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Technical Efficiency and Productivity Gaps in Wheat Farming: A Comparative Analysis of Conservation Agriculture Adopters and Non-Adopters in Nineveh Governorate, Iraq

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Abstract

Technical efficiency (TE) in wheat production is important for achieving food security in resource-constrained regions such as northern Iraq. Nineveh Governorate, a major grain-producing region of Iraq, has experienced productivity shortfalls despite substantial investment in agricultural inputs, creating a need for rigorous efficiency analysis to inform policy and extension programs. This study estimates and compares the TE of 450 wheat farmers in Nineveh Governorate during the 2023–2024 agricultural season using input-oriented data envelopment analysis (DEA) under variable returns to scale (VRS). The sample comprised 225 farmers officially enrolled in a conservation agriculture (CA) program and 225 conventional-tillage farmers selected from the same agro-climatic districts. The estimates indicate a substantial difference in efficiency between the two groups. The mean TE score was 0.849 for CA adopters and 0.551 for non-adopters, corresponding to estimated proportional input-reduction potentials of 15.1% and 44.9%, respectively, relative to the estimated frontier. In the high-efficiency category (TE $\geq$ 0.81), CA adopters accounted for 69.33% of their group, compared with 10.67% of non-adopters. The reported Mann–Whitney test indicated a statistically significant difference between groups ($Z = -14.71$; $p < 0.001$). Descriptive comparisons showed lower mean pesticide, fertilizer, and seed quantities among adopters, although input-specific inefficiency cannot be established from group means alone. The observed efficiency advantage occurred during the relatively favorable rainfall conditions described for the study season. However, a single-season observational comparison cannot isolate management effects from weather, selection into adoption, or other farm characteristics. The findings support further evaluation of CA promotion and targeted extension interventions in Iraq and comparable dryland wheat-producing areas, with attention to appropriate input use and consistent implementation of CA practices.

Keywords: Conservation agriculture; Data envelopment analysis; Food security; Nineveh Governorate; Resource efficiency; Wheat production.

1. INTRODUCTION

Population growth, climate change, and resource degradation increasingly threaten global food security. Agricultural technologies can help address these pressures by improving the timing, monitoring, and management of production activities, as discussed by Khan et al. [1]. Wheat (Triticum aestivum L.) is a major staple crop in the Middle East, especially in Iraq, and an important source of income for farming households. Nineveh Governorate has traditionally been one of Iraq's principal grain-producing regions, but its productive potential remains constrained by inefficient resource use and variable growing conditions. Technical efficiency describes the ability of a production unit to obtain the greatest feasible output from a given combination of inputs, or to produce a given output with the fewest feasible inputs [2]. Geffersa et al. [3] show that estimated agricultural efficiency also varies with agro-ecological conditions and methodological assumptions. Low TE therefore indicates scope for improving performance relative to a specified production frontier, rather than an unconditional guarantee of additional yield. Evidence from Ethiopian wheat production [4], Nigerian plantain production [5], and Indonesian rice production [6] associates technology adoption with improved efficiency, while highlighting the importance of crop-specific and institutional conditions. These comparisons motivate a locally grounded assessment of wheat farming in Nineveh.

Conservation agriculture (CA) is based on three interrelated principles: minimum soil disturbance, permanent soil cover, and diversification of plant species through crop rotations or other appropriate arrangements [7]. These practices may reduce tillage requirements, support soil moisture conservation, and improve the management of nutrients and other inputs. Their benefits nevertheless depend on how they are combined and implemented. Pittelkow et al. [8] found that the yield effects of no-till vary across environments and improve when residue retention and crop rotation accompany reduced tillage. In Ethiopia, Alemayehu et al. [4] found higher wheat efficiency when several climate-smart practices were adopted together. In Nineveh, AlKhulaifi and Al-doski [9] documented socioeconomic and communication differences between CA adopters and non-adopters. Their findings underline the importance of extension contacts and farmers' readiness to change, rather than establishing an agronomic effect by themselves. Adoption has remained uneven despite local demonstration and extension activities. Understanding the efficiency implications of CA is therefore relevant to agricultural advice, incentive design, and extension planning. Evidence on sugarcane technology adoption in Pakistan [10] and soil-fertility management among Ghanaian tomato growers [11] provides additional context for examining these institutional and economic dimensions without assuming identical outcomes across crops.

