conditions in the study area, reflecting the operational constraints encountered in smallholder farming systems. Once the required working width (W) was obtained, it was divided by the mean working width of standard implements commonly used in the province to determine the number of units required per implement type. Subsequently, the power resources demand for each implement was estimated based on technical specifications and matched to available tractor horsepower classes. Aggregating the monthly power requirements across all operations enabled the estimation of the total peak power demand. This, in turn, facilitated the calculation of the number of equivalent tractors necessary to fulfil the mechanisation requirements during the critical operational window.

Estimation of key agricultural indicators, cultivated area, crop yield, and price

In this modelling framework, the temporal evolution of key agricultural indicators, specifically, cultivated area and crop yield, was endogenously captured through empirically derived functional relationships. These relationships were formulated using econometric estimations and production

function theory to better reflect real-world input-output dynamics under varying agro-ecological and policy conditions.

The cultivated area (A) was modelled as a multivariate function of available mechanical power (APS), the volume of irrigation water allocated to non-target crops (OAU), total precipitation ($TPrec$), and commodity price levels (P), as expressed in Equation (6):

$$A_t = f(APS_t, OAU_t, TPrec_t, P_t) \quad (6)$$

This formulation reflects the notion that both biophysical constraints (e.g., water availability and rainfall) and economic incentives (e.g., price) jointly shape farmers' decisions to allocate land to specific crops under mechanised conditions. Crop yield (Y) was specified as a function of key agricultural inputs and environmental variables, including fertiliser consumption (FC), pesticide usage (PC), irrigation water usage (WU), average precipitation (AP), and mechanisation level (ML), as presented in Equation (7):

$$Y_t = f(FC_t, PC_t, WU_t, AP_t, ML_t) \quad (7)$$

This function captures the multidimensional interaction among chemical, hydrological, and technological inputs in determining on-farm productivity, with mechanisation level (ML) explicitly introduced to reflect its contribution to operational timeliness, labour efficiency, and input effectiveness. Total agricultural production (TP) was then determined as the product of cultivated area and yield (Eq. 8):

$$TP_t = A_t \times Y_t \quad (8)$$

The price dynamic was conceptualised using a stock-and-flow approach, in which the rate of price change was formulated as a stock variable representing cumulative deviations driven by macroeconomic factors. The price was represented as an auxiliary variable, computed by exponentiating the base-year price with respect to the accumulated rate of change, thereby capturing the compound effects of temporal fluctuations on market valuation (Eqs. 9 and 10).

$$P_t = P_0 \times e^{\Delta P_t} \quad (9)$$

$$\Delta P_t = \frac{d(\Delta P)}{dt} \quad (10)$$

Estimation of Irrigation water requirement and

water use (Per-Hectare)

Given the lack of reliable field-level data on actual water consumption, primarily due to the absence of systematic measurement protocols by farmers and responsible institutions, this study employs an estimation-based modelling approach to quantify irrigation water use per hectare. Following the proposed methodology (Hoekstra et al., 2009), crop water requirement (CWR) was calculated based on reference evapotranspiration (ET_o) and crop-specific coefficients (K_c), while accounting for effective precipitation (P_{eff}) and irrigation efficiency. The crop water requirement refers to the volume of water needed to meet a crop's total evapotranspiration demand under optimal agronomic conditions from planting to harvest (Hoekstra et al., 2009). Under these ideal conditions, water availability is assumed to be non-limiting throughout the growth period, either through rainfall or supplementary irrigation. CWR is determined using Equation (11):

$$CWR = K_c \times ET_o \quad (11)$$

Under this assumption, the actual crop evapotranspiration (ET_c) is considered equal to the crop water requirement (Eq. 12).

$$ET_c = CWR \quad (12)$$

The ET_o represents the climatic evaporative demand of a standardised surface, typically a hypothetical grass surface with specific biophysical attributes. It is driven solely by meteorological variables, such as temperature, solar radiation, humidity, and wind speed. The K_c adjusts ET_o to reflect the water use characteristics of specific crops and varies throughout the phenological stages. Standard K_c values for various crops and climatic conditions were adopted from the guidelines of Allen et al. (1998). The P_{eff} is defined as the fraction of total rainfall that is stored in the root zone and available for plant uptake (Hoekstra et al., 2009). Not all rainfall contributes to crop water use due to losses from surface runoff and deep percolation. In this study, P_{eff} was estimated using the USDA Soil Conservation Service (SCS) empirical method (Eq. 13), as recommended by Hoekstra et al. (2009):

$$P_{eff} = (P \times (125 - (0.2 \times P))) / 125 \quad (13)$$

where P_{eff} is the effective rainfall and P is the average rainfall. Subsequently, the net irrigation requirement (IR) was calculated as the difference between crop water requirement and effective precipitation. When P_{eff} exceeds CWR , irrigation demand is assumed to be zero, based on the assumption that rainfall fully meets the crop's water requirement (Eq. 14).

$$IR = \max(0, CWR - P_{eff}) \quad (14)$$

Finally, the gross irrigation water use per hectare was estimated by adjusting the irrigation requirement for the irrigation system's efficiency factor (IE). This reflects actual field-level water use, considering conveyance and application losses (Eq. 15).

$$Water\ use\ (\frac{m^3}{ha}) = \frac{IR}{IE} \quad (15)$$

Model Validation

To validate the model, both structure-based and behaviour-based tests were applied. For behaviour validation, coefficient of determination (R^2) (Eq. 16), mean absolute percentage error (MAPE) (Eq. 17), and root mean square error (RMSE) (Eq. 18) were used, as proposed by Taheri, Jahani, and Pishvaei (2024).

$$R^2 = \frac{1}{n} \sum \frac{(x_d - \bar{x}_d)(\bar{x}_m)}{s_d s_m} \quad (16)$$

$$MAPE = \frac{1}{n} \sum \frac{|x_m - x_d|}{x_d} \quad (17)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_m - x_d)^2} \quad (18)$$

The R^2 value indicates the probability and strength of correlation between the simulated and actual data (Wang, Dong, & Sušnik, 2023), while MAPE is employed to evaluate the model's precision in estimating real-world behaviour and trends. RMSE was selected as the primary evaluation metric since it quantifies the average magnitude of prediction errors in the same units as the target variable and places a higher penalty on larger deviations, providing a more sensitive and reliable measure of model performance. These metrics together provide a comprehensive basis for assessing the credibility and

predictive power of the model.

