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Optimizing Nighttime Warming for Solar Greenhouse Cucumber: An Integrated Bio-Economic Framework Combining Non-Linear Cost-Volume-Profit and Data Envelopment Analysis

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Abstract

High energy consumption in winter greenhouses challenges agricultural sustainability. This study integrates nonlinear cost-volume-profit (CVP) and data envelopment analysis (DEA) to balance cucumber yields with energy costs in Northern China. Results show that while a 19 °C treatment (T3) maximizes yield, it suffers from diminishing marginal returns (MR/MC = 0.72) and high sensitivity to energy price fluctuations. Conversely, the 16 °C treatment (T2) emerged as the sole energy-efficient and economically resilient configuration. We conclude that 16 °C is the global optimal point for balancing biological potential and resource efficiency, providing a scientific basis for precision thermal management in cold-region greenhouses.

Keywords: greenhouse cucumber; night temperature; energy use efficiency; non-linear cost-volume-profit analysis; data envelopment analysis; marginal benefit

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1. Introduction

Protected horticulture plays a strategic role in guaranteeing global off-season vegetable supplies and addressing climate uncertainty; however, it faces a sustainability crisis driven by high inputs. To resolve the structural contradiction between high outputs and surging energy consumption, precise control of the greenhouse microenvironment has become a key pathway [1]. Research integrating Life Cycle Assessment (LCA) and Material Flow Cost Accounting (MFCA) demonstrates that the reliance of protected agriculture on fossil energy imposes a heavy economic and environmental burden. [2].Particularly in the high-latitude regions of the Northern Hemisphere during winter, heating demands constitute the core of operational costs. Ahamed et al.[3] pointed out that winter heating energy consumption not only dominates annual energy expenditures, but its price volatility also directly determines the survival boundaries of enterprises. Studies across different climatic zones indicate that energy inputs consistently occupy a dominant position in total production costs [4], therefore, establishing a strategy that balances crop physiological needs with "input-output" optimization is imminent.

Temperature is the primary environmental factor regulating plant growth and yield [5]. However, the asymmetric pattern of nighttime warming occurring faster than daytime warming has a major impact on crop physiology[6]. Greenhouse nighttime management involves a complex physiological trade-off: maintaining metabolic activity while avoiding "carbon starvation" caused by excessive respiratory consumption.Sankarapillai et al.[7] confirmed in soybeans that high night temperatures sharply increase dark respiration rates, disrupting the source-sink balance and reducing yield, a mechanism that has also been verified in rice [8] and quinoa [9] Regarding winter greenhouse cucumbers (*Cucumis sativus* L.), production often faces dual stresses of sub-optimal low temperatures and weak light. Although root zone warming can alleviate some stress [10-11] , however, this cannot substitute for the management of air temperature, which dictates plant morphology and light interception, specifically the precise control of internode elongation and plant height through the modulation of night temperature via the day-night temperature difference (DIF). Research has demonstrated that cucumbers (*Cucumis sativus* L.) are highly responsive to DIF. Specifically, positive DIF promotes internode and stem elongation , while negative DIF induces a compact plant habit by inhibiting cell elongation rather than cell division, thereby facilitating effective control over plant architecture. [12].

More importantly, the biological "maximum yield" is often not equivalent to the economic "maximum benefit." Research by Trépanier et al. [13] on greenhouses in cold climates indicates that the optimal strategy involves dynamic adjustments based on energy tariffs, with the core objective of minimizing energy consumption per unit of yield. Studies byHonoré et al. [14] and Tarr et al. [15] also emphasize that sacrificing a portion of biological yield in exchange for lower energy inputs may arguably yield the highest Return on Investment (ROI). To enhance resource use efficiency, Singh et al.[16] and Aydın et al. [17] conducted in-depth energy audits and management optimizations for rice and apple production, respectively, finding that precise management models can effectively coordinate energy output efficiency with economic returns. Furthermore, the combination of Data Envelopment Analysis (DEA) and optimization algorithms has been proven to be a robust tool for assessing energy flows and emission reduction potential in field crops such as wheat [18]. However, regarding the high-energy-consuming link of greenhouse cucumber nighttime warming, comprehensive evaluations integrating non-linear economic benefits and DEA allocative efficiency remain relatively scarce.

In summary, although previous studies have clarified that temperature is the primary environmental factor regulating crop development [19], and have widely applied energy audits and DEA to optimize resource allocation in different crop systems [16–18], and evaluate economic feasibility [20]. there is still a lack of a systematic framework combining refined thermal energy consumption with non-linear economic benefit assessment for winter greenhouse cucumber production in cold regions. Based on this, this study constructed a comprehensive optimization model integrating marginal benefit, non-linear Cost-Volume-Profit (CVP) analysis, sensitivity analysis, and DEA. By analyzing the effects of different nighttime warming gradients on cucumbers, this study aims to reveal the structural contradiction between biological yield and energy costs. This study aims to analyze the impact of varying nocturnal heating gradients on cucumbers, revealing the structural contradictions between biological yield and energy costs. It seeks to address a pivotal question: how to define 'efficiency frontier' thresholds that balance yield risk mitigation with economic optimization under dynamic energy pricing systems, thereby providing a scientific basis for decision-making in winter solar greenhouse management.

2. Materials and Methods

2.1. Site and Plant Materials

The experiment was conducted from November 2019 to February 2020 in a Liaoshen Type III solar greenhouse at the experimental base of Shenyang Agricultural University (41°48′N, 123°25′E). This location is representative of typical high-latitude protected horticulture regions in the Northern Hemisphere. The greenhouse featured a passive design with a heat-storing back wall, measuring 100 m in length and 9.5 m in span, with a ridge height of 4 m.

The plant material used was the cucumber cultivar 'Bomei 805' (*Cucumis sativus* L.), a hybrid noted for its low-temperature tolerance. Seedlings were propagated in 50-cell plug trays using a substrate composed of perlite, vermiculite, and peat (0.5:1:2 by volume).On November 16, 2019, seedlings at the two-leaf-one-heart stage were transplanted into 4 m long cultivation troughs. A double-row planting strategy was employed with an intra-row spacing of 30 cm. The cultivation substrate consisted of perlite vermiculite, and peat in a volumetric ratio of 1:1:2. All pre-harvest water and fertilizer management was conducted uniformly in accordance with the standard specifications for solar greenhouses.

2.2. Experimental Design

A single-factor experimental design was employed in this study, featuring four distinct nighttime temperature gradients while maintaining consistent daytime environmental conditions. To ensure precise thermal control, the greenhouse was partitioned into independent, insulated compartments (4.5 m × 4.0 m × 2.0 m) using aluminum foil insulation blankets with a heat transfer coefficient of $1.8\ \mathrm{W} \cdot \mathrm{m}^{-2} \cdot {}^{\circ}\mathrm{C}^{-1}$. The experiment followed a Randomized Complete Block Design (RCBD), with three replicates assigned to each treatment.