The economic importance of improving input management is also apparent in studies of wheat and watermelon production in Diyala Governorate. Chaied Al-Fahdawy and Ahmed Al-Jumaily [12] examined production costs, while their companion study [13] compared socioeconomic conditions and irrigation-water sources. These studies provide relevant Iraqi context, although their findings should not be transferred directly to Nineveh without considering differences in production systems. Efficiency measurement requires a clearly specified comparison. DEA is a non-parametric linear-programming method that constructs a production frontier from observed farms and evaluates each decision-making unit against that frontier. It does not require a predefined production function or a distribution for statistical noise; however, it also does not automatically separate noise and measurement error from inefficiency. Under VRS, pure technical efficiency is estimated separately from scale effects; calculating scale efficiency additionally requires a corresponding constant-returns-to-scale model [14]. The present study uses a sample of 450 farms for the 2023–2024 season to examine contemporary efficiency differences in Nineveh. Its objectives are: (i) to estimate and compare the TE of CA adopters and non-adopters; (ii) to quantify the proportional input-reduction potential implied by the efficiency scores; and (iii) to develop extension and policy recommendations relevant to the observed productivity differences. These objectives concern an observational comparison and do not establish a randomized causal effect of adoption.

2. MATERIALS AND METHODS

The study was conducted in Nineveh Governorate, northwestern Iraq, approximately between 35° and 37° N and between 41° and 44° E. The governorate includes limited-rainfall, semi-guaranteed, and guaranteed-rainfall zones, which provide contrasting conditions for wheat production. The study description identifies annual rainfall of approximately 200 mm or less in the limited-rainfall zone and approximately 200–350 mm in the semi-guaranteed zone; a numerical threshold for the guaranteed-rainfall zone was not specified. According to the agricultural-area information supplied for this study, the Nineveh Agriculture Directorate recorded approximately 625,000 ha planted with wheat during the 2023–2024 season. CA demonstration plots and extension campaigns have operated in the area since 2007, providing an established group of program participants for comparison with conventional farmers. The rainfall-zone averages presented later describe the regional production setting and are not separate estimates of CA treatment effects.

The study population comprised 225 officially registered wheat farmers participating in the CA extension program and 836 conventional, non-CA farmers in the same districts. All 225 registered CA adopters were included, constituting a census of this program group. A random sample of 225 conventional farmers was selected from the non-adopter

population, representing approximately 26.9% of its 836 members. The resulting study sample therefore contained 450 farmers, divided equally between the two groups. This design provides complete coverage of registered adopters and a sampled comparison group within the specified districts. It does not, by itself, ensure that adopters and non-adopters are equivalent in farm resources, experience, soil conditions, or access to services. Consequently, differences between the groups are interpreted as observed associations within the study population.

Primary information was collected through structured face-to-face interviews conducted between September 2024 and February 2025 concerning the 2023–2024 agricultural season. The questionnaire covered wheat output and six production inputs: cultivated area (ha), seed quantity (tonnes), mechanized labor (machine-hours), human labor (person-days), fertilizer quantity (tonnes of NPK fertilizer), and pesticide quantity (liters). Agricultural economists and extension specialists reviewed the questionnaire, which was also tested in a pilot survey. Farmers were asked to provide field records or receipts where available to reduce reliance on recall. Table 1 retains the reported quantities and units. The output description requires reconciliation: the questionnaire narrative identifies yield in tonnes per hectare, whereas the original table labels the output as total tonnes. Similarly, the narrative describes seed quantities per hectare, although the table records tonnes. These distinctions must be resolved against the questionnaire and the DEAP input file before the production model can be independently reproduced. Pesticide formulation and active-ingredient concentration also require consistent interpretation.