Results

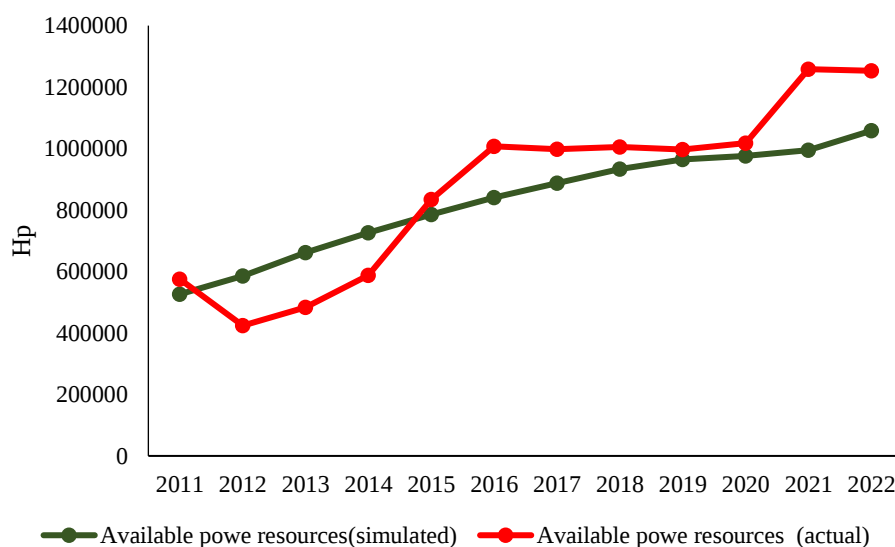
Validation

Data on wheat production in Khuzestan Province from 2011 to 2022 were used to validate the model results. The data were obtained from the Agricultural Research, Education and Extension Organisation and the statistics of the Ministry of Agriculture Jihad. The coefficient of determination (R^2) exceeding 0.8, alongside a mean absolute percentage error (MAPE) below 0.15, indicates a robust level of model accuracy and predictive validity (Figures 4–7). Thereby, the model structure demonstrates a strong capacity to represent the causal relationships and key dynamics of the agricultural production system. The high accuracy observed in the prediction of available power resources and cultivated area reinforces the model's credibility for use in policy analysis and future scenario development. In the case of the mechanisation level index, the model achieves an R^2 of 0.67 and a MAPE of 0.27, indicating

an acceptable level of predictive accuracy. Although slight deviations are observed during peak years, particularly 2018–2019, the model adequately reproduces the overall temporal dynamics. These deviations likely stem from simplifications in the model. For instance, it excludes short-term operational constraints, fails to address policy volatility, and does not capture how agricultural stakeholders adapt nonlinearly to changes.

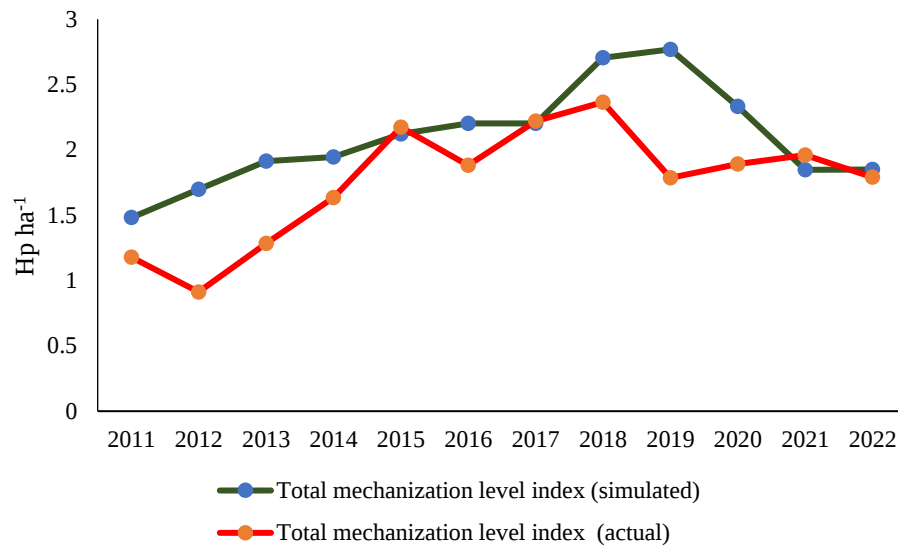
Designing policies and scenarios

Following model validation, a set of targeted policy interventions was formulated and operationalised through a series of dynamic simulation scenarios. These scenarios were designed with the primary objective of evaluating the long-term systemic implications of policy actions under varying conditions of selected external drivers, thereby enabling the extraction of evidence-based managerial and strategic insights. The policy levers, treated as exogenous and controllable parameters within the model, included the following:



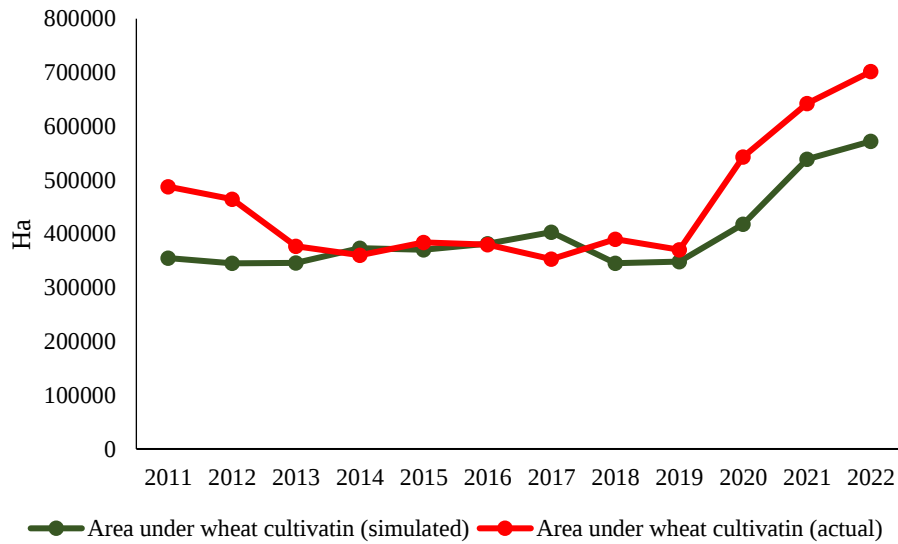
$R^2 = 0.93$, MAPE = 0.15, and RMSE = 140260

Fig. 4. Comparison of historical trends of variables and their simulated values of available power resources



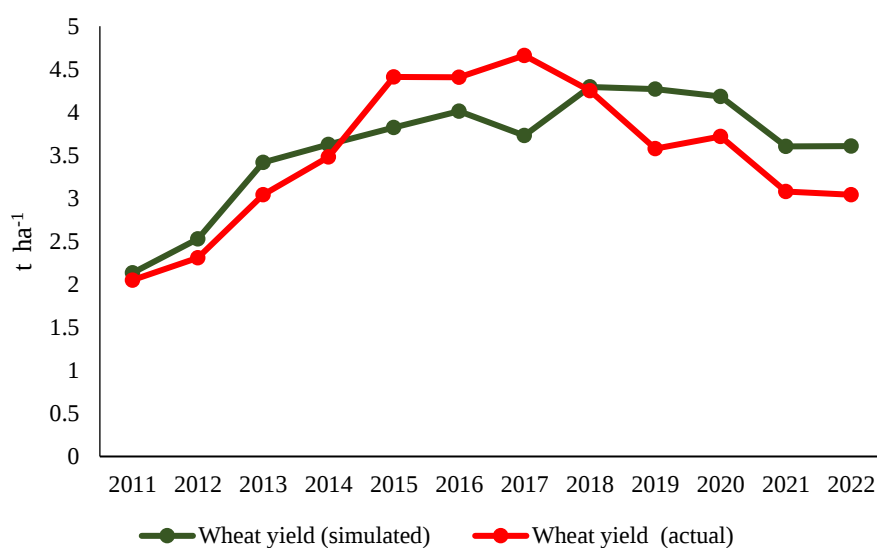
$$R^2 = 0.67, \text{ MAPE} = 0.27, \text{ and RMSE} = 0.4$$