Four treatments based on minimum nighttime temperature targets were established as follows:

CK：Control group, target temperature 10 °C.

T1：Low-level heating, target temperature 13 °C (11 °C on cloudy nights).

T2：Medium-level heating, target temperature 16 °C (14 °C on cloudy nights).

T3：High-level heating, target temperature 19 °C (17 °C on cloudy nights).

The heating treatment was conducted from December 8, 2019, to February 11, 2020. Active heating was provided by air heating cables (3000 W; Zhongbin Electrical Appliance, China) positioned on the ground between the cucumber planting rows and regulated by a high-precision temperature controller (SXDP-1, accuracy: ± 1 °C). Air temperature and relative humidity were continuously monitored at 1-hour intervals using a data logger (Cos-03; Renke Measurement and Control, China), with the sensor probe placed 20 cm above the plant growing point.

2.3. Data Collection

Growth and yield determination: Every five days, three plants were randomly selected and tagged from each treatment for the harvest of commercial-grade fruits (defined as fruit length ≥25 cm). The cumulative yield per unit area (kg/m^2) was then calculated based on these measurements.

Economic data acquisition:

Energy consumption: The electricity consumption for heating in each treatment plot was recorded daily via independent electricity meters.

Cost accounting: Costs are categorized into fixed costs (FC)—including land rent, seedlings, substrates, and depreciation—and variable costs (VC), which encompass electricity, fertilizers, pesticides, and labor. Labor costs and land rent are derived from local market surveys. Depreciation is calculated using the straight-line method, assuming a residual value rate of 10%.

Market prices: Daily wholesale prices of cucumbers were obtained from the official database of the Shenyang Municipal Development and Reform Commission.

2.4. Instrument Data

The primary instrumentation and technical specifications utilized for environmental control and monitoring in this research are presented in Table 1. This table summarizes essential data—including equipment models, operating parameters, measurement accuracy, and manufacturing details—for key components such as temperature controllers, data loggers, air heating lines, and insulation quilts, providing the technical basis for the standardized regulation of the experimental microenvironment.

Table 1. Test Instrument Specific Parameters.

Equipment Name	Temperature Controller	Temperature and Humidity Loggers	Air Heating Line	Insulation Quilt
Type	SXDP-1	Cos-03	ZDR-1	NBW1-0.2
Operating Parameters	Rated voltage 220 V, rated power 3000 W.	DC 5 V, powered by external source or built-in battery	Rated voltage 220 V, output power 1000 W	Heat transfer coefficient 1.8 $W \cdot m^{-2} \cdot {}^{\circ}C^{-1}$, breaking strength 15.6 $kN \cdot m^{-1}$
Measurement Accuracy	±1 °C (ambient temperature 25 °C, 50% RH)	±0.1 °C and ±1.5 RH (at an ambient temperature of 25 °C and 50% RH)[1]		
Working Environment	Temperature 0–55 °C, humidity below 85% RH	Temperature 0–55 °C, humidity below 85% RH	Temperature 0–55 °C, humidity below 85% RH	Temperature 0–55 °C, humidity below 85% RH
Way of Working	Continuous nighttime operation, controlling intermittent work of air heating lines	Continuous nighttime operation, controlling intermittent work of air heating lines	Continuous nighttime operation, controlling intermittent work of air heating lines	Continuous nighttime operation, controlling intermittent work of air heating lines
Manufacturer	Wen'an Zhongbin Electric Appliance Factory	Wen'an Zhongbin Electric Appliance Factory	Wen'an Zhongbin Electric Appliance Factory	Wen'an Zhongbin Electric Appliance Factory

2.5. Non-Linear Cost-Volume-Profit Analysis

Traditional linear CVP models assume constant variable costs and fail to capture the law of diminishing returns in biological systems. Therefore, this study established a non-linear CVP model. The relationships among Total Cost (TC), Total Revenue (TR), and Yield (Q) were fitted using quadratic functions:

$$TC(Q) = \alpha_2 Q^2 + \alpha_1 Q + \alpha_0 \tag{1}$$

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$$TR(Q) = P \cdot Q \tag{2}$$

$$\Pi(Q) = TR(Q) - TC(Q) \tag{3}$$

Where Π represents net profit, P is the average market price, and $\alpha_{0,1,2}$ are the fitting coefficients. α_0 accounts for fixed expenditures, while α_1 and α_2 characterize the linear and non-linear variable cost components, respectively.

The break-even point (Point A) is determined by $\Pi(Q) = 0$. The profit-maximizing point (Point C) is determined by solving the first-order derivative condition $d\Pi/\mathrm{d}Q = 0$.

2.6. Marginal Benefit Analysis

To determine the economic rationality of increased heating inputs, a marginal benefit analysis was conducted. Marginal Revenue (MR) and Marginal Cost (MC) were calculated as the first derivatives of the revenue and cost functions with respect to yield (Q):

$$MR = \frac{dTR}{dQ}, MC = \frac{dTC}{dQ} \tag{4}$$

Optimal economic efficiency is achieved when MR = MC. If MR < MC, the input is considered excessive (diminishing returns).

2.7. Data Envelopment Analysis (DEA)

The data-driven non-parametric method DEA (BCC model) was employed to evaluate the relative efficiency of each treatment (Decision Making Unit, DMU). As a non-parametric evaluation technique, this method has been widely proven to be an effective mathematical tool for assessing the eco-efficiency of agricultural systems and identifying redundancies in resource allocation [21]

Input Indicators: Energy consumption ($MJ \cdot m^{-2}$), material costs, and labor inputs.

Output Indicators: Marketable yield ($kg \cdot m^{-2}$) and economic output value.

Comprehensive Technical Efficiency (TE) is decomposed into Pure Technical Efficiency (PTE) and Scale Efficiency (SE):

$$TE = PTE \times SE \tag{5}$$

Treatments with SE < 1 are judged to be in the stage of Decreasing Returns to Scale (DRS), indicating the presence of resource redundancy. The analysis was completed using the SPSSAU online platform.

2.8. Sensitivity Analysis

To assess the robustness of heating strategies against market risks, sensitivity analysis was used to evaluate the impact of energy price fluctuations on economic resilience. This evaluation paradigm, integrating technical efficiency with sensitivity analysis, has significant reference value for determining the robustness of agricultural production in dynamic market environments [22].The Sensitivity Coefficient (SC) was calculated for key factors (market price, energy cost, labor cost). The sensitivity coefficient represents the percentage change in profit caused by a 1% change in a certain factor (X):

$$SC = \frac{\Delta\Pi/\Pi}{\Delta X/X} \tag{6}$$

SC : Measures the degree of sensitivity of profit to changes in a specific influential factor.