Technical efficiency was estimated using DEAP version 2.1 and an input-oriented DEA model under VRS [15]. The VRS specification accommodates farms operating at different scales and avoids imposing proportional changes in output when all inputs change proportionally [14]. An input orientation examines the potential to reduce inputs while maintaining at least the observed output. In the stated model, cultivated area is included among the inputs subject to proportional contraction; it is therefore not treated as a fixed input. This distinction is important when interpreting recommendations for land and other resources. Each farm is treated as a decision-making unit (DMU). For farm i, the linear program minimizes the scalar θ subject to the observed input and output constraints and the VRS convexity condition:

$$\begin{cases} \mathrm{TE}_i = \min\limits_{\theta,\boldsymbol{\lambda}} & \theta \\ \quad \text{subject to} & X\boldsymbol{\lambda} \le \theta \mathbf{x}_i, \\ & Y\boldsymbol{\lambda} \ge \mathbf{y}_i, \\ & \mathbf{1}^{\mathsf{T}}\boldsymbol{\lambda} = 1, \qquad \boldsymbol{\lambda} \ge \mathbf{0}. \end{cases} \tag{1}$$

Here, θ is the efficiency score for farm i; X and Y are the matrices of observed inputs and outputs; λ is a vector of non-negative intensity weights; and x_i and y_i are the input and output vectors for that farm. Scores lie between zero and one, with TE = 1 indicating radial efficiency relative to the estimated frontier. A score below one identifies the proportional contraction of all modeled inputs that is feasible while maintaining at least the observed output. The corresponding radial input-reduction potential is calculated as $(1 - \mathrm{TE}) \times 100$ [15]. This quantity is referred to as resource waste in the original results, but it is a model-based estimate rather than a direct measurement of physically discarded resources. Additional input-specific slacks are not reported. The supplied classification uses low (0.00–0.70), medium (0.71–0.80), and high (0.81–1.00) categories. Assignment of scores between these displayed boundaries requires clarification of the rounding rule. Descriptive statistics, frequency distributions, and the Mann–Whitney test were used to compare the groups at a 5% significance level. The pooled or group-specific frontier specification and treatment of ties should accompany the original analysis files for verification.

3. RESULTS

The descriptive statistics in Table 1 summarize the six inputs and wheat output for the two farmer groups. CA adopters have lower mean pesticide, fertilizer, seed, and labor quantities, alongside a higher reported mean output value of 5.72 compared with 4.18. Mean cultivated area is higher among adopters, at 2.38 ha compared with 2.15 ha. These are descriptive differences; Table 1 does not provide tests establishing the statistical significance of each input contrast. The overall pattern is compatible with the proposition that CA may support more effective resource management, but the relative contribution of individual practices cannot be identified from these averages. The efficiency studies of Isnurdiansyah et al. [6] and Alemayehu et al. [4] provide relevant comparisons from other cereal systems. Larger standard deviations among non-adopters indicate greater dispersion in the reported input quantities. Such dispersion may reflect differences in farm size, growing conditions, and management, rather than demonstrating uninformed input use.

Seed use is particularly relevant to the comparison. The reported group means are 0.21 for adopters and 0.31 for non-adopters in the units presented in Table 1. Their difference corresponds to approximately 32.3% lower mean seed quantity among adopters, calculated relative to the non-adopter mean. This arithmetic comparison does not establish a seed-rate effect until the area basis of the measurements has been confirmed. Mechanized placement can improve

the consistency of sowing depth and spacing, whereas broadcasting may produce uneven establishment; however, these mechanisms were not separately tested in the present analysis. The local adoption study by AlKhulaifi and Al-doski [9] provides information on farmers' socioeconomic and communication characteristics, rather than a direct estimate of seed savings. The production-cost study from Diyala [12] further motivates attention to the financial consequences of input choices. Costs, however, depend on quantities, prices, and operating conditions. For that reason, a lower physical input quantity should not automatically be interpreted as an equivalent percentage reduction in total production cost or an independently demonstrated increase in profitability.

Tables 2 and 3 present the distribution and summary statistics of technical efficiency, respectively. The mean TE was 0.849 for CA adopters (SD = 0.068) and 0.551 for non-adopters (SD = 0.184). The reported Mann–Whitney result indicates a statistically significant difference between the distributions ($Z = -14.71$; $p < 0.001$). The corresponding radial input-reduction potentials are 15.1% and 44.9%, making the latter approximately 2.97 times the former. This ratio summarizes the supplied estimates; it should not be interpreted as a directly observed ratio of wasted materials. Verification of the test statistic requires the individual efficiency scores and the original treatment of tied observations.