Fig. 5. Comparison of historical trends of variables and their simulated values of the mechanisation level index



$$R^2 = 0.86, \text{ MAPE} = 0.12, \text{ and RMSE} = 82225$$

Fig. 6. Comparison of historical trends of variables and their simulated values of area under cultivation



$$R^2 = 0.80, \text{MAPE} = 0.11, \text{and RMSE} = 0.49$$

Fig. 7. Comparison of historical trends of variables and their simulated values of yield

Table 3- Suggested scenarios for examining system changes

Scenario	Rate of replacement and modernisation (%)	Annual precipitation (%)	Availability of water resources (%)
Base-line	-	-	-
S ₁	+10	-	-
S ₂	+20	-	-
S ₃	+30	-	-
S ₄	+10	+10	+10
S ₅	+20	+10	+10
S ₆	+10	-10	-10
S ₇	+20	-10	-10

- The rate of replacement and modernisation of agricultural power resources (e.g., tractors and combines),

- Annual precipitation (as a proxy for climate variability), and

- Availability of water resources for irrigation.

To ensure analytical clarity and isolate the marginal effect of each policy variable, scenario simulations were initially conducted separately for each exogenous factor. This modular approach enabled a more robust understanding of the individual contribution of each policy measure to system behaviour. Subsequently, composite scenarios were constructed by integrating multiple policy levers, enabling exploration of synergies and trade-offs. The complete configuration of

scenario designs is presented in Table 3.

Analysis of results

In Scenarios 1, 2, and 3, the regional mechanisation development coefficient, reflecting investment in the agricultural tractor fleet, was incrementally increased by 10%, 20%, and 30%, respectively. This policy intervention led to a sequential increase in the number of tractors and combines (Figs. 8 and 9), thereby enhancing the total stock of mechanical power available to the agricultural system (Figure 10). The resulting enhancement in operational capacity facilitated the expansion of the cultivated area (Figure 11). However, this expansion, in turn, induced a relative decline in the mechanisation level (Figure 12), thereby widening the gap between

actual and desired mechanisation intensity. In response to this shortfall, the system activated reinforcing feedback mechanisms that stimulated effective demand for additional power resources, prompting further capital inflows and equipment acquisition within the sector (Figs. 8 and 9). Among these three scenarios, Scenario 3, which featured the most aggressive rate of mechanisation development (Figure 12), demonstrated the most substantial positive impacts, including greater expansion of cultivated land (Figure 11), more pronounced improvements in the mechanisation index (Figure 12), and a notable enhancement in crop yield (Figure 13). Despite these interventions, the overall increase in cultivated area relative to the baseline scenario remained limited (approximately 1%), reflecting the influence of balancing feedback loops embedded within the system dynamics structure that restrict unbounded expansion (Figure 11). Moreover, inter-scenario variability in cultivated area growth was minimal, with differences remaining below 1%. With respect to yield, Scenario 3 yielded the most significant improvement, exhibiting an approximate 7% increase over the baseline (Figure 13). The average yield growth differential across all three scenarios was about 2.5%, highlighting the influence of mechanisation intensity on production efficiency. Given the simultaneous, albeit moderate, improvements in both cultivated area and yield, a cumulative increase in total wheat production was not only expected but also consistent with system feedback behaviour (Figure 14). In the combined Scenarios 4 and 5, a 10% increase in both precipitation and water availability was introduced alongside a parallel improvement in mechanisation development. However, contrary to expectations, these combined interventions led to a smaller expansion in the wheat-cultivated area relative to the mechanisation-only scenarios (Figure 11). This result is attributed to shifting farmer preferences toward higher-value or export-oriented crops, such as vegetables and horticultural products, especially in the context

of improved water availability and regional agroecological diversity. As a result, while wheat cultivation still experienced growth relative to the baseline (approximately 1–1.5%), the rate of expansion was less than that observed in Scenarios 1 through 3. This relatively slower land expansion translated into a more modest increase in demand for new power resources, thereby moderating the growth in mechanisation levels (Figure 12). Since mechanisation is a principal determinant of yield enhancement, the deceleration in its growth (approximately 4% lower than the mechanisation-only scenarios) led to a smaller yield increase (1–3%) (Figure 13). Consequently, the reduced growth rates in both cultivated area and yield resulted in a modest increase in total wheat production, reflecting the inherent constraints and feedback captured by the system dynamics model (Figure 14). Scenarios 6 and 7 introduced a 10% reduction in both precipitation and irrigation water availability, while maintaining the trajectory of mechanisation expansion. Interestingly, these adverse water conditions, in conjunction with increased tractor availability, resulted in the largest increase in wheat-cultivated area among all scenarios (Figure 11). This dynamic was driven by two reinforcing mechanisms: (1) the operational advantages of mechanisation, and (2) a policy and behavioural shift among farmers, who, faced with declining water security, strategically reallocated land to wheat, a relatively water-efficient and stable crop. The resulting expansion in the cultivated area triggered increased demand for mechanical power, leading to a further increase in the stock of available tractors and combines (Figs. 8 and 9). Although the relative growth rate of the mechanisation index was suppressed due to rapid land expansion, the absolute mechanisation level remained comparable to Scenarios 4 and 5 due to continuous inflows of power resources (Figure 12). In terms of yield, gains in efficiency and timeliness from mechanisation were partially offset by irrigation constraints, which limited the

realisation of yield potential. Nevertheless, improved precision in field operations, particularly during critical growth stages (e.g., flowering), mitigated climatic stresses such as heat waves and high evapotranspiration. This stabilisation-maintained yields close to pre-experiment baseline levels (Figure 13). Overall, total wheat production in Scenarios 6

and 7 increased modestly relative to the baseline, with the expansion in cultivated area compensating for stagnation in per-hectare yields (Figure 14). These results highlight the complex interplay between resource constraints, mechanisation, and adaptive farmer behaviour, as represented in the model's integrated feedback structure.

