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Shifting the Production Frontier: The Dominance of Irrigation Modernization over Crop Reallocation in Groundwater Conservation

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Abstract

Balancing agricultural productivity with groundwater conservation remains a critical challenge in water-stressed regions. The current study attempted to provide a quantitative framework to evaluate agricultural water conservation policies, shifting the focus from administrative mandates to technological advancement. Using a calibrated Positive Mathematical Programming (PMP) model, we evaluated groundwater management strategies in Iran's Safiabad district. Three controlled scenarios were evaluated: progressive crop restrictions (5%-30%), low-pressure irrigation coupled with cropping pattern optimization, and irrigation modernization with fixed cropping patterns. The results reveal shifting the technological production frontier significantly outweighs managerial reallocations along the existing frontier. **Under the assumptions of our calibrated PMP model and the specific conditions of the Safiabad case study**, a decomposition of the policy gains **suggests** irrigation modernization accounts for **approximately** 93% of total productivity improvements—achieving a simultaneous +26.7% increase in profit and a 65.4% reduction in water use. Conversely, cropping pattern re-optimization contributed only about 7%, despite requiring a mean absolute adjustment of 17.84% across eight crops. **This model-dependent** 13:1 technology-to-management contribution ratio **indicates that, in this context**, relying solely on behavioral restrictions or cropping shifts may be insufficient for achieving substantial water conservation without economic losses**. Based on these findings**, **sustained groundwater conservation while maintaining rural livelihoods would likely benefit from** expanding production possibilities through targeted infrastructure investments**, though further research is needed to test the generalizability of these results.**

Keywords: Agricultural water policy, Iran, Policy decomposition, Positive Mathematical Programming (PMP), Smallholder farming, Technology adoption, Water scarcity.

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1. Introduction

The global water crisis represents one of the most pressing challenges of the 21st century, with groundwater overexploitation reaching critical levels in arid and semi-arid regions worldwide (Mokadem *et al*., 2018). Iran exemplifies this crisis acutely, where agriculture accounts for approximately 90–95% of national water consumption, creating severe pressure on already-depleted aquifer systems (Water Quality Research Center, 2024). The Safiabad region in North Khorasan Province, Iran, faces particularly severe groundwater depletion, with water tables declining 9 meters between 1989 and 2021—representing a volumetric loss of 220 million cubic meters—threatening both agricultural productivity and socio-economic stability (Bahrami Nasab *et al*., 2025). This crisis is exacerbated by increasing water demand driven by population growth, agricultural intensification, and climate change impacts, resulting in deteriorated water quality, progressive salinization, and widespread well failures.

Addressing agricultural water scarcity requires policy interventions that simultaneously reduce water consumption while maintaining or enhancing farm profitability and productivity. The agricultural economics literature introduces a range of approaches for achieving these dual objectives, among which two of the most prominent are the following: First, cropping pattern adjustment—restricting cultivation of high-water-use crops and promoting drought-resistant alternatives—has demonstrated potential for water conservation in various contexts (Richter *et al*., 2023). Boser *et al*. (2024) documented 9% water savings through modest 5% reductions in high-water crop areas in California, while Bashiri (2021) reported 21.58% water consumption reductions following 40% rice cultivation restrictions in Iran. Chakraborti *et al.* (2023) found 32% water reductions coupled with 140% profit increases through strategic crop substitution in Indian agricultural systems. Second, irrigation technology modernization—transitioning from traditional surface methods to modern systems—offers substantial efficiency improvements. Askaraliev *et al.* (2024) documented 50% water reduction combined with 30% yield increases under modern irrigation in Kyrgyzstan's arid regions, while Liu *et al*. (2022) reported 18.4% maize yield increases, over 50% water use efficiency improvements, and 60% net profit gains under drip irrigation in China. Regional Iranian studies demonstrate consistent patterns, with Asadi *et al*. (2023) documenting 162.9% profit increases (wheat) and 72.9% (corn) under pressurized irrigation in Alborz Province, accompanied by 22.8% and 27.6% water savings respectively, and Rahmani *et al*. (2017) reporting 17% water consumption reductions with enhanced economic productivity in Ardabil Province.

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Despite extensive empirical evidence that both approaches generate benefits, a fundamental policy question remains: How should limited financial resources be allocated between enforcing behavioral/cropping changes versus investing in technological modernization? This question connects to the core premise of Schultz's (1964) efficient farmer hypothesis. Rather than testing this hypothesis, the study adopts it as an underlying behavioral premise: smallholder farmers are assumed to optimize skillfully within their existing technological and resource constraints. Following Schultz's efficiency hypothesis, the PMP approach assumes farmers behave rationally to maximize their utility given their specific local conditions. However, it is essential to distinguish between the revealed behavior replicated by the model and macroeconomic or global economic efficiency. The PMP methodology fully reproduces baseline cropping patterns while implicitly accounting for various unmodeled constraints, including institutional barriers, information asymmetries, and financial limitations that restrict farmers' choices. Therefore, although the baseline pattern represents a real and locally optimal outcome for the farmer under actual existing conditions, it does not necessarily correspond to a normative absolute production possibility frontier (PPF). Consequently, policy interventions designed to alter cropping patterns or manage water demand are not inherently welfare-reducing; as long as such interventions successfully alleviate these structural constraints, they can generally improve overall welfare. Conversely, expanding technological capabilities (e.g., irrigation modernization) shifts the entire PPF. This behavioral premise perfectly aligns with the fundamental logic of PMP, allowing us to evaluate policies without artificially distorting observed farmer rationality.

Existing research often evaluates these policy interventions in isolation or compares instrument mechanisms (e.g., pricing vs. quotas) without systematically decomposing the exact relative contributions of technology adoption versus management optimization. This identification gap precludes answering a vital question for policymakers: What precise proportion of agricultural productivity gains and water savings stems from technological upgrades versus behavioral crop adjustments? Furthermore, many efficiency studies ignore stakeholder acceptance, treating farmers as passive policy recipients.

This study addresses these limitations by serving as an illustrative case study that employs PMP combined with participatory stakeholder engagement to evaluate water conservation policies. PMP (Howitt, 1995) is particularly suited for this analysis because its exact calibration mechanism embeds the assumption of farmer rationality; the model replicates observed farmer behavior precisely before simulating policy responses, thereby avoiding the oversimplifications of standard normative linear programming. To ensure practical relevance and address endogeneity bias, the technological interventions modeled in this study were not predetermined by the researchers. Instead, through structured consultations assessing Safiabad's specific climatic conditions, salinity levels, and capital constraints, local stakeholders (farmers and water managers) identified low-pressure irrigation as the most viable intervention.

The research pursues two interconnected objectives. First, we evaluate the socio-economic and environmental impacts of participatory water management scenarios in Safiabad's smallholder systems. Second, we provide a quantitative decomposition of total profitability gains, isolating the specific contributions of irrigation technology modernization versus cropping pattern optimization.

By offering a rigorous quantitative framework, this study provides actionable insights for agricultural development policy in water-scarce regions. While relying on a stylized regional model, the findings demonstrate sustainable groundwater conservation fundamentally requires expanding production possibilities through targeted infrastructure investments, rather than solely relying on behavioral restrictions. Our integrated framework—combining PMP's behavioral realism with participatory scenario design—provides a replicable template for evaluating the productivity-conservation trade-off in similar arid and semi-arid regions globally.

Rebound effects (improved efficiency paradoxically increasing water use) may occur when farmers expand irrigated area or switch to more water-intensive crops (Grafton et al., 2018; Pfeiffer & Lin, 2014). In our Safiabad case, such effects are unlikely due to severe land scarcity (98% of farms <10 ha; fixed 4.08 ha constraint) and limited crop-switching opportunities (processing capacity and market demand constraints). Consequently, the main channels for Jevons-type effects are weak here. Nevertheless, we acknowledge our deterministic, single-period PMP model does not explicitly simulate dynamic rebound mechanisms. This limitation is discussed in Section 6.