Table 1. *Descriptive Statistics of Wheat Production Inputs and Output*

	CA Adopters ($n = 225$)				Non-Adopters ($n = 225$)		
Variable	Mean	SD	Min	Max	Mean	SD	Max
Cultivated area (ha)	2.38	0.74	0.50	6.00	2.15	0.88	8.00
Seed quantity (tonnes)	0.21	0.06	0.08	0.45	0.31	0.09	0.65
Mechanized labor (hours)	8.60	2.10	3.00	18.00	11.40	3.20	22.00
Human labor (person-days)	4.20	1.30	1.00	10.00	6.80	2.10	14.00
Fertilizer (tonnes)	0.18	0.05	0.05	0.38	0.26	0.07	0.52
Pesticides (L)	1.85	0.62	0.50	4.20	2.90	0.95	6.50
Wheat output (tonnes)*	5.72	1.48	2.10	12.40	4.18	1.62	10.80

Source: Primary survey, September 2024–February 2025, concerning the 2023–2024 season. SD = standard deviation. Non-adopter minimum values were not supplied. *The table unit is retained from the source; the per-hectare description in the methods requires reconciliation.

The remaining input comparisons reinforce the need to distinguish descriptive resource use from input-specific inefficiency. Relative to non-adopters, adopters have approximately 24.6% lower mean mechanized-labor use, 38.2% lower human-labor use, 30.8% lower fertilizer quantity, and 36.2% lower pesticide quantity. Their mean cultivated area is approximately 10.7% higher. These percentages are calculated directly from Table 1 and describe the average quantities as supplied, without changing the underlying observations. They do not account for differences in output composition, soil quality, labor timing, or input quality. In an Afghan wheat study, Radmand et al. [16] used a square-root production function to identify input-specific productivity relationships, including negative associations with excessive use of several inputs. Their approach provides a useful comparison but is different from a radial DEA score. Likewise, evidence of efficiency gains from combined climate-smart practices in Ethiopia [4] does not establish which input generates the greatest inefficiency in Nineveh. Farm-level targets and slack estimates would be needed to make that diagnosis. The aggregate results instead identify priorities for more detailed farm visits, input-record review, and agronomic assessment before specific reductions are recommended to individual farmers.

The distribution in Table 2 helps interpret the mean difference in Table 3. A much larger share of adopters falls in the high-efficiency category, while non-adopters are concentrated in the low-efficiency category. However, an efficiency category is defined relative to the estimated frontier and the stated classification rule, not by an absolute agronomic standard. The difference of 0.298 between the group means is equivalent to 29.8 percentage points on the zero-to-one efficiency scale. Relative to the adopter mean, the non-adopter mean is approximately 35.1% lower. This relative percentage differs from the percentage-point difference and from the radial input-reduction potential. Keeping these measures separate avoids overstating the size or economic meaning of the observed contrast.

Table 2. *Distribution of Farmers by Technical Efficiency Category*

		CA Adopters		Non-Adopters		Difference
Score Range	Category	Frequency	%	Frequency	%	(pp)
0.00–0.70	Low	1	0.44	179	79.56	−79.11
0.71–0.80	Medium	68	30.22	22	9.78	+20.44
0.81–1.00	High	156	69.33	24	10.67	+58.67
Total		225	100.00	225	100.00	

Source: Supplied DEAP version 2.1 estimates. Differences are adopter minus non-adopter percentages calculated from counts; pp = percentage points. Percentages may not sum to 100 because of rounding. The displayed category boundaries require confirmation of the score-rounding rule.

Table 3. *Summary Statistics of Technical Efficiency by Farmer Group*

Statistic	CA Adopters	Non-Adopters	Difference	Relative Gap (%)
Minimum TE Score	0.686	0.188	0.498	72.6
Maximum TE Score	1.000	1.000	0.000	0.0
Mean TE Score	0.849	0.551	0.298	35.1
Standard Deviation	0.068	0.184	-0.116	–
Input-reduction potential	15.1%	44.9%	−29.8 pp	–
Radially efficient (TE = 1)	16 (7.1%)	14 (6.2%)	0.9 pp	–

Source: Supplied DEAP version 2.1 estimates. Differences are adopters minus non-adopters. Relative gaps use the adopter value as denominator. Input-reduction potential = (1 − TE) × 100. TE = 1 denotes radial efficiency; input slacks were not supplied.