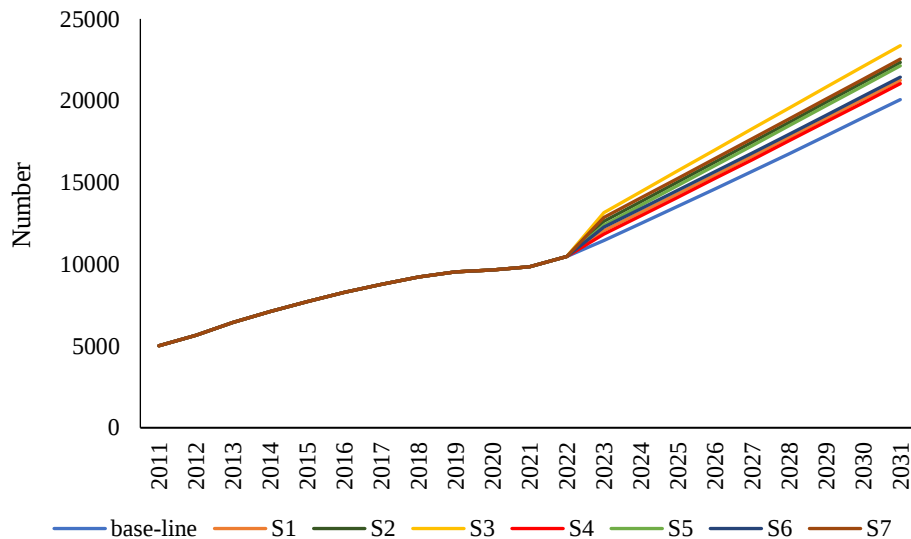


Fig. 8. Trends of simulated values of the number of available tractors

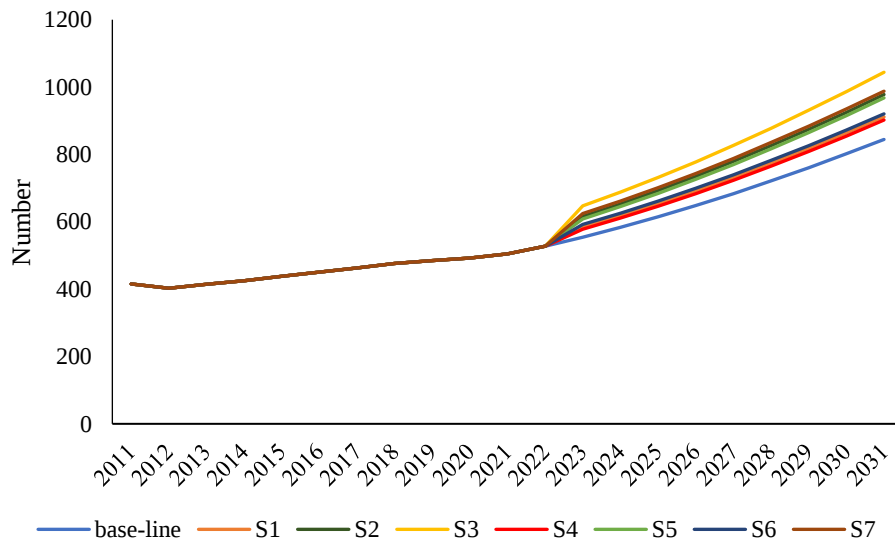


Fig. 9. Trends of simulated values of the number of available combines

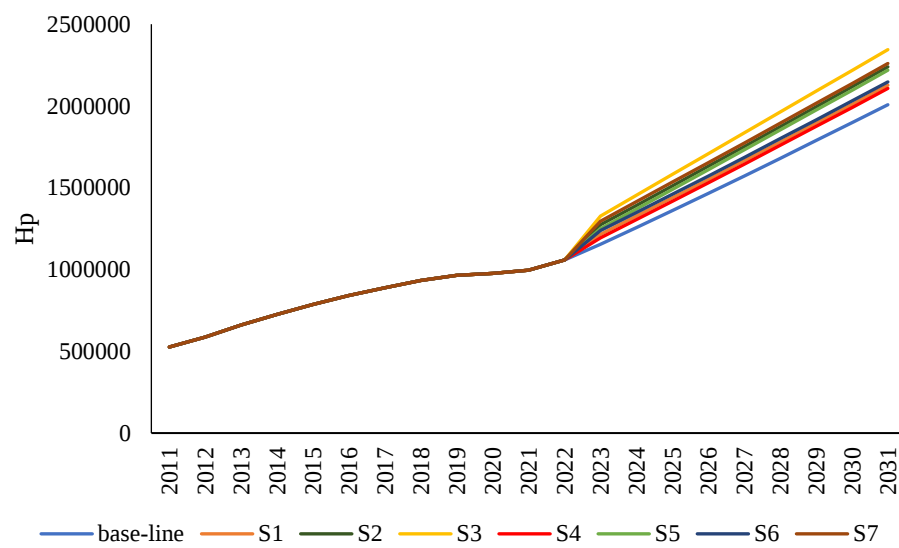


Fig. 10. Trends of simulated values of available total power

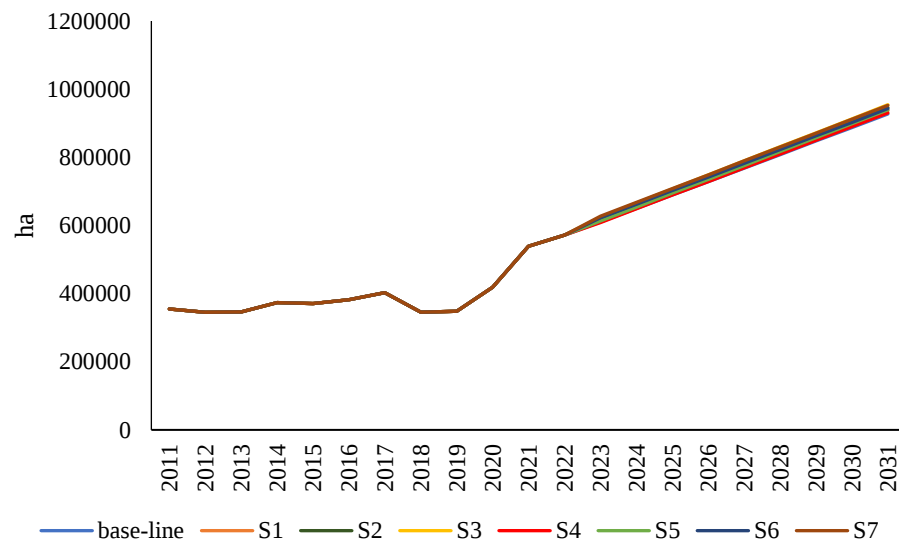


Fig. 11. Trends of simulated values of the area under wheat cultivation

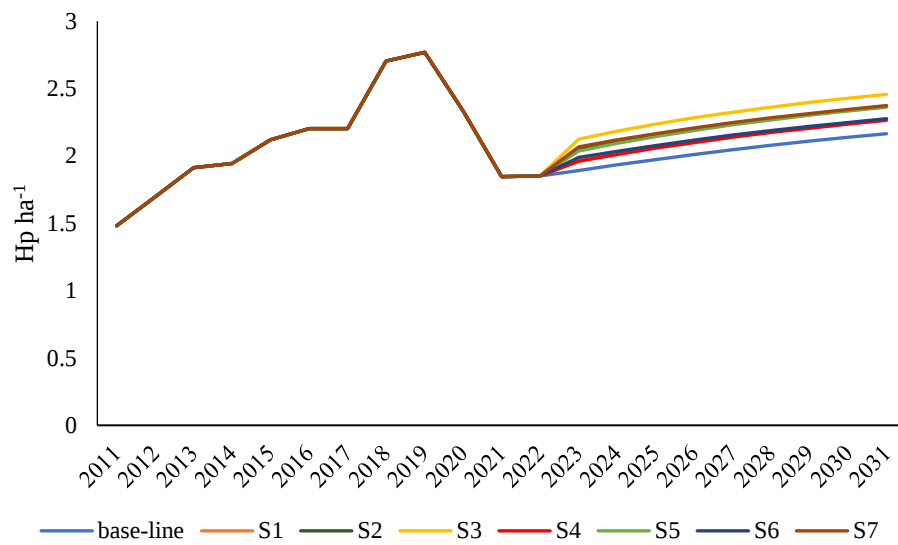


Fig. 12. Trends of simulated values of the mechanisation level index

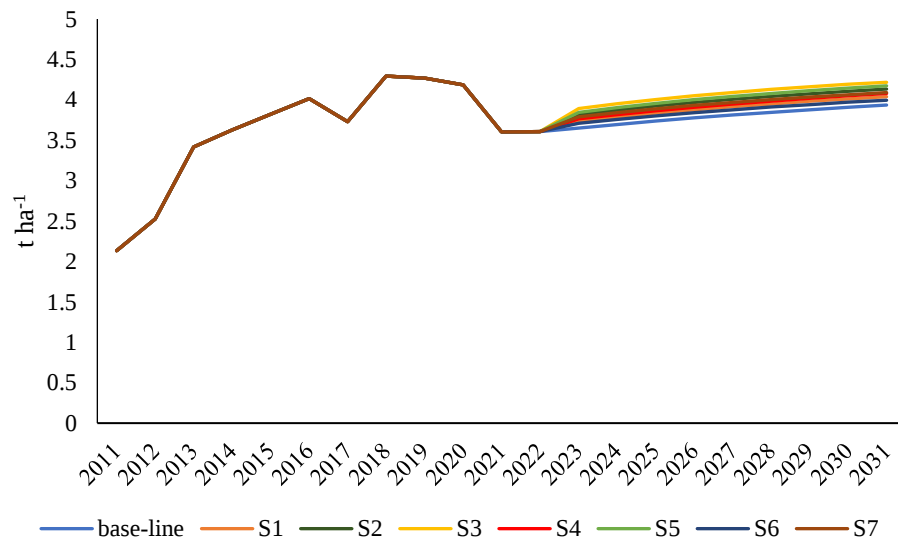


Fig. 13. Trends of simulated values of yield

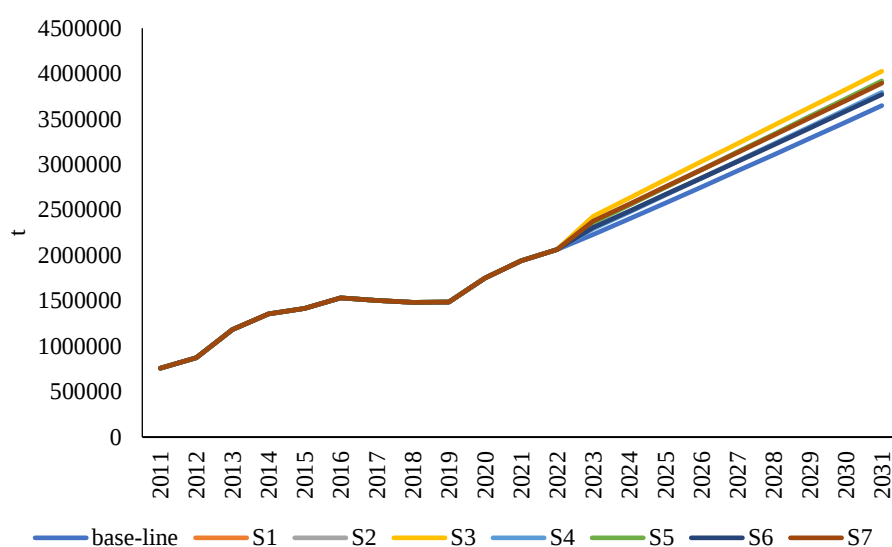


Fig. 14. Trends of simulated values of production

In summary, Scenarios S1–S3 and S6–S7 are dominated by the reinforcing loop R1 (power–area expansion), whereas scenarios S4–S5 are primarily governed by the balancing loop B1 that constrains excessive growth. These causal linkages correspond directly to the feedback structure in Figure 2. The above behavioural patterns can be mechanistically explained by the interaction of the reinforcing loop (R1) and the balancing loop (B1) in the causal loop diagram (Figure 2). In scenarios S1–S3 and S6–S7, the R1 loop dominates, driving expansion through power–area feedback, while under S4–S5 the B1 loop counteracts this process by reducing the mechanisation gap and moderating land expansion.

The analysis of guaranteed wheat price and cultivated area from 2011 to 2031 reveals a dynamic and policy-dependent behaviour between price movements and land allocation (Figure 15). In the early years, increases in the guaranteed price directly stimulated the expansion of the wheat cultivated area. Specifically, the