2. Theoretical Framework and Behavioral Assumptions

2.1. The "Poor but Efficient" Premise as a Modeling Foundation

Theodore Schultz (1964) argued smallholder farmers are "poor but efficient" — they optimize skillfully within severe constraints. While econometric literature has tested this hypothesis (Sauer, 2007; Lundahl, 1987), we adopt it as the behavioral assumption governing our PMP framework. Farmers behave rationally given their shadow prices and constraints; low productivity reflects outdated technology and water scarcity, not mismanagement.

However, the Schultzian hypothesis has faced valid criticisms: risk aversion (Binswanger & Sillers, 1983; Dercon, 1996), missing markets (de Janvry et al., 1991), liquidity constraints (Feder et al., 1985), and bounded rationality (Simon, 1955; Kahneman & Tversky, 1979).

Despite these criticisms, adopting Schultz's premise is methodologically defensible for three reasons. First, PMP replicates observed behavior without claiming global efficiency. Second, our deterministic setting abstracts from risk and market imperfections to isolate technology versus management contributions. Third, incorporating these factors is an important direction for future research (Section 6). Within this study's scope, the Schultzian premise provides a coherent foundation for decomposing policy impacts.

2.2. Shifting the Frontier: Technology vs. Management

Viewing the agricultural water crisis through this microeconomic lens shifts the policy focus dramatically. Under the maintained assumption that farmers are already optimizing their resource allocation given their existing constraints—an assumption that our PMP model operationalizes by exactly reproducing observed behavior—enforcing restrictive top-down policies (such as mandating shifts in cropping patterns or limiting water allocations) would primarily force them to reallocate resources along the existing, technologically constrained PPF. Within the framework of our calibrated model and its specific assumptions, such coercive policies may result in economic losses without generating substantial water conservation gains. However, this finding is model-dependent and should not be generalized to contexts where farmers face different constraints, market conditions, or behavioral frictions not captured by our deterministic PMP framework. In contrast, modernizing agricultural infrastructure (e.g., upgrading irrigation systems) represents an exogenous technological shock that shifts the entire PPF outward.

Therefore, rather than testing macroeconomic growth theories, this study focuses on a critical policy evaluation question: *In a water-stressed system where farmers are assumed to be economically rational, what is the relative contribution of technological advancement (irrigation modernization) versus managerial reallocation (shifting cropping patterns) in achieving water conservation without sacrificing rural livelihoods?*

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2.3. Scenario Design and Effect Decomposition

To quantitatively explore this dynamic, the research adopts a participatory decision-making framework involving key regional stakeholders—including farmers, water resource experts, and local authorities. This stakeholder-driven approach, previously validated (Bahrami Nasab *et al.,* 2025), ensures that proposed policies are socially acceptable. Through structured consultations assessing Safiaabad's specific climatic conditions and capital constraints, stakeholders identified localized low-pressure irrigation systems as the most appropriate technological intervention.

We employ a three-scenario comparative framework to decompose the impacts of policy interventions:

1. **Command-and-Control Restriction Scenario:** This scenario progressively restricts the area of the four most water-intensive crops (sugar beet, watermelon, melon, seed watermelon) under traditional irrigation by 5–30% in 5% increments, following a targeted rule based on water use per hectare. Restricted area is reallocated proportionally to unrestricted crops (cumin, kidney bean, wheat, barley), keeping total area constant at 4.08 ha. The 5% increments were chosen based on preliminary sensitivity analysis: finer resolutions (1%, 2.5%) identified two critical thresholds (profit maximization at 5% and break-even at 15%) with no additional inflection points between them.
2. **Unconstrained Modernization Scenario:** Provides modern irrigation technology while allowing farmers complete freedom to re-optimize their cropping patterns. This measures the total potential gains when both technology and management adjust.
3. **Fixed-Pattern Modernization Scenario:** Applies identical irrigation technology improvements but mathematically constrains cropping patterns to the observed baseline. This isolates the "pure" effect of technological change.

The controlled experimental design allows for a precise mathematical decomposition of policy impacts. By comparing total gains against the isolated technological scenario, we can extract the marginal value of managerial reallocation. Under our operationalized Schultzian assumption, we anticipate the technological shift will account for the dominant share of productivity and conservation gains, while managerial readjustments will offer only marginal supplementary benefits. This framework provides policymakers with a realistic, ex-ante assessment of whether development funds are better spent on trying to alter farmer behavior or on upgrading physical infrastructure.

3. Materials and Methods

3.1. Study Region: The Safiabad Case

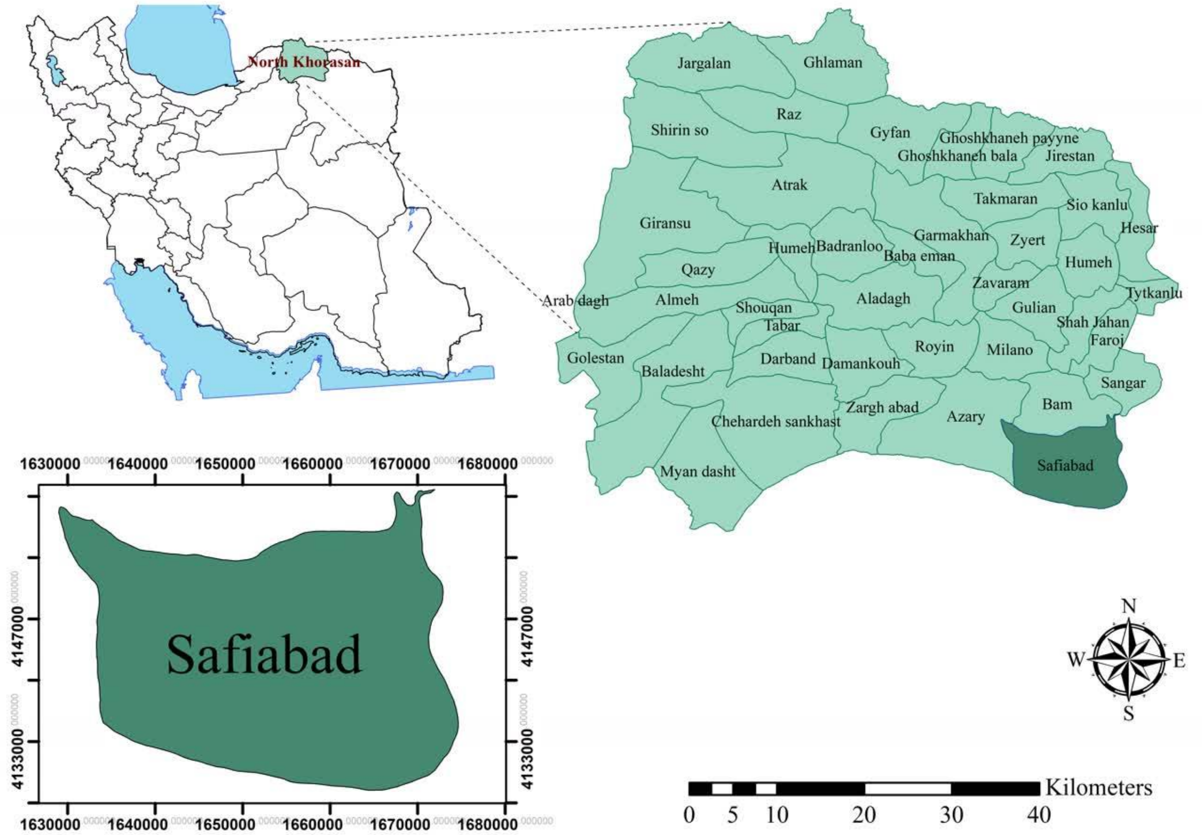

Figure 1. Geographical Location of the Study Area in North Khorasan Province, Iran.