X : Refers to variables within the model, such as market price, energy costs (heating expenses), or labor costs.

$\Delta\Pi/\Pi$: Represents the relative rate of change in net profit resulting from a variation in factor X.

$\Delta X/X$: Typically set at 1% to observe the chain reactions triggered by minor fluctuations.

Treatments with $|SC| > 1$are classified as highly sensitive (high risk).

To evaluate the economic feasibility of different nighttime warming strategies and their robustness in uncertain environments, this study first calculated the benchmark Net Profit（**NP**）,for each treatment group using the following formula:

$$NP = (P \times Y) - C \tag{7}$$

Where $\boldsymbol{P}$ represents the cucumber market price (CNY/kg), $\boldsymbol{Y}$ represents the yield per unit area (CNY/ m²), and $\mathbf{C}$ represents the total production cost (CNY/ m²), including electricity, labor, and other fixed inputs. Subsequently, a single-factor sensitivity analysis was employed to assess the responsiveness of net profit to fluctuations in key economic variables. This study selected market price ($\boldsymbol{P}$) and production cost ($\boldsymbol{C}$) as variable factors, with variation ranges set at $\pm\mathbf{5}\%$ and $\pm\mathbf{10}\%$. The sensitivity calculation models are as follows:

（1）Market Price Fluctuation Model:

$$NP_{\alpha} = P \times (1+\alpha) \times Y - C \tag{8}$$

（2）Production Cost Fluctuation Model:

$$NP_{\beta} = (P \times Y) - C \times (1+\beta) \tag{9}$$

Where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ represent the variation proportions for market price and production cost, respectively ($\boldsymbol{\alpha} \in \{-\mathbf{10}\%, -\mathbf{5}\%, +\mathbf{5}\%, +\mathbf{10}\%\},, \boldsymbol{\beta} \in \{-\mathbf{10}\%, -\mathbf{5}\%, +\mathbf{5}\%, +\mathbf{10}\%\}$). By calculating the NP values under different scenarios, the risk resilience of each warming strategy was identified.

2.9. Comprehensive Optimization Model

Finally, integrating biological responses, management efficiency, and economic constraints, a unified objective function was constructed to determine the optimal energy input (E). The objective is to maximize net profit (Π) while satisfying efficiency constraints:

$$\max_{E} \Pi = P \cdot [\theta_{DEA} \cdot f(E)] - (FC + w \cdot E) \tag{10}$$

E ： Energy input (function of nighttime temperature).

P： Market price of cucumber.

$f(E)$ ： Temperature-based theoretical biological production function.

θ_{DEA}： Efficiency score derived from DEA (correction coefficient for scale/technical inefficiency).

FC： Fixed production costs.

w ： Unit cost of energy.

This model explicitly considers the fact that potential biological yield ($f(E)$) may not translate into economic profit if scale efficiency (θ_{DEA}) declines due to excessive input.

2.10. Statistical Analysis

Data analysis was performed using SPSS 27.0.1. Differences in yield and economic indicators among treatments were evaluated via one-way analysis of variance (ANOVA). Mean comparisons were conducted using Duncan's multiple range test, with the significance level set at $P < 0.05$. Plotting using Python 3.12.3.

3. Results

3.1. Yield Response and Biological Characteristics

The implementation of night heating strategies significantly influenced the reproductive growth of greenhouse cucumbers. As illustrated in Figure 1, the marketable fruit yield exhibited a consistent upward trend in response to increasing temperature targets. The T3 treatment achieved the highest marketable yield of5.74 kg/m^2, representing a significant difference compared to both the CK and T1 treatments ($P < 0.05$). Specifically, compared with the control group (CK,2.72 kg/m^2), the yields of the T3 and T2 treatments increased by 111.09 and101.87%, respectively.

However, as the temperature increased further, the rate of yield increase showed a diminishing trend. Although the yield gap between T1 and CK was substantial, the yield difference between the high-temperature treatment groups, T3 and T2, narrowed to only 0.25 $kg \cdot m^{-2}$. This indicates the existence of a biological saturation point, implying that the agronomic returns yielded by further temperature increases are limited.

3.2. Cost Structure and Marginal Benefit Analysis

The economic impact of warming strategies was evaluated by analyzing cost composition and marginal benefits. Table 2 details the cost structure, showing that electricity expenditure for warming was the primary driver of the increase in variable costs. Electricity costs surged from CNY 4.49 in CK to CNY 12.97 in T3, representing an increase of 189.1%

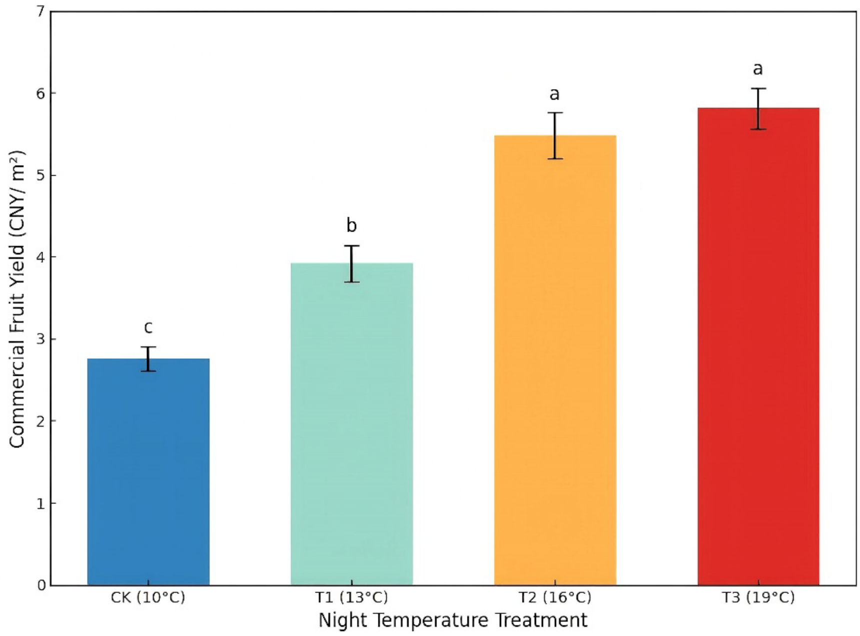

Figure 1. Commercial fruit yield of greenhouse cucumber under different night temperature treatments. Bars represent mean ± SE; different letters indicate significant differences ($p < 0.05$) according to Duncan's multiple range test.

Table 2. Breakdown of greenhouse cucumber production costs under different nighttime temperature treatments.