stock variable defined in Eqs. 9–10 feeds into the land-allocation loop, capturing delayed farmer responses to price fluctuations. This growth reflects the rise in expected profit and farmers' willingness to allocate more land to wheat production, thereby activating reinforcing feedback (R1).

At this stage, the price signal serves as a key market driver, justifying higher investment in inputs and mechanisation. However, after the guaranteed price exceeds approximately 20,000 Rials per kilogram, the rate of area expansion declines, and its sensitivity to further price increases weakens (Figure 16). This pattern indicates the emergence of balancing feedback (B1) in which structural and policy constraints become dominant. From an economic perspective, two factors explain this behaviour. First, the government's procurement capacity and budget constraints limit the total quantity of wheat that can be purchased at the guaranteed rate. Hence, price increases beyond that threshold do not necessarily translate into higher net profits for farmers. Second, rising production costs, including inputs, labour, and energy, partially offset the price incentive, leading to a moderated real growth in cultivated area and movement toward a new equilibrium. Therefore, the guaranteed price policy in Iran performs a dual economic function: in the short term, it acts as an instrument to stimulate production (Figure 15), while in the long term, it serves as a control mechanism to prevent excessive or unsustainable expansion of cultivated land (Figure 16). This dual dynamic demonstrates that the guaranteed price is not a static economic variable but a policy-driven

dynamic factor that simultaneously shapes farmers' behaviour and governmental decisions.