Regional Context and Policy Relevance

The research was conducted in Safiabad District, North Khorasan Province, northeastern Iran (57°39′–58°06′ E, 36°35′–36°55′ N). Safiabad provides an ideal empirical setting for evaluating water conservation policies under resource scarcity because it exhibits key characteristics of highly constrained smallholder agriculture: **Traditional Technology Dominance:** The region relies heavily on traditional surface irrigation with low efficiency (35-37%), compared to modern low-pressure systems (60-65%). This stark contrast provides an excellent baseline for simulating exogenous technological shocks. **Severe Resource Pressure:** Groundwater levels declined by 9 meters between 1989 and 2021 (a 220 million m^3 loss). This severe environmental pressure implies that farmers have had to optimize their survival strategies over the past 32 years under extreme constraints, reinforcing our behavioral assumption of economic rationality. **Smallholder Scale:** With 98% of farms ≤ 10 hectares, the

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region typifies developing-country agriculture. These small-scale operators absorb the full economic shock of any top-down water policies, making precise policy impact decomposition crucial. **Groundwater Dependence:** Agriculture consumes 90% of regional water, with 79% sourced from groundwater (Sima-ye Ab Esfarayen, 2021). This direct dependence ensures any managerial interventions (like forced cropping pattern shifts) immediately manifest in farm profitability.

3.2. Research Design and Sampling Framework

We employ a representative farm approach rather than aggregate regional modeling for three methodological advantages. First, evaluating behavioral responses requires precise calibration to actual decision-making units where resource allocation occurs, rather than aggregate outcomes that obscure farm-level constraints. Second, farm-level modeling enables identification of threshold effects and nonlinear economic frictions that aggregate models mask. Third, farm-scale analysis aligns with our participatory approach, enabling farmers to directly validate policy feasibility.

The study population comprises smallholder producers in Safiabad District. Using simple random sampling, we selected 50 farmers. Structured questionnaires achieved a 100% response rate, capturing cropping patterns, input costs, water use practices, and operational constraints. Using mean values, we constructed a representative farm operating at 4.08 hectares. This statistical construct reflects the dominant regional farming system, encompassing eight major crops: cumin, kidney bean, sugar beet, wheat, barley, seed watermelon, watermelon, and melon. All input-output coefficients were cross-validated with regional agricultural extension data to ensure technical accuracy.

Empirical homogeneity assessment: To formally assess whether farm-level heterogeneity could bias our representative farm approach, we conducted several statistical tests. The standard deviation of farm size across the 50 sampled farms was 0.15 hectares around a mean of 4.08 hectares, yielding a coefficient of variation of just 3.68%, indicating very low dispersion. Furthermore, 98% of farms in the district operate on ≤10 hectares, confirming that the representative farm accurately reflects the central tendency of the population. Equality-of-means tests confirmed no statistically significant differences across farms for key economic variables (profitability, available water per hectare) at conventional significance levels. These results confirm that the Safiabad region exhibits high empirical homogeneity for the key dimensions that could otherwise bias representative farm aggregation. Nevertheless, as discussed in Section 6, even with empirical homogeneity, our findings may not generalize to regions with greater farm-level heterogeneity.

3.3. Positive Mathematical Programming: Calibrating Baseline Behavior

Positive Mathematical Programming (PMP), introduced by Howitt (1995), is utilized here not to *test* whether farmers are efficient, but to *operationalize* the assumption that they are. By exactly replicating observed baseline behavior without relying on arbitrary constraints, PMP provides a rigorous mathematical foundation for simulating responses to technological and managerial policy shocks.

Following the standard PMP framework (Howitt, 1995; Paris and Howitt, 1998), the methodology proceeds through three sequential stages: (1) identification of resource shadow values, (2) calibration of non-linear behavioral cost functions, and (3) policy simulation.

Stage 1: Linear Programming Formulation

A linear programming model maximizes farm profit subject to resource availability and calibration constraints to extract the shadow prices of binding resources:

Objective Function:

$$\text{Max}\pi = \sum_{j} (P_j yld_j) X_j - \sum_{j} C_j X_j \tag{1}$$

Subject to Resource Constraints:

Land Constraint:

$$\sum_{j} X_j \leq \text{Land} \quad \forall g \tag{2}$$

Crop rotation Constraint:

$$\sum_{j_M} X_{j_M} \leq \text{land}_M \tag{3}$$

Monthly Water Constraints:

$$\sum_{j} w_{j,m} X_j \leq water_m \quad \forall m \tag{4}$$

Labor Constraint:

$$\sum_{\text{j}} \text{L}_j X_j \leq Labour \tag{5}$$

Capital Constraint:

$$\sum_{j} ca_j X_j \leq Capital \tag{6}$$

Calibration Constraints:

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$$X_j \leq \tilde{X}_j + \varepsilon \quad \forall j \tag{7}$$

Non-negativity Constraints:

$$X_j \geq 0 \quad \forall j \tag{8}$$

Variable Definitions:

- j: Crop index
- P_j: Market price of crop j
- yld_j: Average yield of crop j
- C_j: Production cost per hectare of crop j
- X_j: Cultivated area of crop j (decision variable)
- $w_{j,m}$: Water requirement per hectare of crop j in month m
- $water_m$: Available irrigation water in month m
- L_j: Labor requirement per hectare of crop j
- ca_j: Capital requirement per hectare of crop j
- $\tilde{X}_j$: Observed area of crop j in base year
- ε: Small positive parameter preventing linear dependency.

Stage 2: Nonlinear Cost Function Calibration via Maximum Entropy

This stage uses shadow values from Stage 1 to estimate the parameters of a quadratic cost function:

$$cost = \sum_j [\alpha_j + \frac{1}{2}\sum_j \beta_{j,j} X_j] X_j \tag{9}$$

Given the ill-posed nature of the estimation problem (more parameters than observations), Maximum Entropy (ME) is employed to ensure convergence. To satisfy the second-order condition for cost minimization, the Hessian matrix (B, consisting of β parameters) must be positive definite. This is achieved via Cholesky decomposition ($B=LL'$) requiring positive diagonal elements of L (Howitt, 2005; Judd, 1999).

ME Objective:

$$max - \sum_j \sum_k p\alpha_{k,j} \ln p\alpha_{k,j} - \sum_j \sum_{j'} \sum_k pl_{k,j,j'} \ln pl_{k,j,j'} \tag{10}$$

Subject to standard parameter consistency and probability normalization constraints, yielding:

$$\alpha_j = \sum_k z\alpha_{k,j} p\alpha_{k,j} \quad \forall j \tag{11}$$

$$\boldsymbol{\beta_{j,j'}} = \left(\sum_{\boldsymbol{k}} \boldsymbol{zl_{k,j,j'}pl_{k,j,j'}}\right) \times \left(\sum_{\boldsymbol{k}} \boldsymbol{zl_{k,j',j}\, pl_{k,j',j}}\right) \forall \boldsymbol{j,j'} \quad (12)$$

Stage 3: Policy Simulation Model

The estimated non-linear cost function is integrated into the final objective function, removing the arbitrary calibration bounds (ϵ) from Stage 1. This enables the model to endogenously adjust cropping areas in response to policy scenarios:

$$\text{Max}\, \pi = \sum_j (P_j yld_j) X_j - \sum_j [\alpha_j + \frac{1}{2} \sum_j \beta_{j,j} X_j] X_j \quad (13)$$

(Subject to all standard resource constraints).