Item	CK (10℃)	T1 (13℃)	T2 (16℃)	T3 (19℃)
Fixed Costs (CNY/m²)	4.45	4.45	4.45	4.45
Variable Costs (CNY/m²)	12.1	14.92	20.16	22.41
Heating Electricity	4.49	6.28	10.59	12.97
Labor	5.79	6.72	7.6	7.32
Fertilizer	0.93	0.93	0.93	0.93
Pesticides	0.59	0.57	0.48	0.48
Equipment Depreciation	0.3	0.42	0.56	0.71
Total Cost	16.54	19.37	24.61	26.86

To determine the economic rationality of these inputs, a marginal benefit analysis was conducted (Table 3). When transitioning from T1 to T2, the marginal benefit-to-cost ratio (MR/MC) was 1.94, indicating a profitable investment where every 1 unit of additional cost generated 1.94 units of return. Conversely, when transitioning from T2 to T3, the MR/MC ratio dropped to 0.72. This indicated a negative marginal net profit (CNY -0.62), confirming that the biological yield increase in T3 was insufficient to cover the escalating energy costs.

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Table 3. Marginal benefit analysis of stepwise temperature increases. (Unit: CNY/m²).

Comparison Group	Marginal Cost (MC)	Marginal Revenue (MR)	Marginal Net Profit	Marginal Benefit-Cost Ratio (MR/MC)
T1 vs CK	2.83 CNY	7.85 CNY	+5.02 CNY	2.77
T2 vs T1	5.24 CNY	10.17 CNY	+4.93 CNY	1.94
T3 vs T2	2.25 CNY	1.63 CNY	0.62 CNY	0.72

Note:MR/MC > 1 indicates profit, while MR/MC < 1 indicates loss.

3.3. Nonlinear CVP Analysis and Economic Optimization

The non-linear Cost-Volume-Profit (CVP) model developed from empirical data (Figure 2) clearly reveals the marginal benefit dynamics of nighttime warming strategies. The results indicate that T2 (16°C) located at the peak of the net profit curve, achieving an optimal balance between biological potential and resource efficiency, thus establishing it as the global optimal solution for economics under the experimental conditions.

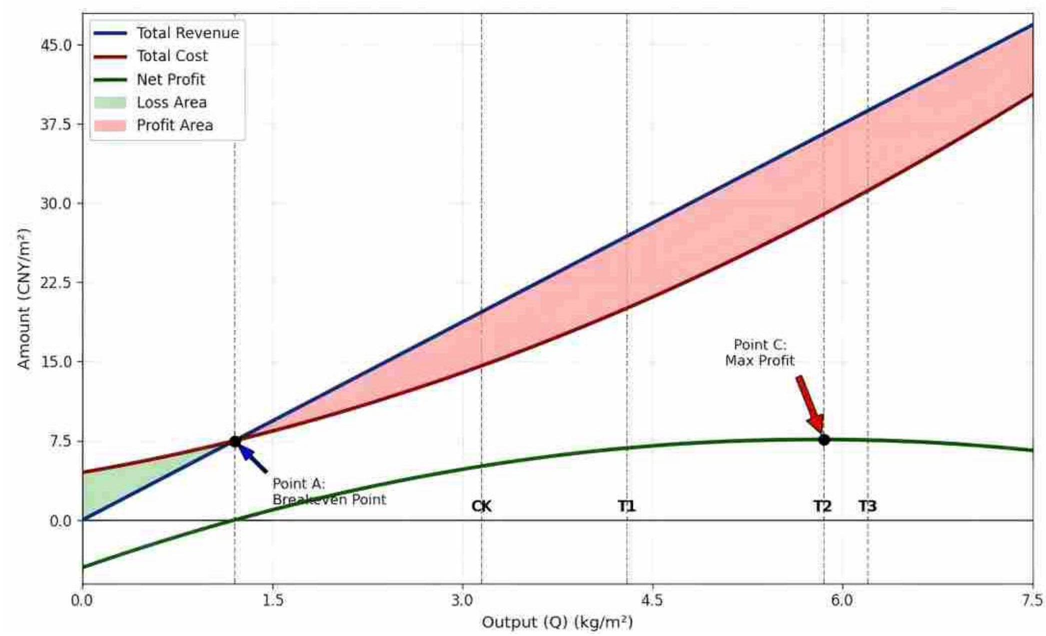

Figure 2. Non-linear Cost-Volume-Profit (CVP) analysis.

In contrast, although T3 (19°C) achieved the highest biological yield, it is clearly situated in the declining phase on the right side of the maximum profit point. This geometric characteristic confirms that, due to the non-linear escalation of marginal costs, the input for T3 has crossed the critical threshold of economic efficiency. This resulted in a significant "Profit Erosion" effect, where net profit was constrained by the law of diminishing marginal returns, leading to a decline rather than an increase.

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3.4. Efficiency Evaluation Based on DEA

Data Envelopment Analysis (DEA) provided a structural explanation for the observed economic performance. As shown in Figure 3, the T2 treatment achieved a perfect score of 1.00 in Overall Efficiency (OE), Pure Technical Efficiency (PTE), and Scale Efficiency (SE), identifying it as the sole DEA-strongly efficient unit.

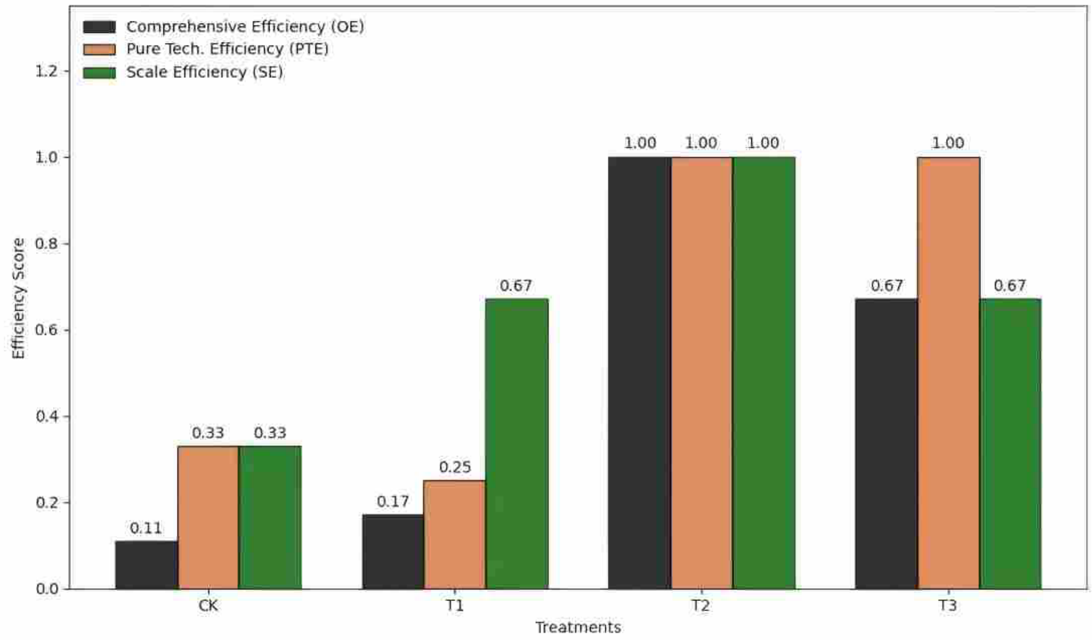

Figure 3. Bar chart showing the decomposition of DEA efficiency scores across treatments.