The direction of the observed difference is consistent with several agricultural efficiency studies, although their methods and production settings differ. Jimmy et al. [5] found higher mean technical efficiency among adopters of improved plantain technologies in Nigeria. Geffersa et al. [3] emphasize that efficiency estimates vary with agro-ecology and model specification, which cautions against treating estimates from different studies as directly interchangeable. Isnurdiansyah et al. [6] also found higher efficiency among adopters of climate-smart rice practices in Indonesia. In Nineveh, only one adopter (0.44%) belongs to the low-efficiency category, whereas 156 adopters (69.33%) are classified as highly efficient. Among non-adopters, 179 farmers (79.56%) are in the low-efficiency group and 24 (10.67%) are in the high-efficiency group. The presence of highly efficient non-adopters shows that adoption status does not fully determine performance. Farm size, soil conditions, experience, and other management practices may contribute to this variation, but the present summaries do not identify their separate effects. In particular, no evidence is supplied to attribute the efficiency of these 24 farmers specifically to fallowing. CA adoption and performance should be interpreted in their local socioeconomic and agronomic context [17].

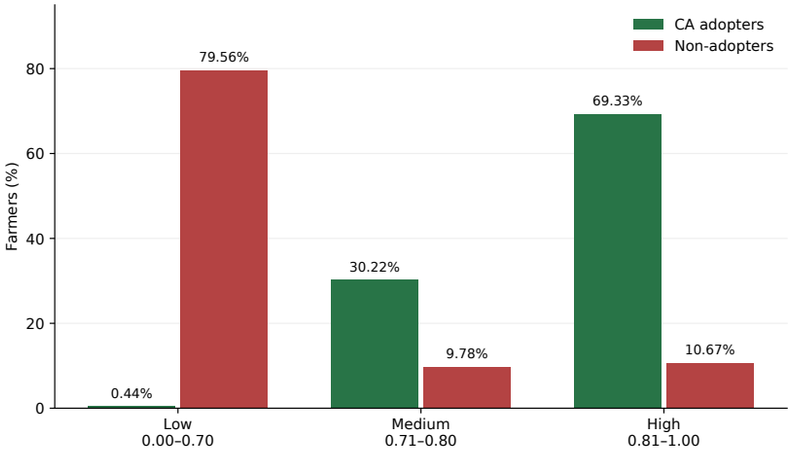


Figure 1. *Percentage Distribution of Farmers by Technical Efficiency Category*

The contrast across efficiency categories is shown in Figure 1, while Figure 2 summarizes the group means and standard deviations from Table 3. The predominance of non-adopters in the low-efficiency category indicates substantial distance from the estimated frontier for much of that group. It does not imply that every farm faces the same practical opportunities for improvement. Endalew et al. [18] found that wheat inefficiency in northwestern Ethiopia was associated with factors including distance to extension services and markets, illustrating why institutional access matters alongside input quantities. In resource-constrained settings, unrealized production potential may affect both farm income and aggregate food supply, although these consequences were not monetized here. Among CA adopters, 68 farmers (30.22%) remain in the medium-efficiency category. Their position suggests scope for further improvement even within the adopter group. Differences in implementation, experience, and training are plausible explanations that require farm-level assessment. The summary bars in Figure 2 show dispersion, not confidence intervals, and cannot establish the shape of either group's underlying score distribution.

Research on adoption decisions helps explain why participation in a technology program should not be equated with uniform implementation. Aynalem et al. [19] examined the determinants of adopting climate-smart practices among vegetable growers in northwestern Ethiopia; their study concerns adoption choices rather than the efficiency categories used here. Kassa and Sakurai [20] found that digital ability and rice-technology adoption in Benin had context-dependent relationships with farming outcomes, including adverse effects when the two were poorly integrated. Their results do not imply that digital support invariably improves efficiency. In the present study, the high-efficiency category contains 69.33%

of adopters, a potentially important result for extension planning. Wongnaa et al. [11] found household-welfare benefits associated with integrated soil-fertility management among Ghanaian tomato farmers, providing a separate economic perspective on adoption. Together, these studies support attention to implementation quality, institutional access, and farmer circumstances. They do not establish that the Nineveh efficiency difference is a causal structural change attributable solely to CA. Such an interpretation would require explicit control for selection and other relevant differences between farmer groups.