Models implemented in GAMS (v51.4.0) via the NEOS Server, using CONOPT (LP) and CONOPT3 (ME & NLP). ε = 0.0001 (Howitt, 1995). Uniform priors, K=5 (Paris & Howitt, 1998). Positive definiteness enforced via Cholesky (LTL≥0.01), guaranteeing unique global optimum. All runs optimal (Status 1). Entropy: 63.09 (traditional), 51.04 (modern).

3.4. Model Parameterization for Technology Assessment

To isolate technological effects from management, traditional irrigation assumes 36% efficiency with 40% water shortage. The modern low-pressure system operates at 62.5% efficiency (expert estimates: 60–65%, Regional Water and Soil Research Center), eliminating the shortage constraint. Cost structure includes annualized investment (equipment, distribution networks, and valves) and maintenance. Yield recovery uses FAO (2011) Ky values (0.8 for cumin to 1.15 for kidney bean), applying the water-yield relationship:

$$1 - Ya/Ym = Ky \times (1 - ETa/ETm) \quad (14)$$

$$Ym = Ya/(1 - 0.4 \times Ky) \quad (15)$$

4. Results

4.1 Model Validation and Baseline Calibration

The PMP model demonstrated exceptional calibration accuracy, successfully replicating observed land allocation patterns under traditional irrigation conditions. Model validation results showed deviations of less than 0.01% between observed and predicted crop areas for both Linear Programming (LP) and Maximum Entropy-Positive Mathematical Programming (ME-PMP) formulations across all eight crop types (Table 1). This high level of precision

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ensures the baseline effectively captures the revealed preferences and hidden costs of regional farmers, providing a reliable foundation for subsequent policy simulations.

Table 1. Model Validation: Observed versus Predicted Land Allocation **(ha).**

Crop	Observed Area	LP Model	PMP Model	Deviation (%)
Cumin	0.46	0.460046	0.460046	0.0100
Kidney bean	0.40	0.399984	0.399984	-0.0039
Sugar beet	0.40	0.399972	0.399972	-0.0071
Wheat	0.80	0.799920	0.799920	-0.0100
Barley	0.62	0.620058	0.620058	0.0094
Seed watermelon	0.60	0.599945	0.599945	-0.0091
Watermelon	0.28	0.280005	0.280005	0.0018
Melon	0.52	0.520052	0.520052	0.0100

The baseline scenario established fundamental performance metrics under current production conditions. Total farm profit reached 719.58 million IRR with a total water consumption of 23,617 cubic meter (m^3) across the 4.08-hectare representative farm. The traditional surface irrigation system exhibited characteristic low efficiency, with average field application efficiency ranging from 35−37%, reflecting typical conveyance and distribution losses in the region. Water productivity under baseline conditions measured 0.030 million IRR per cubic meter.

The existing cropping pattern demonstrates typical diversification strategies employed by regional farmers to manage production risks under water-constrained conditions. Validated against survey data from 50 regional farms, the representative farm approach ensures that baseline conditions reflect typical operational characteristics of the dominant smallholder category (≤10 hectares), which comprises 98% of regional agricultural operations.

4.2 Scenario 1: Evaluation of Command-and-Control Crop Restrictions

Progressive restrictions on water-intensive crops (sugar beet, watermelon, melon, seed watermelon) generated variable economic outcomes with clear threshold effects, illustrating the limitations of coercive, demand-side management policies (Table 2).

Optimal economic performance occurred at a marginal 5% restriction level, generating 740.77 million IRR (a +2.9% profit increase) while achieving 1.2% water conservation. However, this optimization space is extremely narrow. Beyond a 15% restriction (where economic break-even is achieved at 719.15 million IRR, approximately 0% change from baseline with 5%water savings), the policy creates a strict trade-off. Increasing restriction levels produced progressively declining economic returns. For instance, a 30% restriction resulted in 683.03 million IRR (−5.1% profit decline) while achieving a maximum water savings of 12.7%.

Table 2. Economic and Hydrological Impacts of Progressive Crop Restrictions.

Restriction Level (%)	Total Profit (Million IRR)	Profit Change (%)	Water Use (×10³ m³)	Water Savings (%)
0 (Baseline)	719.58	0.0	23.617	0.0
5	740.77	+2.9	23.322	1.2
10	730.43	+1.5	23.050	2.4
15	719.15	-0.1	22.440	5.0
20	707.49	-1.7	21.830	7.6
25	695.45	-3.4	21.220	10.1
30	683.03	-5.1	20.610	12.7

This trajectory (Fig.2) demonstrates under current technological constraints, farmers are already operating near their efficiency frontier. While the restriction approach yielded approximately 2.6% additional water conservation for each 5% increment in restrictions, the marginal economic cost of these savings increased substantially beyond the 15% threshold.

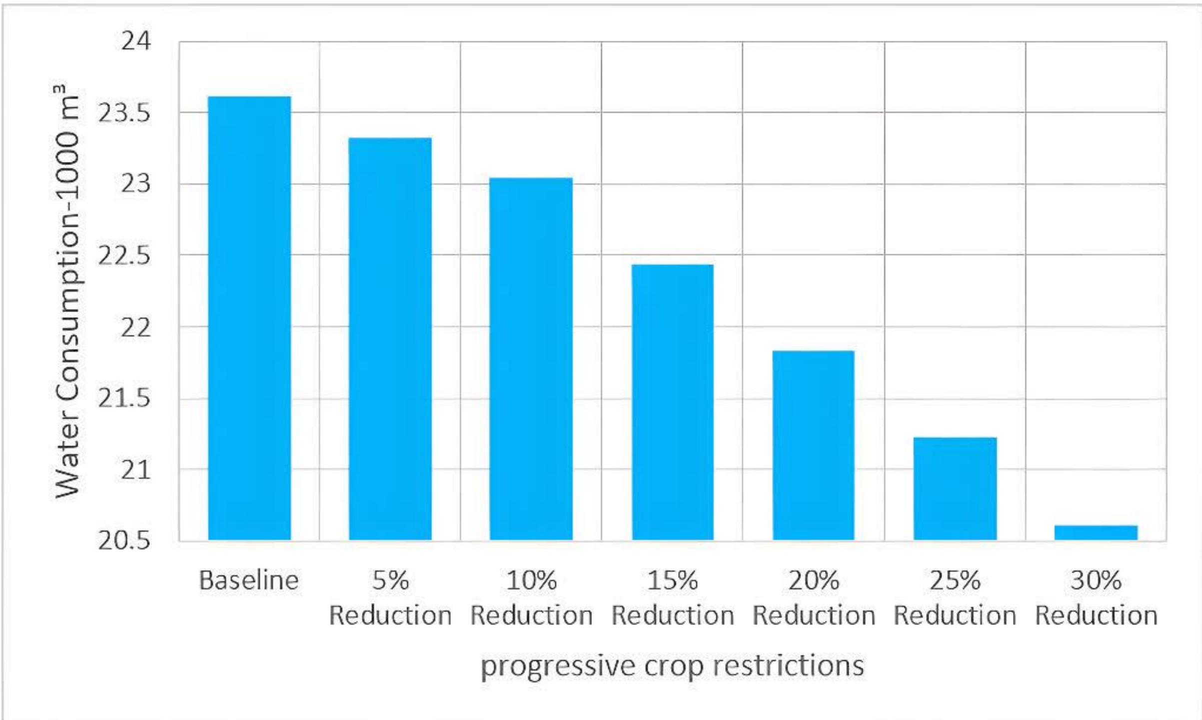

Figure 2. Water consumption declines by ~2.6% per 5% restriction, but economic costs rise sharply beyond the 15% threshold.

The trade-off analysis (Fig.3) reveals aggressive crop restriction policies—often favored by water authorities—are inherently inefficient in this context. Beyond the narrow 15% threshold, the relationship becomes inversely proportional, indicating that forcing farmers to abandon water-intensive crops without providing technological alternatives primarily results in economic penalties and loss of livelihood for smallholders.