Conversely, while the T3 treatment maintained optimal Pure Technical Efficiency (PTE = 1.00), its Scale Efficiency (SE = 0.67) dropped sharply. This indicates that T3 is in a state of Decreasing Returns to Scale (DRS), confirming that its input scale exceeded the optimal economic boundary defined by the model. Meanwhile, CK and T1 exhibited lower efficiency across all indicators, primarily attributed to insufficient input (Increasing Returns to Scale).

3.5. Sensitivity Analysis

To evaluate the impact of external economic fluctuations on different thermal management strategies, this study conducted a one-way sensitivity analysis focused on market price and production cost (Figure 4). The results indicate that the net profit across all treatment groups was positively correlated with market price and negatively correlated with production cost. Furthermore, under all fluctuation gradients, the MR/MC ratio for each group remained above 1, demonstrating robust profitability resilience.

Regarding fluctuation sensitivity (Figure 4a), the profit curve for the T2 $(16°C)$ treatment exhibited the steepest slope and consistently remained above those of the other groups, indicating that it possesses the highest profit elasticity in response to market price recovery. As the price increased from-10, the net profit of T2 grew linearly from 9.81 to16.35 CNY/m^2. Notably, even in an adverse scenario where market prices declined by 5%, the net return of T2 (11.45CNY/m^2) remained significantly superior to T3's performance under identical conditions (10.93CNY/m^2), validating the robust competitive advantage of the T2 strategy against downside price risks.

In terms of cost resistance (Figure 4b), although rising production costs suppressed overall profitability levels, the profit curve for the T2 treatment demonstrated exceptional risk-mitigation characteristics. Even in the extreme scenario of a 10% cost increase, T2 maintained a high return of 11.12CNY/m^2, outperforming other treatments under 5% cost increases or even baseline conditions.

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In summary, the T2 (16°C) strategy not only offers the highest profit ceiling during market upturns but also exhibits optimal economic robustness amidst economic volatility.

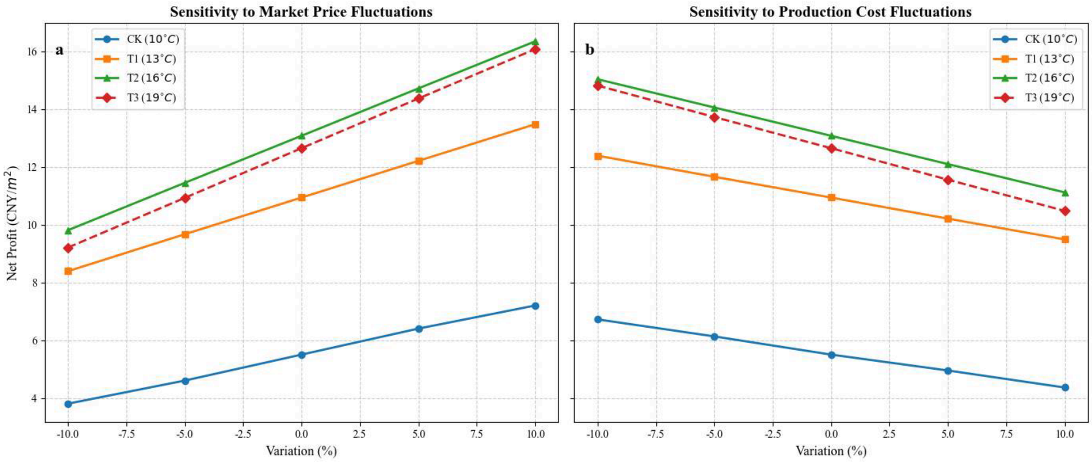

Figure 4. Sensitivity analysis of net profit to fluctuations in market price and production cost under different night temperature treatments.

The sensitivity coefficients in Table 4 further elucidated the intrinsic mechanism of this economic resilience. The T2 treatment recorded the lowest total cost sensitivity coefficient (-2.22), indicating the highest anti-risk capability among all warming treatments. In contrast, the electricity cost sensitivity coefficient for T3 was -1.24, which was notably higher (in magnitude) than that of T2 (-0.95). This confirms that the economic performance of the T3 strategy is heavily dependent on energy price stability, whereas T2 achieves a global optimal balance between biological yield and resource input, offering superior buffering capacity against economic risks.

Table 4. Sensitivity coefficients of profit-influencing factors in cucumber production under different nighttime temperature targets.

Treatment	Sensitivity Level	Total Cost Sensitivity Coefficient	Heating Electricity Sensitivity	Labor Cost Sensitivity	Fixed Cost Sensitivity	Fertilizer Cost Sensitivity	Pesticide Cost Sensitivity	Depreciation Sensitivity
CK	High Sensitivity	-14.46	-3.92	-5.06	-3.89	-0.81	-0.52	-0.26
T1	Moderate Sensitivity	-3.14	-1.02	-1.09	-0.72	-0.15	-0.09	-0.07
T2	Moderate Sensitivity	-2.22	-0.95	-0.69	-0.4	-0.08	-0.04	-0.05

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T3	Moderate Sensitivity	-2.56	-1.24	-0.7	-0.42	-0.09	-0.05	-0.07

3.6. Construction of a Comprehensive Economic Optimization Model

To synthesize the biological, economic, and efficiency dimensions derived from the aforementioned analyses, a unified optimization model was constructed. This model aims to maximize net profit (Π) by identifying the optimal energy input （E）subject to efficiency constraints (Equation 7):

$$\max_{E} \Pi = P \cdot [\theta_{DEA} \cdot f(E)] - (FC + w \cdot E) \quad (11)$$

P：Market price of cucumber (CNY/kg)

$\boldsymbol{f(E)}$：heoretical biological yield function, which increases with energy input E (nighttime temperature).

$\boldsymbol{\theta_{DEA}}$：Efficiency score derived from DEA (correction coefficient for scale/technical inefficiency).

$\boldsymbol{W \cdot E}$：Variable energy cost.