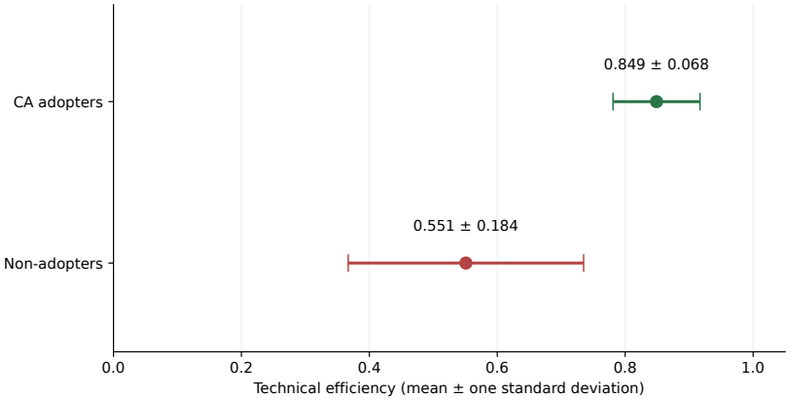


Figure 2. *Mean Technical Efficiency and Standard Deviation by Farmer Group*

3.1. INPUT UTILIZATION AND SOURCES OF INEFFICIENCY

The relative input-use chart in Figure 3 expresses each adopter mean as a ratio to the corresponding non-adopter mean, which is set to 1.00. The ratios calculated from Table 1 are approximately 1.107 for cultivated area, 0.677 for seed, 0.754 for mechanized labor, 0.618 for human labor, 0.692 for fertilizer, and 0.638 for pesticides. Thus, adopters have a higher mean cultivated area but lower mean quantities for the other five inputs. The largest proportional reduction among these reported quantities is in human labor, followed by pesticides and seed. Reduced labor requirements may be compatible with fewer field operations or more coordinated mechanized sowing, but the survey summaries do not identify the number of tractor passes or the operations replaced. The chart presents relative quantities, not input-specific efficiency scores. A ratio below one is therefore insufficient, on its own, to demonstrate technically or economically optimal use.