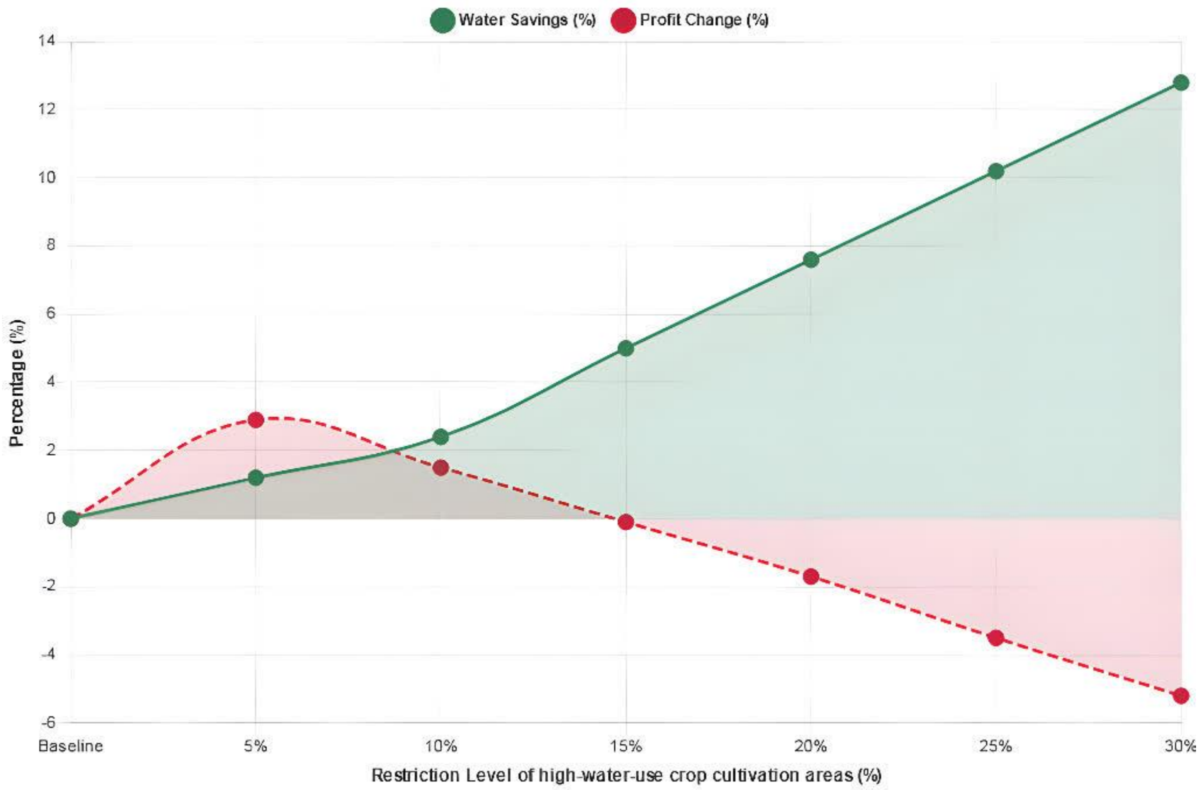

Figure 3. Beyond 15% restriction, water savings slow while profits turn negative, imposing economic penalties on smallholders.

4.3 Scenario 2: Technology Modernization with Endogenous Pattern Optimization

In stark contrast to restrictive policies, the implementation of low-pressure irrigation technology—coupled with unrestricted cropping pattern optimization—produced transformational improvements across all performance metrics. Total profit increased to 926.37 million IRR, representing a 28.7% improvement over baseline conditions. Simultaneously, water consumption decreased by 66.4%, demonstrating the potential for substantial resource conservation without sacrificing agricultural income. The optimization process identified several advantageous cropping pattern modifications under modern irrigation conditions (Table 3).

The observed cropping pattern adjustments under modern irrigation can be explained by three factors: First, water productivity differences drive land reallocation. Crops that generate higher economic return per unit of water consumed tend to expand, while those with lower water productivity contract. This reflects the profit-maximizing behavior embedded in the PMP

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framework. Second, crops with higher Ky coefficients (yield response factors) benefit more from the elimination of the 40% water shortage under modern irrigation. These crops show substantial yield recovery, making them more profitable and leading to area expansion. Conversely, crops with similar Ky but lower baseline profitability are partially replaced. Third, substitution effects occur among competing crops. The model reallocates land from less profitable to more profitable crops under the new technology. For example, a cereal with higher water productivity and higher per-hectare profit partially replaces another cereal with lower performance under modern irrigation. While some crops have excellent water productivity, their expansion may be limited by relatively lower per-hectare profit compared to other crops. The final land allocation reflects the simultaneous optimization of both water productivity and total profit.

Table 3. Optimal Cropping Pattern under Low-Pressure Irrigation.

Crop	Traditional System (ha)	Optimized System (ha)	Change (%)	Unit Profit per crop (Million IRR)
Cumin	0.460	0.524	+13.93	7,345
Kidney bean	0.400	0.361	-9.80	8,574
Sugar beet	0.400	0.372	-7.07	16,413
Wheat	0.800	0.657	-17.84	12,311
Barley	0.620	0.664	+7.20	12,845
Seed watermelon	0.600	0.478	-20.37	7,174
Watermelon	0.280	0.449	+ 60.32	11,966
Melon	0.520	0.488	-6.20	16,009
Mean absolute change	-	-	17.84 %	-

Comparative analysis of cropping patterns (Fig.4) demonstrates the rational producer response to improved water-use efficiency. With a mean absolute change of 17.84% from baseline allocations, the adjustments reflect how farmers dynamically adapt to changed relative profitability under enhanced irrigation technology, naturally favoring crops with superior water productivity characteristics once technological constraints are lifted.

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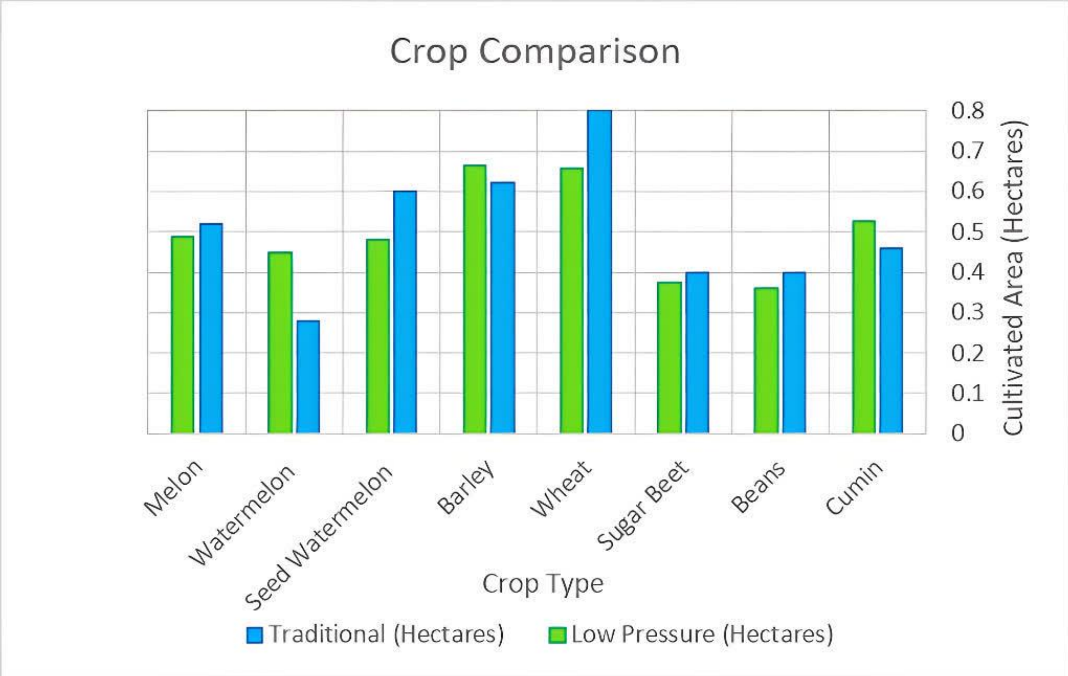

Figure 4. Farmers reallocate land toward crops with higher water productivity under low-pressure irrigation (mean change: 17.84%).