Applying this model to the experimental data revealed the mechanism underlying the profit loss observed in high-temperature treatments:For the T2 treatment, the system operated on the efficiency frontier, with $\theta_{DEA} \approx 1.00$ and marginal revenue equaling marginal cost ($MR \approx MC$), thereby achieving the maximization ofΠ.For the T3 treatment, although the biological yield potential $f(E)$ reached its maximum (5.74kg/m²), excessive energy input (E) precipitated a sharp decline in scale efficiency (θ_{DEA}dropped to 0.67).Consequently, the “effective economic yield” term $[\theta_{DEA} \cdot f(E)]$ in the equation was discounted (diminished), whereas the cost term ($w \cdot E$) continued to rise quadratically. This mathematical disparity demonstrates that T2 represents the global optimal solution where biological potential is perfectly aligned with resource efficiency.

4. Discussion

4.1. The Balance Between Biological Yield and Energy Costs

Temperature is a primary environmental factor driving crop metabolic rates. Our results indicate that increasing the nighttime temperature target from 10 °C (CK) to 19 °C (T3) significantly increased commercial fruit yield (Figure 1). This aligns with established physiological principles, where higher night temperatures (within a physiological range) accelerate assimilate translocation and fruit expansion. However, a critical phenomenon observed was the “diminishing marginal utility” of temperature elevation. While the yield gap between CK and T1 was substantial, the increase from T2 to T3 was relatively marginal (+0.25 kg/m), despite a 3 °C rise in the heating target.

This saturation effect can be attributed to the trade-off between photosynthesis and respiration. As noted by Sankarapillai et al. [7] and Su et al. [8] , excessive night temperatures stimulate dark respiration (R_d), consuming significant amounts of non-structural carbohydrates (NSC) accumulated during the day. In our T3 treatment (19 °C), the metabolic cost of maintaining high tissue temperatures likely approached the limit of carbon acquisition, resulting in a biological plateau. This confirms that the blind pursuit of high temperatures, while yielding diminishing biological returns, incurs exponential energy costs.

This observation is consistent with the ‘trade-off framework’ proposed by White et al. [23] when evaluating small-scale production systems: agricultural optimization is not about the blind maximization of physical yield, but rather about finding a sustainable balance between marginal profit and resource input. This trade-off logic, based on economic margins, is also strongly supported by recent thermodynamic assessments;Öztürk et al. [24] through energy-exergy analysis, confirmed that identifying and eliminating resource utilization ‘slacks’ within production systems is a core pathway for coordinating facility agriculture output performance with environmental sustainability.

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Such trade-off relationships have been widely verified across different crop systems. For instance,Wen et al. [25] noted in their study on crop rotation systems that input-driven strategies aimed at maximizing yield per unit area—which often exceed the ecosystem's self-regulatory capacity—may boost productivity but are frequently accompanied by a disproportionate escalation in environmental costs. Research on greenhouse cucumbers by Zhanbota et al.[26] also demonstrated that integrated resource management models achieve significantly higher Energy Use Efficiency (EUE) than single models by avoiding extreme inputs. The decline in the marginal return of the T3 treatment (0.72) in this study further quantifies the physical boundary of "exchanging high energy consumption for low incremental gains" in thermal management.

4.2. Economic Efficiency and the Profit Erosion Effect of High-Input Strategies

A core contribution of this study is the integration of non-linear CVP and DEA models to reveal the economic efficiency of solar greenhouse heating. Traditional linear assumptions often mislead growers into believing that "high input equals high output." However, our analysis identified T2 (16 °C) as the only DEA-strong efficient unit. This result aligns highly with the views emphasized by Thakur et al. [27] in sustainable agriculture research, where Resource Efficiency (RE) is considered a core indicator for evaluating modern agricultural models. While Thakur et al 's system focused on improving efficiency through the "multi-dimensional integration" of crop-livestock pathways, this is also highly consistent with the conclusions of Oukil et al. [28] who used inverse DEA to optimize greenhouse cucumber energy use. They found that precise resource allocation optimization can significantly reduce the energy footprint and enhance overall system efficacy. This study demonstrates from the perspective of micro-environmental regulation that avoiding ineffective inputs through "precise thermal environment control" is another effective pathway to achieving similar high levels of Technical Efficiency.

Although T3 achieved the highest gross revenue, its position on the profit curve indicates that the marginal gains generated were offset by the quadratic growth of energy costs ($w \cdot E$). Data Envelopment Analysis (DEA) provides a structural explanation for this phenomenon. The T3 treatment exhibited optimal Pure Technical Efficiency (PTE = 1.00) but low Scale Efficiency (SE = 0.67), characterized by Decreasing Returns to Scale (DRS). The DEA model results provide direct evidence of "diseconomies of scale." This complements the findings of Behroozeh et al. [29] regarding energy efficiency in greenhouse cucumbers; while they emphasized the impact of greenhouse type, this study proves that temperature threshold setting is key to determining the energy efficiency frontier. Furthermore, Elhami et al. [30] andIlahi et al. [31] utilized DEA to identify significant resource "slacks" in chickpea and wheat production, respectively. Moreover, this phenomenon of "diseconomies of scale" is highly consistent with the findings of Pishgar-Komleh et al. [32] in evaluating EU agricultural eco-efficiency. They noted that slack-based DEA models can precisely identify resource "slacks" in production systems, revealing the negative impact of input redundancy on comprehensive system efficacy. In this study, the low scale efficiency of T3 (SE = 0.67) accurately captured the system ineffectiveness caused by thermal energy input overload; this imbalance in resource allocation is the core inducer of profit erosion. This mathematical finding provides a rigorous explanation for the profit erosion effect: T3's failure was not due to poor agronomic management (technical efficiency was high), but rather due to an excessive scale of resource input. Conversely, the T2 treatment (16 °C) achieved a perfect balance between biological potential and economic constraints ($\theta_{DEA} = 1.00$), validating it as the global optimal solution.

4.3. Impact of Energy Price Fluctuations on System Economic Resilience

The sensitivity analysis in this study further deepens the understanding of the robustness of different heating strategies. In the context of global energy price instability and agricultural market volatility, evaluating production models should not rely solely on static baseline values but must also examine their resilience against risks in extreme scenarios.

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The results confirm that the high-input T3 strategy possesses distinct economic vulnerability. Due to its large energy consumption base and position in the decreasing returns to scale zone, once faced with a "double blow" of rising energy prices (increased production costs) or declining market prices, its profit erosion effect amplifies rapidly. This phenomenon reflects that the excessive pursuit of physical yield maximization may cause the system to lose the buffer space needed to cope with external cost shocks.