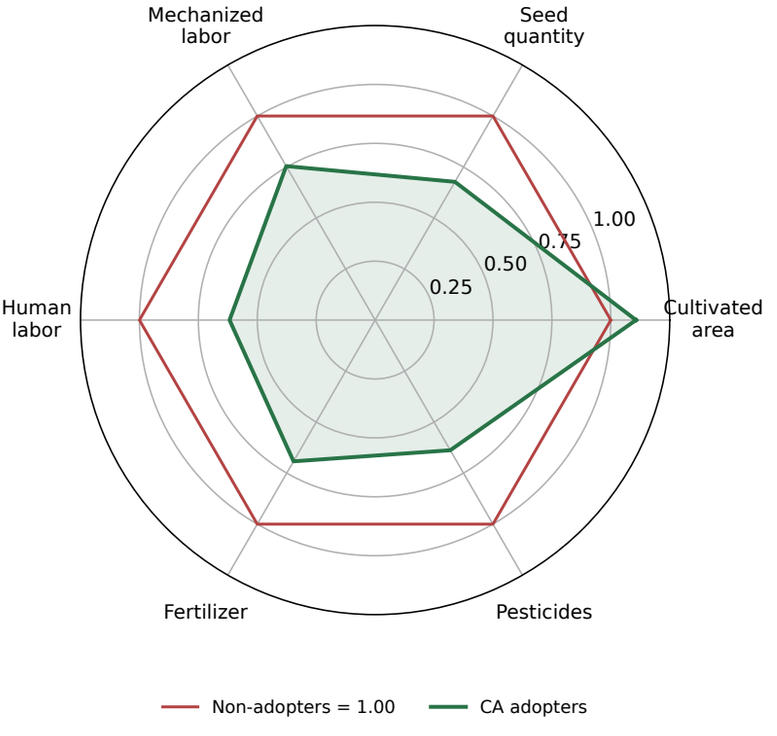


Figure 3. *Relative Mean Input Quantities of CA Adopters and Non-Adopters*

Pesticide, fertilizer, and seed management are reasonable priorities for extension assessment because the group means differ substantially. Nevertheless, the radial efficiency scores do not establish that these inputs are the principal causes of inefficiency in individual farms. Radmand et al. [16] provide direct input-productivity evidence from Afghan wheat cultivation, while the sugarcane adoption study by Farooq et al. [10] addresses the institutional conditions influencing technology uptake. These are complementary questions and should not be treated as equivalent tests of over-application. Precautionary pesticide use, limited access to pest forecasts, and input subsidies could influence application decisions, but their roles in Nineveh remain hypotheses. Katengeza et al. [21] discuss the integration of input subsidies with climate-smart agriculture in Malawi and emphasize complementary practices and recommended application rates. For Nineveh, this suggests evaluating subsidy advice alongside agronomic recommendations rather than assuming that additional inputs will necessarily improve performance. Extension visits should examine crop condition, soil fertility, pest pressure, equipment calibration, and application timing before recommending reductions, increases, or substitutions in particular inputs.

The rainfall-zone averages in Table 4 and Figure 4 provide context for regional wheat productivity. Average yield is 1.020 t/ha in the limited-rainfall zone, 2.070 t/ha in the semi-guaranteed zone, and 3.040 t/ha in the guaranteed-rainfall zone. The highest average is approximately 2.98 times the lowest, indicating a pronounced geographic contrast. These averages are not separated by adoption status and therefore cannot demonstrate that CA changes the relationship between rainfall and yield. Soil cover, crop rotation, and reduced disturbance may influence water conservation and crop performance, but these processes require direct measurement or appropriate comparisons. The analysis by Pittelkow et al. [8] shows why the combined implementation of CA principles and the climatic setting matter when evaluating productivity outcomes. The regional figures should therefore inform the interpretation of the study environment, rather than be used as evidence that differences in water availability have been eliminated between the two farmer groups.

Table 4. *Average Wheat Yield by Rainfall Zone*

Rainfall Zone	Yield (t/ha)	% of Highest Yield	Productivity Level
Limited Rainfall Zone	1.020	33.6	Low
Semi-Guaranteed Zone	2.070	68.1	Moderate
Guaranteed Rainfall Zone	3.040	100.0	High

Source: Nineveh Agriculture Directorate (2024), as attributed in the manuscript. The underlying directorate record was not supplied. Percentages use the guaranteed-rainfall average as the denominator.