Comparative water consumption analysis (Fig.5) illustrates the dramatic difference in conservation potential between technology-based interventions (66.4% reduction) and crop management approaches (maximum 12.7% reduction). The technological approach dissolves the conventional conflict between water conservation and farm profitability.

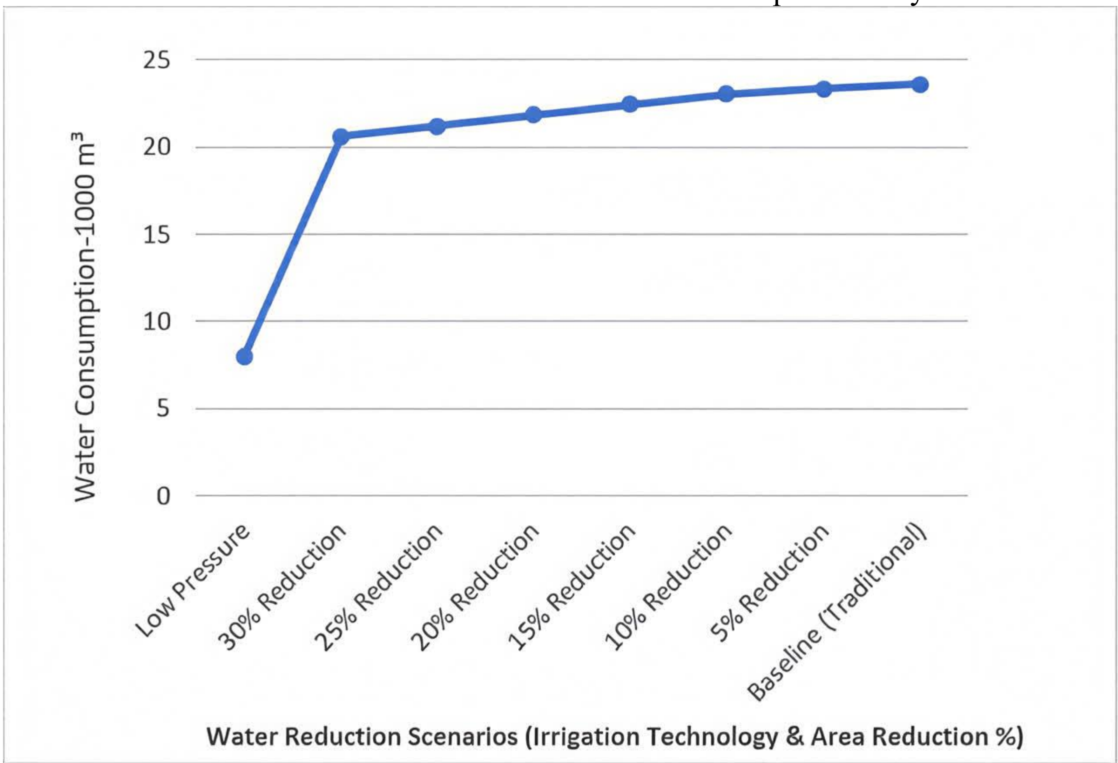

Figure 5. Low-pressure irrigation achieves 66.4% water saving relative to traditional baseline, far exceeding the 12.7% maximum from crop restrictions.

4.4 Scenario 3: Decomposing the Effects: Technology vs. Reallocation

To isolate the policy impact of technology adoption from the behavioral impact of crop reallocation, Scenario 3 evaluated technological modernization while strictly maintaining the baseline cropping pattern. Under this condition, total profit reached 911.70 million IRR, representing a 26.7% improvement over baseline conditions. Water consumption decreased by 65.4%, nearly identical to Scenario 2.

Crucially, the marginal profit difference between Scenario 2 (unrestricted optimization: 926.4 million IRR) and Scenario 3 (fixed pattern: 911.7 million IRR) was only 14.7 million IRR, representing just 1.59% of Scenario 2's total returns. Under our model assumptions and the specific conditions of the Safiabad case study, this decomposition yields a profound policy insight: the overwhelming majority of economic and hydrological gains derive purely from the physical enhancement of irrigation technology, rather than from reoptimizing the cropping pattern.

The near-identical profitability between the two scenarios demonstrates farmers can achieve substantial resource and economic improvements through technology adoption alone, even while maintaining their traditional cultural cropping preferences. This fundamentally challenges the current policy emphasis on mandating cropping pattern shifts.

However, this finding is model-dependent and context-specific. The estimated 93-to-7 contribution ratio is conditional upon our PMP calibration structure, the assumed efficiency levels, the representative farm construct, and the fixed price and water scarcity conditions in Safiabad. The decomposition may change under stochastic conditions (e.g., climate variability, price shocks), alternative price scenarios, heterogeneous farm characteristics (e.g., varying farm sizes, water access, or risk exposure), or different technology adoption costs (e.g., lower or higher investment and maintenance expenses). We have discussed these limitations in Section 6 and recommend future research to test the robustness of this decomposition across these varying conditions.

4.5 Water Productivity Enhancement and Comparative Analysis

Economic Water productivity—defined as economic return per unit of water consumed—provides a comprehensive metric for evaluating irrigation system performance. Under baseline conditions with traditional surface irrigation (36% efficiency), water productivity measured

0.030 million IRR m^3, reflecting the combined effect of high conveyance losses and water shortage-induced yield penalties.

Modern low-pressure irrigation dramatically transformed water productivity to 0.117 million IRR m^3 (Table 4). This improvement is driven by a dual mechanism: (1) increased application efficiency that reduces physical water loss, and (2) the elimination of crop water stress, which improves yields according to crop-specific response factors.

Table 4. Comparative scenario analysis.

Performance indicator	Baseline	Scenario 1*	Scenario 2	Scenario 3
Total profit (million IRR)	719.58	740.77	926.37	911.70
Profit change (%)	0.0	+2.9	28.7	26.7
Water consumption (×10^3 m^3)	23.617	23.322	7.944	8.162
Water savings (%)	0.0	1.25	66.4	65.44
Water productivity (million IRR m^{-3})	0.030	0.032	0.117	0.112

*Optimal restriction level (5%)

Fig.6 synthesizes total farm profit outcomes under both progressive crop-restriction scenarios and modern technology scenarios. The continuous decline in total profit under stringent restriction levels (>15%) highlights the substantial economic costs of command-and-control crop management policies. By contrast, both low-pressure irrigation scenarios significantly outperform all restriction cases. These findings strongly suggest policy interventions in water-scarce regions should prioritize capital investment in irrigation modernization rather than externally imposing production constraints.