In contrast, T2 (16 °C) achieved optimal economic performance across all simulated scenarios, confirming its superiority as a risk-averse decision. T2 not only achieved a balance between biological potential and energy efficiency, but its robust revenue curve also indicates that this medium-intensity heating strategy possesses a wider survival window in uncertain economic environments. This finding emphasizes that greenhouse thermal management should shift from being "yield-driven" to "efficiency and resilience-driven" to withstand future resource and environmental uncertainties. This enhancement of economic resilience stems from the system's buffering capacity against external shocks. Houshyar et al.(2015) pointed out that agricultural decisions must find a balance between profit and environmental costs. Research by Wei et al. [33] also confirmed that units with higher technical efficiency are more viable when facing economic pressure. This study, through sensitivity analysis, proves that the T2 treatment, positioned on the efficiency frontier, is not only the optimal choice in static scenarios but also demonstrates a wider profitability margin under simulated energy cost shocks. As emphasized by Thakur et al.(2025), the improvement of resource efficiency directly enhances the robustness of small-scale production systems in uncertain market environments.

5. Conclusions

This study successfully established an integrated bio-economic evaluation framework to address the structural contradiction between biological yield and energy consumption in winter greenhouse cucumber production. The findings provide a critical shift from "yield-driven" to "efficiency-driven" management strategies for high-latitude protected horticulture. The core conclusions are as follows:

Yield-Energy Trade-off: While increasing nighttime temperatures significantly enhances agronomic yield, reaching a maximum of 5.74 kg/m^2 at 19 °C (T3), it is subject to the law of diminishing marginal returns. The marginal benefit-to-cost ratio (MR/MC) dropped to 0.72 when transitioning from 16 °C to 19 °C, indicating that excessive energy input leads to "profit erosion".

Identification of the Efficiency Frontier: The DEA (BCC model) and nonlinear CVP analysis identified 16 °C (T2) as the global optimal configuration point. It was the sole unit to achieve perfect scores in Overall Efficiency (OE), Pure Technical Efficiency (PTE), and Scale Efficiency (SE). In contrast, the 19 °C (T3) treatment exhibited severe decreasing returns to scale (SE = 0.67), confirming resource redundancy despite high technical management.

Economic Resilience and Risk Mitigation: Sensitivity analysis proved that the 16 °C (T2) strategy possesses the highest profit elasticity and risk-mitigation capacity against fluctuations in market prices and energy costs. Compared to the high-input T3 strategy, T2 offers a wider survival window and stronger economic robustness in volatile market environments.

In summary, maintaining a minimum nighttime temperature of 16 °C represents the optimal balance between maximizing biological potential and ensuring resource use efficiency for solar greenhouse cucumbers in cold regions. This research offers a robust mathematical tool for growers and policymakers to define efficiency thresholds, facilitating the transition toward a more sustainable and resilient agricultural system.

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Conflicts of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

Abbreviation	**Full Name**
CVP	**Cost-Volume-Profit**
DEA	**Data Envelopment Analysis**
DMU	**Decision Making Unit**
DRS	**Decreasing Returns to Scale**
EUE	**Energy Use Efficiency**
FC	**Fixed Costs**
LCA	**Life Cycle Assessment**
MC	**Marginal Cost**
MFCA	**Material Flow Cost Accounting**
MR	**Marginal Revenue**
NP	**Net Profit**
OE	**Overall Efficiency (Comprehensive Efficiency)**
PTE	**Pure Technical Efficiency**
RCBD	**Randomized Complete Block Design**
RE	**Resource Efficiency**
RH	**Relative Humidity**
ROI	**Return on Investment**
SC	**Sensitivity Coefficient**
SE	**Scale Efficiency**
TC	**Total Cost**
TE	**Technical Efficiency**
TR	**Total Revenue**
VC	**Variable Costs**

References

1. Achour Y, Ouammi A, Zejli D. Technological progresses in modern sustainable greenhouses cultivation as the path towards precision agriculture. *Renewable and Sustainable Energy Reviews* (2021) **147**:111251. doi:10.1016/j.rser.2021.111251
2. Dekamin M, Sadeghimofrad T, Ahmadloo A. Energy, economic, and environmental (3E) assessment of the major greenhouse crops: MFCA-LCA approach. *Environ Sci Pollut Res* (2024) **31**:21894–21912. doi:10.1007/s11356-024-32576-8
3. Ahamed MS, Guo H, Taylor L, Tanino K. Heating demand and economic feasibility analysis for year-round vegetable production in Canadian Prairies greenhouses. *Information Processing in Agriculture* (2019) **6**:81–90. doi:10.1016/j.inpa.2018.08.005
4. Banaeian N, Omid M, Ahmadi H. Energy and economic analysis of greenhouse strawberry production in Tehran province of Iran. *Energy Conversion and Management* (2011) **52**:1020–1025. doi:10.1016/j.enconman.2010.08.030
5. Houshyar E, Dalgaard T, Tarazkar MH, Jorgensen U. Energy input for tomato production what economy says, and what is good for the environment. *J Clean Prod* (2015) **89**:99–109. doi:10.1016/j.jclepro.2014.11.022