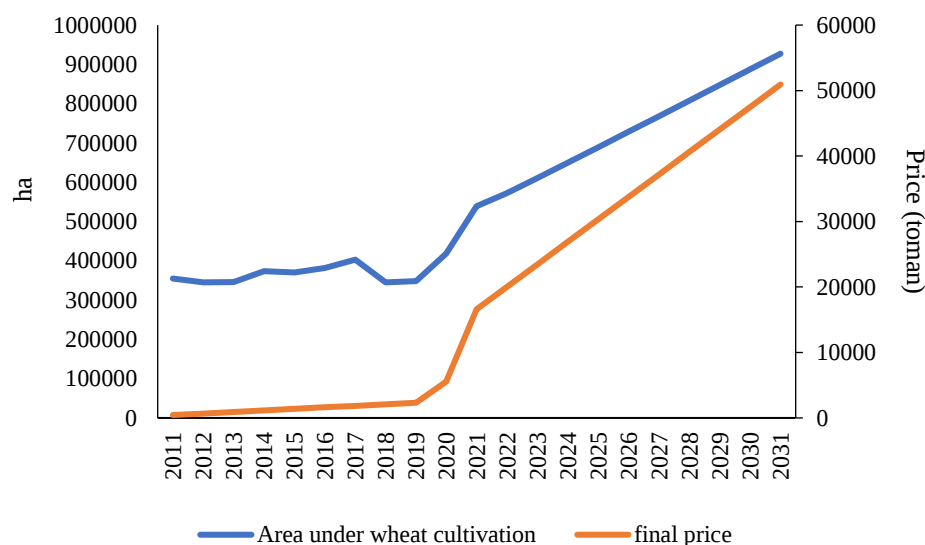


Fig. 15. Time series of guaranteed price and cultivated area



Fig. 16. Nonlinear relationship between guaranteed price and cultivated wheat area

Sensitivity Analysis

The sensitivity analysis was performed to examine the behavioural stability of the model under variations in its key structural parameters, rather than to introduce new policy scenarios. Two parameters closely related to the scenario framework were selected for this test: the total inflow of agricultural power resources, representing the overall mechanisation capacity entering the sector, and the available irrigation water for

wheat cultivation. A $\pm 20\%$ variation in the total inflow of power resources produced a proportional and consistent response in wheat yield, with higher inflows improving yield by approximately 5–7%, and lower inflows resulting in a moderate decline (Figure 17). This finding confirms the central role of mechanisation development and equipment availability in sustaining operational efficiency and enhancing productivity over time. Similarly, varying the available irrigation

water for wheat within a $\pm 20\text{--}40\%$ range led to only minor adjustments in the cultivated area (less than 1%), with a slight expansion observed under reduced water availability (Figure 18). This reaction aligns with the model's internal logic and the adaptive behaviour reflected in the scenario analysis: under water stress, wheat, being a relatively water-efficient and policy-supported crop, occupies a slightly larger share of arable land,

whereas under favourable water conditions, farmers tend to diversify toward high-value crops.

Overall, the sensitivity tests demonstrate that the model maintains logical, proportional, and stable responses to variations in both structural and resource-related parameters, thereby confirming the robustness and behavioural validity of its feedback structure.