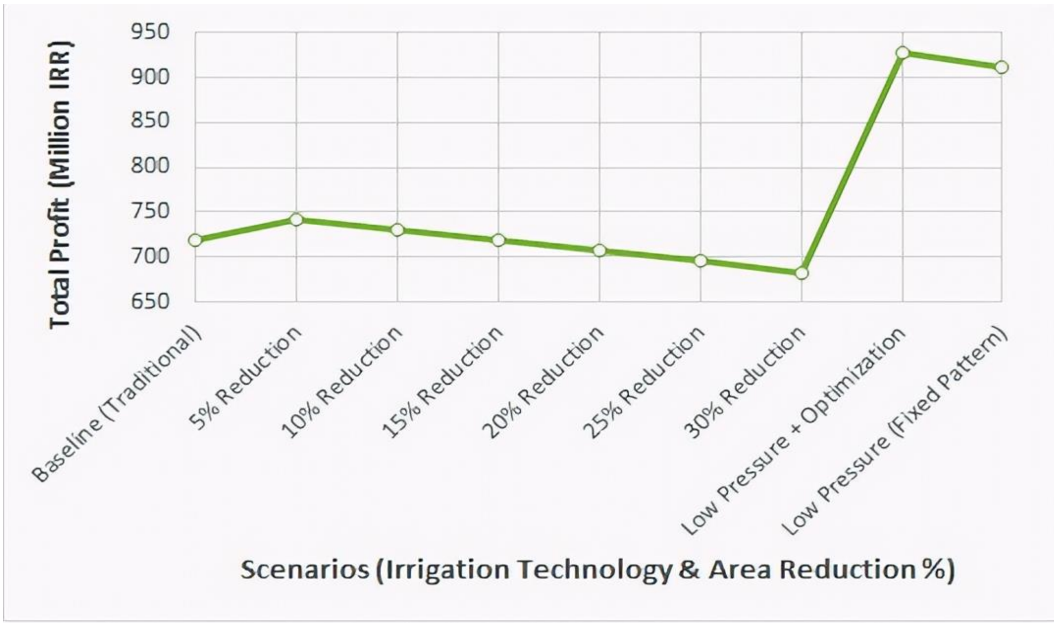

Figure 6. Low-pressure irrigation increases total farm profit from 720 (traditional baseline) to 910-920 million IRR, whereas crop restrictions beyond 15% reduce profit to 680 million IRR.

4.6 Sensitivity Analysis: Impact of Water Availability Reduction on Three Scenarios

We simulated progressive water reductions (2–20%) across three scenarios: Baseline (traditional irrigation), S2 (modern irrigation with optimized cropping), and S3 (modern irrigation with fixed baseline cropping). As shown in Table 5, S2 achieves 66% water savings even at 0% reduction (*Baseline:* 23.62×10³ m³), declining further to 6.51×10³ m³ at 20% reduction. Table 5 also decomposes total gains into technology versus management contributions. At mild restrictions (2–7%), technology contributes 93–98% of gains. However, at 10% reduction, the management share jumps sharply from 2% to 18%. At 20% reduction, management (53%) slightly exceeds technology (47%). This reveals a nonlinear policy insight: under severe water scarcity, adaptive cropping reallocation becomes as important as — and eventually more important than — the irrigation technology itself. Consequently, fixed cropping patterns under technology adoption (S3) are inferior to flexible, profit-maximizing reallocation (S2).

Table 5. Summary of water use, profit, and decomposition.

Water Reduction (%)	Baseline Water Use	S2 Water Use	S3 Water Use	Baseline Profit	S2 Profit	S3 Profit	Technology Share (%)	Management Share (%)
0	23.62	7.94	8.16	71.96	92.64	91.17	93	7
2	23.08	7.92	7.98	71.29	92.42	91.93	98	2
5	22.27	7.73	7.70	70.29	91.72	91.37	98	2
10	20.92	7.33	7.23	68.59	89.73	85.90	82	18
15	19.52	6.92	6.75	66.70	87.28	76.92	50	50
20	18.35	6.51	6.34	64.37	84.42	73.73	47	53

Note: Water use in ×10³ m³. Profit in Million IRR.

5. Discussion

The baseline scenario illustrates a fundamental reality of smallholder farming in water-stressed regions: farmers operate efficiently within severe technological constraints. Traditional irrigation systems yield a low water productivity of 0.030 million IRR m⁻³. However, this inefficiency is structural rather than behavioral. Consistent with Schultz's (1964) premise of the rational peasant—which forms the behavioral foundation of our PMP framework—allocative efficiency coexists with technological poverty. Farmers optimize their resource allocation meticulously, yet these physical constraints prevent substantial economic gains.

While higher water productivity could theoretically induce expansionary rebound effects at larger spatial scales, such responses are unlikely in the Safiabad context due to binding land constraints (98% of farms operate below 10 hectares with no scope for area expansion) and limited crop-switching flexibility — as discussed in Section 1 and elaborated in Section 6.

Beyond the farm level, it is important to contextualize these findings within a broader macro-level perspective. At the basin or regional scale, the aggregate effect of widespread technology adoption by all farms in Safiabad would translate into a potential reduction of approximately 66% in total agricultural water withdrawal from the shared aquifer system. Given that agriculture accounts for the dominant share of water extraction in the region, this magnitude of reduction could substantially relieve pressure on declining groundwater tables and improve water availability for downstream users, municipal systems, and environmental flows. However, realizing these macro-level benefits requires coordinated basin-wide governance — individual farm-level efficiency gains do not automatically translate into regional water savings without institutional mechanisms to prevent rebound extraction by other users.

Scenario 1 demonstrates the severe limitations of command-and-control policies (restricting water-intensive crops). While a marginal 5% restriction provides a narrow optimization space (saving 1.2% water with a 2.9% profit increase), pushing restrictions beyond 15% results in severe economic trade-offs. At a 30% restriction, profits decline by 5.1% to save only 12.7% water. This trajectory highlights the deadweight loss associated with behavioral mandates: forcing already-efficient decision-makers to abandon profitable crops without providing technological alternatives primarily results in livelihood penalties rather than meaningful resource conservation.

In stark contrast, S2 and S3 produce transformational gains, dissolving the traditional trade-off between farm profitability and water conservation. The adoption of low-pressure irrigation leads to a 26.7–28.7% increase in profit and a massive 65.4% reduction in water use. More importantly, the decomposition of these total productivity gains provides a profound policy insight. The total profit increase when both technology and cropping patterns are allowed to change (S2) is 206.79 million IRR over the baseline. However, upgrading the irrigation technology alone—while holding the cropping pattern constant (S3)—accounts for 192.12 million IRR, representing approximately 93% of the total gain. The marginal benefit of subsequently allowing the cropping pattern to re-optimize alongside the new technology (the difference between Scenarios 2 and 3) contributes only the remaining 14.67 million IRR (approximately 7%). This yields a striking 13-to-1 ratio of technology-driven gains versus management-driven gains.

The 93-to-7 decomposition ratio suggests that, under our model assumptions and the specific conditions of Safiabad, cropping pattern re-optimization contributed only 7% of total productivity gains. This finding is consistent with the interpretation that farmers were already operating near their constrained optimum under traditional technology. However, we caution that observed cropping patterns may still be influenced by factors not explicitly modeled in our deterministic PMP framework, including risk management (e.g., diversification to hedge against drought or price volatility), institutional rigidities (e.g., customary land use rules), imperfect information (e.g., limited knowledge of market prices or new crop varieties), or market distortions (e.g., subsidies or price controls). Therefore, the minimal remaining "optimization space" we estimate is conditional upon our model structure and should not be interpreted as evidence of fully optimal long-run adaptation. Rather, the binding constraint on agricultural development in this region—under our model assumptions—appears to be the physical limits of the PPF, with irrigation modernization shifting the PPF outward and contributing 93% of the gains.

These findings address a critical debate in agricultural development policy: whether to prioritize behavioral correction (e.g., extension services, mandated crop changes) or capital investment (e.g., infrastructure modernization). Our results strongly suggest because farmers are already efficient managers of their current technology set, behavioral interventions provide minimal marginal returns. Development in such water-scarce smallholder systems is fundamentally a capital investment challenge, not a farmer education problem. Policy should therefore prioritize expanding farmers' technological capabilities rather than attempting to engineer their cropping choices.