doi:10.20944/preprints202602.1178.v1

6. Ingram KT. "Effects of higher day and night temperatures on growth and yields of some crop plants," in *Effects of higher day and night temperatures on growth and yields of some crop plants* (Global Climate Change and Agricultural Production: Direct and Indirect Effects of Changing Hydrological, Pedological and Plant Physiological Processes), 120–140. Available at: https://agris.fao.org/search/en/providers/122621/records/64722c8a77fd37171a7376b0 [Accessed January 21, 2026]
7. Sankarapillai LV, Adhikari B, Bista MK, Shrestha A, Stetina SR, Reddy KR, Bheemanahalli R. High night temperature disrupts the assimilate utilization and yield potential in soybean. *Plant Stress* (2025) **16**:100826. doi:10.1016/j.stress.2025.100826
8. Su Q, Rohila JS, Ranganathan S, Karthikeyan R. Rice yield and quality in response to daytime and nighttime temperature increase – A meta-analysis perspective. *Science of The Total Environment* (2023) **898**:165256. doi:10.1016/j.scitotenv.2023.165256
9. Lesjak J, Calderini DF. Increased Night Temperature Negatively Affects Grain Yield, Biomass and Grain Number in Chilean Quinoa. *Front Plant Sci* (2017) **8**: doi:10.3389/fpls.2017.00352
10. Wang X, Zhang W, Miao Y, Gao L. Root-Zone Warming Differently Benefits Mature and Newly Unfolded Leaves of Cucumis sativus L. Seedlings under Sub-Optimal Temperature Stress. *PLoS ONE* (2016) **11**:e0155298. doi:10.1371/journal.pone.0155298
11. Bi X, Wang X, Zhang X, Bi X, Wang X, Zhang X. Effects of Different Root Zone Heating Methods on the Growth and Photosynthetic Characteristics of Cucumber. *Horticulturae* (2022) **8**: doi:10.3390/horticulturae8121137
12. Myster J, Moe R. Effect of diurnal temperature alternations on plant morphology in some greenhouse crops—a mini review. *Scientia Horticulturae* (1995) **62**:205–215. doi:10.1016/0304-4238(95)00783-P
13. Trépanier M-P, Gosselin L, Jørgensen BN. Best combinations of energy-efficiency measures in greenhouses considering energy consumption, yield, and costs: Comparison between two cold climate cities. *Applied Energy* (2025) **382**:125163. doi:10.1016/j.apenergy.2024.125163
14. Honoré MN, Belmonte-Ureña LJ, Navarro-Velasco A, Camacho-Ferre F, Honoré MN, Belmonte-Ureña LJ, Navarro-Velasco A, Camacho-Ferre F. Profit Analysis of Papaya Crops under Greenhouses as an Alternative to Traditional Intensive Horticulture in Southeast Spain. *International Journal of Environmental Research and Public Health* (2019) **16**: doi:10.3390/ijerph16162908
15. Tarr ST, Valle De Souza S, Lopez RG. Influence of Day and Night Temperature and Radiation Intensity on Growth, Quality, and Economics of Indoor Green Butterhead and Red Oakleaf Lettuce Production. *Sustainability* (2023) **15**:829. doi:10.3390/su15010829
16. Singh P, Singh G, Sodhi GPS. Energy auditing and optimization approach for improving energy efficiency of rice cultivation in south-western Punjab, India. *Energy* (2019) **174**:269–279. doi:10.1016/j.energy.2019.02.169
17. Aydın B, Aktürk D, Özkan E, Hurma H, Kiracı MA. Comparative Energy Use Efficiency and Economic Analysis of Apple Production in Turkey: Case of Thrace Region. *Erwerbs-Obstbau* (2019) **61**:39–45. doi:10.1007/s10341-018-0387-5
18. Nabavi-Pelesaraei A, Hosseinzadeh-Bandbafha H, Qasemi-Kordkheili P, Kouchaki-Penchah H, Riahi-Dorcheh F. Applying optimization techniques to improve of energy efficiency and GHG (greenhouse gas) emissions of wheat production. *Energy* (2016) **103**:672–678. doi:10.1016/j.energy.2016.03.003
19. Hatfield JL, Prueger JH. Temperature extremes: Effect on plant growth and development. *Weather and Climate Extremes* (2015) **10**:4–10. doi:10.1016/j.wace.2015.08.001
20. Semerci A, Ural M. ECONOMIC ANALYSIS OF SUGAR BEET PRODUCTION: A CASE STUDY OF BALIKESİR PROVINCE, TÜRKİYE. *International Journal of Agricultural and Natural Sciences* (2025) **18**:242–260. doi:10.5281/ZENODO.17011737
21. Picazo-Tadeo AJ, Gómez-Limón JA, Reig-Martínez E. Assessing farming eco-efficiency: A Data Envelopment Analysis approach. *Journal of Environmental Management* (2011) **92**:1154–1164. doi:10.1016/j.jenvman.2010.11.025
22. Hesampour R, Hassani M, Hanafiah MM, Heidarbeigi K. Technical efficiency, sensitivity analysis and economic assessment applying data envelopment analysis approach: A case study of date production in

Khuzestan State of Iran. *Journal of the Saudi Society of Agricultural Sciences* (2022) **21**:197–207. doi:10.1016/j.jssas.2021.08.003

23. White M, Heros E, Graterol E, Chirinda N, Pittelkow CM. Balancing Economic and Environmental Performance for Small-Scale Rice Farmers in Peru. *Front Sustain Food Syst* (2020) **4**:564418. doi:10.3389/fsufs.2020.564418
24. Öztürk M, Kayabaşı R, Yildizhan H, Ameen A, Öztürk M, Kayabaşı R, Yildizhan H, Ameen A. Resource Use Efficiency and Environmental Impacts in Strawberry Production: An Energy–Exergy Analysis. *Energies* (2025) **18**:5572. doi:10.3390/en18215572
25. Wen Y, Yao W, Tian B, Liu Q, Yang Y, Zeng Z, Zamanian K, Yang L, Qi Z, Pavinato PS, et al. Trade-offs between productivity, economic benefits, and environmental sustainability of vegetable-rice rotation system in the tropics. *Journal of Integrative Agriculture* (2025)S2095311925002059. doi:10.1016/j.jia.2025.07.025
26. Zhanbota A, Noor RS, Wang GY. Yield, Energy and Economic Analysis of Greenhouse Cucumber (cucumis Sativus L.) Production Under Different Farming Treatments. *J Anim Plant Sci-JAPS* (2021) **31**:509–521. doi:10.36899/JAPS.2021.2.0240
27. Thakur NP, Kachroo D, Kumar P, Gupta AK, Ravishankar N, Khajuria V, Koul V, Attri M, Mehta S, Avila-Quezada GD, et al. Sustainable integrated farming system model for enhancing profitability, resource efficiency, and soil health for smallholders in the Indian Mediterranean ecosystem of the North-Western Himalayan region. *Front Sustain Food Syst* (2025) **9**:1655465. doi:10.3389/fsufs.2025.1655465
28. Oukil A, Soltani AA, Al-Mezeini N, Al-Ismaili A, Nourani A. Mergers as an alternative for energy use optimization: evidence from the cucumber greenhouse production using the Inverse DEA approach. *Environ Dev Sustain* (2025) **27**:21075–21100. doi:10.1007/s10668-023-04144-6
29. Behroozeh S, Hayati D, Karami E, Nassiri SM, Rezaei-Moghaddam K. Evaluation and comparison of energy use efficiency among cucumber greenhouses. *Front Sustain Food Syst* (2024) **8**:1427530. doi:10.3389/fsufs.2024.1427530
30. Elhami B, Akram A, Khanali M. Optimization of energy consumption and environmental impacts of chickpea production using data envelopment analysis (DEA) and multi objective genetic algorithm (MOGA) approaches. *Information Processing in Agriculture* (2016) **3**:190–205. doi:10.1016/j.inpa.2016.07.002
31. Ilahi S, Wu Y, Raza MAA, Wei W, Imran M, Bayasgalankhuu L. Optimization Approach for Improving Energy Efficiency and Evaluation of Greenhouse Gas Emission of Wheat Crop using Data Envelopment Analysis. *Sustainability* (2019) **11**:3409. doi:10.3390/su11123409
32. Pishgar-Komleh SH, Čechura L, Kuzmenko E. Investigating the dynamic eco-efficiency in agriculture sector of the European Union countries. *Environ Sci Pollut Res* (2021) **28**:48942–48954. doi:10.1007/s11356-021-13948-w
33. Wei W, Mushtaq Z, Ikram A, Faisal M, Wan-Li Z, Ahmad MI. Estimating the Economic Viability of Cotton Growers in Punjab Province, Pakistan. *Sage Open* (2020) **10**:2158244020929310. doi:10.1177/2158244020929310