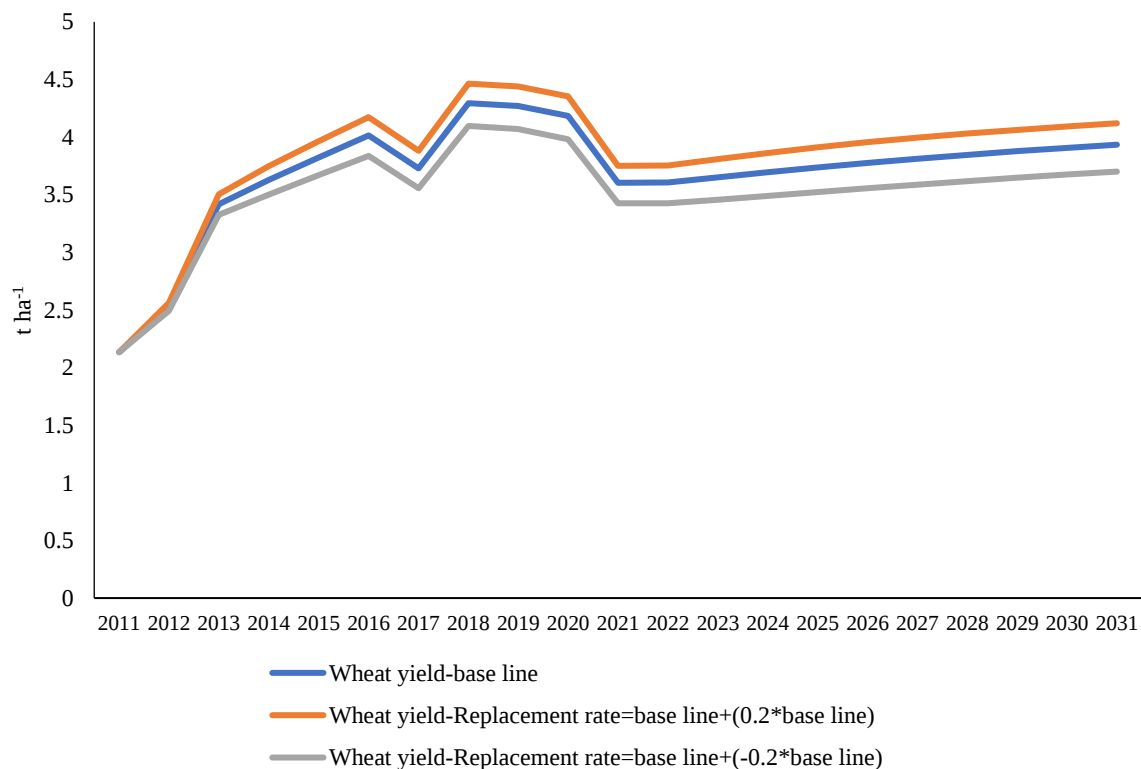


Fig. 17. Sensitivity of wheat yield to replacement rate of power resources

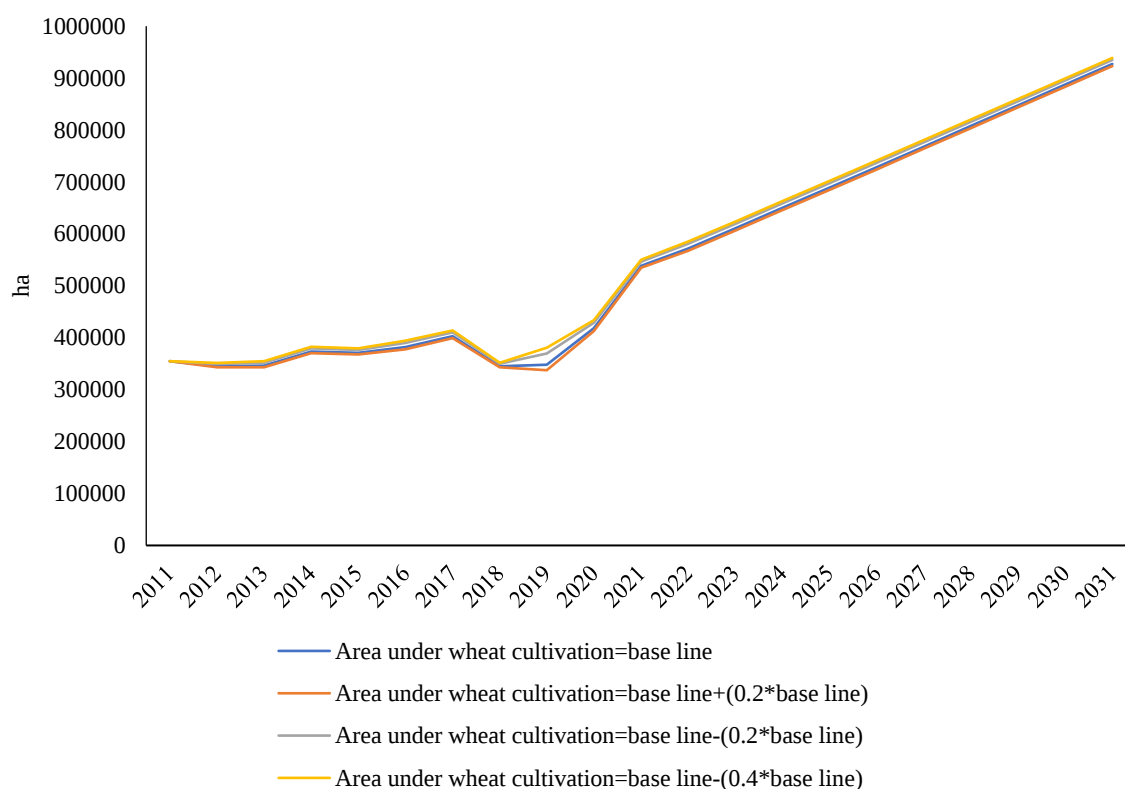


Fig. 18. Sensitivity of cultivated area to available irrigation water for wheat

Discussion

A comprehensive review of the existing literature identifies agricultural mechanisation as a fundamental driver of agricultural development in numerous developed countries. Broadly defined, mechanisation entails the use of mechanical power to execute various farm operations. Nonetheless, in many developed nations, the comprehensive and seamless implementation of mechanisation has yet to be fully realised, largely due to prevailing economic, social, and cultural constraints. In recent years, however, there has been notable progress in this domain. While beyond conventional mechanisation, modern mechanisation, characterised by the integration of artificial intelligence and robotics, is increasingly being adopted and advanced in developed countries.

Empirical evidence suggests that despite substantial systemic challenges, primarily stemming from the predominance of smallholder farming and fragmented

landholdings, the adoption and diffusion of mechanisation technologies in several developing countries, including India, Bangladesh, Nepal, and South Africa, as well as in China, have garnered significant farmer engagement (Ahmed & Ahmed, 2023; Aryal, Rahut, Thapa, & Simtowe, 2021; Huo *et al.*, 2022; Mohammed, Batung, Saaka, Kansanga, & Luginaah, 2023; Aryal *et al.*, 2021). The attractiveness of mechanisation in these contexts is not predicated on a singular, transformative innovation, but rather on the aggregate effect of its decreased post-harvest losses, particularly in grain crops (Belton *et al.*, 2021). Quantitative studies, such as those by Liu and Li (2023), have established that the elasticity of agricultural machinery utilisation with respect to rice production, wheat, and maize is positive and statistically significant, estimated at 0.0059, 0.0148, and 0.0607, respectively. Moreover, findings by Peng *et al.* (2022) indicate that a 1% increase in the mechanisation index corresponds to yield improvements of 1.2151% across all crops and

1.5941% for cereals. Similarly, [Sun et al. \(2024\)](#) demonstrate that mechanisation expansion increases cultivated land area, and, *ceteris paribus*, each 1% rise in mechanisation results in a 0.467% increase in the benefit-cost ratio for maize production. Regional assessments across small, medium, and large-scale farms in South Asia and the Pacific coastline further corroborate the significant and positive impact of mechanisation on crop productivity, with particularly pronounced effects observed in rice cultivation ([Rath et al., 2024](#)). In Pakistan, mechanisation has facilitated the reclamation and productive use of fallow lands, thereby augmenting the cultivated area and yield of key staples, wheat, rice, and maize, by 0.4%, 10.4%, and 27.3%, respectively ([Yamin, Tahir, Awan, & Yaseen, 2011](#)). Comparative analyses also reveal that full mechanisation across all stages of crop production enhances food security by up to 125% compared to semi-mechanised systems ([Yasar et al., 2024](#)). Additionally, panel data analysis of 30 Chinese provinces spanning the period of 2000 to 2021 reveals that mechanisation positively influences green total factor productivity in agriculture. This occurs through three primary transmission mechanisms: enhanced managerial capacity in farm systems, improved input use efficiency, and increased diversification within the agricultural industrial structure ([Lu, Meng, & Cheng, 2024](#)). Accordingly, mechanisation not only drives productivity but also facilitates the transition toward environmentally sustainable and climate-smart agricultural systems ([Fang, Chen, Wang, & Chen, 2024](#); [Lu et al., 2024](#)). Further, findings by [Fang et al. \(2024\)](#) indicate that mechanisation, by boosting food production and reducing vulnerability to natural disasters, generates both direct and spatial spillover effects that enhance the climate resilience of agricultural production. Specifically, each 1% increase in mechanisation is associated with a 0.012-unit improvement in local food system resilience. The capacity of mechanisation to ensure the timeliness of field operations positions it as a critical lever for safeguarding food security

and adapting to climatic shifts ([Daum, 2023](#); [Liu, Yasir, Tahir, & Awan, 2025](#); [Rahman et al., 2021](#); [Yamin et al., 2011](#)). Conversely, certain studies, such as those by [Zou, Chen, Mishra and Hirsch \(2024\)](#), report a negative correlation between mechanisation and local GDP in China. These findings attribute the decline to the disproportionate concentration of mechanisation efforts in cereal production, which has skewed cropping patterns toward lower value-added commodities. This reallocation of resources is posited to have constrained the cultivation of high-value crops, thereby exerting downward pressure on regional economies. Additionally, [Min and Paudel \(2021\)](#) argue that suboptimal farm scale, particularly in rice cultivation below the economically efficient threshold, has led to allocative inefficiencies and underutilisation of mechanised assets.

In sum, the reviewed body of evidence affirms the internal consistency and logical coherence of the present study's findings. The results highlight the synergistic potential of integrated mechanisation strategies in enhancing incremental, overlapping, and complementary benefits. These advantages include reductions in labour requirements, alleviation of manual drudgery, operational convenience, improved timeliness and efficiency of field operations, enhanced adaptive capacity to climate variability, and agricultural performance metrics and underscore the critical importance of targeted, evidence-based policy interventions. Ultimately, the strategic advancement of agricultural mechanisation offers a viable pathway to long-term productivity gains and the sustainable intensification of land use. Despite the positive impacts demonstrated in this study, the findings should be interpreted in the light of potential challenges associated with agricultural mechanisation. While improved access to machinery can enhance productivity, it may also lead to increased energy consumption, greenhouse gas emissions, and potential soil degradation if not managed sustainably ([Lu et al., 2024](#); [Yan et al., 2024](#); [Zhu et al., 2022](#)). Furthermore,

mechanisation can unintentionally widen socio-economic disparities between large-scale and smallholder farmers, since resource-rich farmers are typically better positioned to adopt modern technologies and benefit from economies of scale (Liu & Li, 2023; Mohammed *et al.*, 2023; Peng *et al.*, 2022). From a policy perspective, these findings highlight the need for balanced mechanisation strategies. Investments in agricultural machinery should be complemented by capacity-building programs, credit access for smallholders, and environmentally sustainable practices (Aryal *et al.*, 2021; Emami *et al.*, 2018; Lu *et al.*, 2024). Future studies could integrate broader environmental, social, and economic dimensions into the modelling framework to better capture potential trade-offs and synergies between mechanisation, resource efficiency, and sustainability (Daum, 2023; Fang *et al.*, 2024; Lu *et al.*, 2024). Incorporating these aspects would enhance the relevance of simulation results for policy design, particularly in regions facing resource constraints and climate variability (Rahman *et al.*, 2021; Winarno *et al.*, 2025).