5.1 Comparison with International and Regional Studies

Our finding that technology dominates management aligns with international evidence. Askaraliev et al. (2024) reported 50% water savings following modern irrigation adoption in Kyrgyzstan. Abdelrahman et al. (2020) documented 67% profit increases under drip irrigation in Egypt. Liu et al. (2022) found >60% net profit gains under drip irrigation and 1,800 m^3 ha^{-1} water savings in China.

Iranian studies provide additional validation. Asadi et al. (2023) in Alborz province reported net profit increases of 162.9% (wheat) and 72.9% (corn) with 22.8–27.6% water savings under drip irrigation. Rahmani et al. (2017) demonstrated 17% water savings under modern irrigation in Ardabil.

The minimal difference between optimized and fixed cropping patterns under modern irrigation (S3 vs. S2) suggests that technology-focused interventions may avoid farmer resistance and market disruption risks while maintaining comparable outcomes. Our results support Pérez-Blanco et al. (2020), who argued that irrigation technologies should be viewed as economic efficiency tools rather than merely water conservation instruments.

A comprehensive long-run vision for water management necessitates looking beyond direct physical water savings towards the concept of virtual water. Incorporating virtual water flow analysis into future iterations of this model can guide regional agricultural policies to import water-intensive crops while locally optimizing drought-resistant, high-value commodities. Such a long-term strategic alignment would not only improve economic efficiency but also ensure structural water sustainability amidst changing climatic conditions.

6. Conclusions

This study provides a rigorous quantitative evaluation of agricultural water policies by integrating mathematical programming (PMP) with farm-level empirical data. By shifting the analytical lens from aggregate water accounting to micro-level behavioral modeling, we demonstrated that traditional smallholder farmers are highly efficient optimizers trapped by obsolete technology.

Our central finding—that technological modernization accounts for 93% of potential farm improvements compared to just 7% from cropping pattern optimization—fundamentally challenges the prevailing command-and-control approach to water management. We show that policies aimed at restricting farmer behavior or forcing crop substitution (S1) are economically painful and hydrologically inefficient. In contrast, expanding the farmers' constraint set through capital investment in modern irrigation (S2 & S3) creates a true win-win outcome: reducing water consumption by over 65% while boosting farm profits by nearly 30%.

Under the specific conditions of the Safiabad case study—characterized by severe land and water scarcity, smallholder dominance, and binding capital constraints—our findings suggest that infrastructure modernization and technology provision may generate larger water conservation and profit gains compared to punitive cropping restrictions. However, this result does not imply that behavioral, institutional, or extension policies are universally ineffective. In contexts where farmers face different constraints (e.g., larger farms, better access to credit, less severe water scarcity, or weaker technical capacity), well-designed behavioral interventions or institutional reforms may play a complementary or even primary role. The appropriate policy mix likely depends on local conditions. In settings similar to Safiabad, prioritizing technological investments appears justified, but this recommendation should not be generalized without local validation. Where farmers already optimize effectively within their limits—as our model assumes—the role of the policymaker in such contexts may shift from correcting farmer behavior to expanding their production possibilities through targeted infrastructure investments.

Methodological Limitations and Future Directions

First, deterministic single-period PMP model: Our analysis does not incorporate climate variability, price volatility, or risk aversion. The current model does not incorporate risk—such as yield uncertainty, price shocks, or drought-induced water shortages—which may influence farmers' willingness to adopt modern irrigation technologies or modify cropping patterns. Future research should extend this framework using stochastic PMP models to evaluate intervention resilience under uncertainty.

Second, rebound effects: As justified in the Introduction, rebound effects are unlikely in Safiabad due to land scarcity (98% of farms ≤10 ha, no expansion margin) and limited crop-switching opportunities (processing capacity and market demand constraints). However, our model does not simulate aquifer-scale groundwater rebound — individual farm savings may be partially offset if no basin-wide extraction limits exist. Future research should integrate farm-level PMP with basin-scale hydrological models.

Third, representative farm approach: Despite high empirical homogeneity (mean farm size 4.08 ha, SD 0.15 ha, CV=3.68%; t-tests confirm no significant differences), this approach may mask subtle distributional effects. Future research should use farm-household panel datasets to explore potential heterogeneity in policy responses across different farm types and socioeconomic strata.

Fourth, full and immediate adoption assumption: The model assumes immediate technology adoption once made available, abstracting from learning curves, diffusion lags, credit constraints, and peer effects. Future research should incorporate agent-based or dynamic optimization models simulating technology diffusion trajectories.

Fifth, case-specific findings: Quantitative results (e.g., 93:7 decomposition) should not be generalized without local recalibration. However, the qualitative insight — technology dominates cropping reallocation when farmers are already efficient constrained optimizers — may hold in similar water-stressed smallholder contexts. Future research should test the replicability of our decomposition framework across multiple sites, scales, and model specifications.

Sixth, third-party and environmental sustainability: Our analysis focuses on direct beneficiaries without fully accounting for basin-scale sustainability. Technology adoption must be accompanied by regulatory frameworks (e.g., caps on total basin extraction) to prevent rebound effects. Comprehensive sustainability assessment requires integrating ecological water requirements, social equity, and intergenerational water accounting.

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جابجایی مرز تولید: غلبه نوسازی آبیاری بر بازتخصیص الگوی کشت در حفظ آب‌های زیرزمینی

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چکیده

ایجاد تعادل بین بهره‌وری کشاورزی و حفظ آب‌های زیرزمینی، هنوز یکی از چالش‌های اساسی در مناطق با تنش آبی است. مطالعه حاضر تلاش کرده است تا چارچوبی کمّی برای ارزیابی سیاست‌های حفاظت از آب کشاورزی ارائه دهد و تمرکز را از دستورالعمل‌های اداری به سمت پیشرفت فناوری تغییر دهد. با استفاده از یک مدل برنامه‌ریزی ریاضی مثبت (PMP) کالیبره‌شده، راهبردهای مدیریت آب زیرزمینی را در شهرستان صفی‌آباد ایران ارزیابی کردیم. سه سناریوی کنترل‌شده مورد ارزیابی قرار گرفت: محدودیت تدریجی کشت (۵ تا ۳۰ درصد)، آبیاری کم‌فشار همراه با بهینه‌سازی الگوی کشت، و نوسازی آبیاری با الگوهای کشت ثابت. نتایج نشان می‌دهد که جابجایی مرز تولید فناورانه به طور قابل توجهی بر تخصیص مجدد مدیریتی در امتداد مرز موجود برتری دارد. تحت مفروضات مدل PMP کالیبره‌شده ما و شرایط خاص مطالعه موردی صفی‌آباد، تجزیه منافع سیاست نشان می‌دهد که نوسازی آبیاری تقریباً ۹۳ درصد از کل بهبودهای بهره‌وری را به خود اختصاص می‌دهد — که به طور همزمان به افزایش ۲۶.۷ درصدی سود و کاهش ۶۵.۴ درصدی مصرف آب منجر می‌شود. در مقابل، بهینه‌سازی مجدد الگوی کشت تنها حدود ۷ درصد سهم دارد، با وجود اینکه نیاز به میانگین تغییر مطلق ۱۷.۸۴ درصدی در هشت محصول دارد. این نسبت ۱۳ به ۱ وابسته به مدل برای سهم فناوری به مدیریت نشان می‌دهد که در این بافت خاص، تکیه صرف بر محدودیت‌های رفتاری یا تغییرات الگوی کشت ممکن است برای دستیابی به صرفه‌جویی قابل توجه آب بدون ضرر اقتصادی کافی نباشد. بر اساس این یافته‌ها، حفظ پایدار آب زیرزمینی در عین حفظ معیشت روستایی احتمالاً از گسترش امکانات تولید از طریق سرمایه‌گذاری‌های هدفمند در زیرساخت سود خواهد برد، هرچند برای آزمایش تعمیم‌پذیری این نتایج به تحقیقات بیشتری نیاز است.