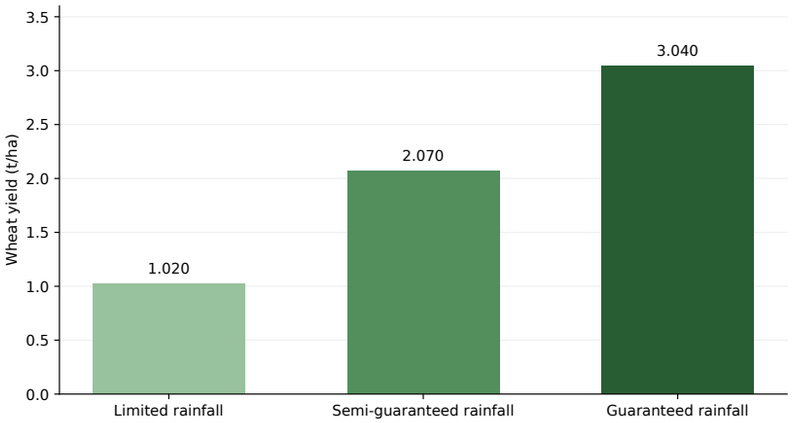


Figure 4. *Average Wheat Yield by Rainfall Zone in Nineveh Governorate*

The study description characterizes 2023–2024 as a season in which increased precipitation improved conditions in previously drought-affected rain-fed areas. The observed efficiency contrast is therefore relevant to a comparatively favorable season, but it cannot establish persistence across years with different rainfall patterns. Favorable regional rainfall also does not imply equal water availability for every farm or the removal of water constraints. Differences in soils, planting dates, drainage, and access to supplementary irrigation may still affect production. Research on efficiency across agro-ecological settings [3] supports considering such heterogeneity explicitly. In a different Iraqi agricultural sector, Nadhim et al. [22] found efficiency differences among buffalo milk producers associated with technology adoption; this provides regional context without directly validating a wheat-specific intervention. Table 4 identifies lower average productivity in the limited- and semi-guaranteed rainfall zones, but it does not quantify the gains achievable through CA in either zone. Targeting extension to these areas should therefore be accompanied by local evaluation of soil moisture, management constraints, and adoption feasibility, together with comparisons over multiple seasons. Such information would strengthen the basis for distinguishing weather-related variation from persistent management differences.

4. DISCUSSION

The findings have practical implications for agricultural policy and extension services in Iraq and comparable dryland wheat-growing areas. First, the higher mean TE among CA adopters motivates careful expansion and evaluation of CA promotion through locally adapted extension programs, demonstration activities, and farmer learning groups. The observational design supports testing these interventions rather than assuming that the full observed difference will be reproduced by every new adopter. Sharna et al. [23] show that information access and extension services are associated with rice-variety adoption in climate-exposed locations, emphasizing the value of context-sensitive advice. Second, extension messages should address the suitability and timing of pesticide, fertilizer, and seed applications instead of relying solely on general technology promotion. The descriptive input differences indicate useful topics for diagnosis but do not supply farm-specific optimal rates. Farooq et al. [10] examine factors influencing sugarcane chip-bud adoption, including the role of agricultural support and farmer characteristics. Their evidence reinforces attention to the conditions enabling uptake, while recommendations for wheat require agronomic advice suited to local soils, crops, and equipment. Follow-up support can help farmers identify practical implementation difficulties and document whether changes improve production outcomes.

Third, the variation within the CA group indicates that adoption status alone is insufficient to describe performance. The reported adopter scores range from 0.686 to 1.000, and a substantial minority remains below the high-efficiency category. Extension programs should record the implementation of minimum soil disturbance, soil cover, and crop diversification separately, while considering how these practices operate together. The review by Knowler and Bradshaw [17] emphasizes that adoption is context-dependent, supporting locally tailored services rather than a single uniform package. Farmer networks can facilitate discussion of equipment access, residue management, and crop rotations, although their effectiveness should be evaluated rather than presumed. Monitoring should include the consistency of input records, crop output, and growing conditions, as well as the farmer's ability to maintain the practices over time. Efficiency estimates may help identify farms for further assessment, but they should not be used as the sole basis for subsidy eligibility. Model specification, measurement quality, and agro-ecological differences must be considered before attaching financial consequences to a farm's estimated score.

5. CONCLUSION

This study identifies a substantial association between CA adoption and the estimated technical efficiency of wheat farming in Nineveh Governorate, Iraq. The mean TE is 0.849 among adopters and 0.551 among conventional farmers, with a reported statistically significant difference between the two distributions. These scores imply radial input-reduction potentials of 15.1% and 44.9%, respectively, relative to the specified frontier. Nearly 70% of adopters fall in the high-efficiency category, compared with approximately 10.7% of non-adopters. The descriptive comparisons also show lower mean pesticide, fertilizer, seed, and labor quantities among adopters, alongside a higher mean cultivated area. These differences identify useful priorities for extension assessment, but neither the group averages nor the radial scores establish the optimal reduction for each input. The findings support further evaluation of CA as an approach to improving resource use in Iraqi wheat production. They do not independently establish effects on profitability, environmental outcomes, or performance across rainfall conditions. Targeted support should address input calibration, the coordinated implementation of CA practices, and continuing advice after adoption. Before stronger policy conclusions are drawn, the output and input units must be reconciled with the underlying records, the frontier specification documented, and the farm-level scores checked. Comparisons across seasons and appropriate adjustment for farm characteristics would help determine how much of the observed difference can be attributed to CA. Efficiency assessment can then contribute to extension planning alongside agronomic evidence and farmers' practical constraints.

Author Contributions

Both authors contributed equally to this study. Both authors reviewed and approved the final version of the manuscript.

Conflict of Interest

The authors declare no conflicts of interest.

Data Availability

The datasets are available from the corresponding author upon request.

Funding Information

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