Conclusion

The findings of this study demonstrate that the development of agricultural mechanisation can play a significant role in enhancing crop yield, optimising resource utilisation, and strengthening the resilience of agricultural production systems in the face of climatic challenges and structural constraints. The results of the system dynamics-based simulations indicate that a 30% increase in the development of power sources results in a 7% improvement in wheat yield and approximately a 1% increase in the cultivated area compared to the baseline scenario. These outcomes underscore the potential of mechanisation to enhance agricultural productivity and profitability. Moreover, the integrated analysis of mechanisation scenarios in conjunction with water resource variability reveals that under conditions of resource abundance, farmers tend to shift toward the cultivation of higher value-added crops. This

behavioural shift diminishes the direct impact of mechanisation on the expansion of wheat cultivation. In contrast, under water-scarce conditions, the area under wheat cultivation increases significantly, an outcome attributed to wheat's agro-climatic suitability and the operational efficiencies enabled by mechanisation under water-stressed environments. However, yield gains under such conditions remain comparatively limited due to irrigation constraints.

Overall, the study underscores the critical importance of employing dynamic, simulation-based analytical frameworks in the design of mechanisation policies. It further demonstrates that well-targeted mechanisation strategies, beyond enhancing productivity and food security, can act as a pivotal tool for climate adaptation and the long-term sustainable development of the agricultural sector. To enhance the model's utility across broader contexts, future work could explore integrating socio-economic and behavioural dynamics, thereby expanding its scope for regional and national decision-making.

Limitations and Future Research Directions

While this study provides valuable insights into the dynamic interactions between agricultural mechanisation, cultivated area, and yield, several limitations should be acknowledged.

First, the model was calibrated using data from Khuzestan Province, Iran, which may constrain the generalisability of the findings to other agroecological contexts. Nevertheless, the overall framework and methodological approach are transferable to regions with similar climatic, socio-economic, and technological conditions. Second, the model primarily captures long-term structural feedback and does not explicitly incorporate short-term policy fluctuations, market shocks, or farmers' behavioural responses, which could influence real-world outcomes. Third, potential environmental and social consequences of mechanisation, such as soil degradation, shifts in rural employment, energy use, and equity concerns, were not

explicitly modelled and merit further investigation. Furthermore, the policy scenarios examined in this study were intentionally narrow in scope to ensure conceptual clarity. Future research should consider a broader range of interventions, including institutional mechanisms, credit accessibility, technology diffusion, and integration with multi-crop systems. Finally, although the forecasts up to 2031 provide meaningful directional insights, they should be interpreted cautiously due to inherent uncertainties arising from climate variability, technological advancements, and socio-economic dynamics. Addressing these limitations in future studies will improve model robustness, enhance the policy relevance of findings, and support more sustainable agricultural development strategies.

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Authors Contribution

A. Keshvari: Conceptualization, Data acquisition, Data processing, Visualization, Writing original draft

A. Marzban: Supervision, Conceptualization, Methodology, Review and editing

M. A. Asoodar: Supervision, Technical advice, Review and editing

A. Abdeslahi: Statistical advice, Review and editing

M. S. Pishvae: Methodology, Software, Validation.

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مدل سازی پویایی سیستم اثرات بلندمدت مکانیزاسیون کشاورزی بر سطح زیر کشت و عملکرد گندم

آتنا کشوری^۱، افشین مرزبان^{۱*}، محمدمبین آسودار^۱، عباس عبدشاهی^۲، میرسامان پیشوایی^۳

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چکیده

با تشدید فشارهای ناشی از محدودیت منابع، تغییرات اقلیمی و کمبود نیروی کار روستایی، مکانیزاسیون کشاورزی به اهرمی استراتژیک برای ارتقای بهره‌وری تبدیل شده است. این مطالعه یک مدل پویایی سیستم را برای بررسی اثرات بلندمدت مکانیزاسیون بر سطح زیر کشت و عملکرد گندم در نظام‌های خرده‌مالکی توسعه داد. پژوهش با ترسیم نمودار حلقه علی (CLD) برای مفهوم‌سازی ساختارهای بازخورد کلیدی آغاز شد. سپس یک مدل شبیه‌سازی موجودی و جریان، با استفاده از داده‌های استان خوزستان (۲۰۱۱-۲۰۲۲) تدوین و اعتبارسنجی شد. نتایج، همخوانی قوی بین روندهای شبیه‌سازی شده و مشاهداتی را در شاخص‌های اصلی نشان داد. از مدل برای شبیه‌سازی سناریوهای سیاستی مختلف شامل نوسازی ناوگان ماشین‌ها، دسترسی به آب و تغییرپذیری بارندگی استفاده شد. افزایش ۳۰ درصدی نرخ جایگزینی ماشین‌آلات منجر به افزایش ۷ درصدی عملکرد و ۱ درصدی سطح زیر کشت نسبت به پایه شد. هنگامی که بهبود مکانیزاسیون با دسترسی بهتر آب ترکیب شد، اثر نهایی آن بر استفاده از زمین کاهش یافت که نشان‌دهنده تمایل کشاورزان به کشت محصولات باارزش در شرایط هیدرولوژیک مطلوب است. در مقابل، در شرایط کم‌آبی، کشت گندم به دلیل سازگاری و کارایی ناشی از مکانیزاسیون، گسترش یافت. این یافته‌ها بر اهمیت توجه به تعامل آب و مکانیزاسیون در طراحی سیاست‌ها، به‌ویژه در مناطق خشک تأکید می‌کنند. مدل ارائه‌شده، ابزار انعطاف‌پذیر و مبتنی بر تجربه برای پشتیبانی از تصمیم‌گیری در راستای بهبود تاب‌آوری اقلیمی و استفاده بهینه از منابع فراهم می‌کند.

واژه‌های کلیدی: پویایی سیستم، سناریوسازی، گندم، مدیریت منابع آب، مکانیزاسیون کشاورزی

۱- گروه مهندسی ماشین‌های کشاورزی و مکانیزاسیون، دانشکده مهندسی زراعی و عمران روستائی، دانشگاه علوم کشاورزی و منابع طبیعی خوزستان، ملائانی، ایران

۲- گروه مهندسی اقتصاد کشاورزی، دانشکده مهندسی زراعی و عمران روستائی، دانشگاه علوم کشاورزی و منابع طبیعی خوزستان، ملائانی، ایران

۳- گروه مهندسی سیستم‌های هوشمند، دانشکده مهندسی صنایع، دانشگاه علم و صنعت ایران، تهران، ایران

(* - نویسنده مسئول: Email: Afshinmarzban@asnrukh.ac.ir)