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Modeling Yield and Energy Efficiency in Sugar Beet Cultivation Using Multivariate and Stepwise Regression Approaches: A Case Study from Chaharmahal and Bakhtiari Province, Iran

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Abstract

This study compared multivariate and stepwise regression models for predicting yield and energy indices in sugar beet under semi-arid conditions, using data from 83 farms in Shahrekord, Iran. Energy indices—energy ratio (ER), energy productivity (EP), specific energy (SE), and net energy gain (NEG)—were calculated from input/output energy equivalents. Average yield was 56.11 t ha^{-1}, with ER = 40.89, EP = 2.43 kg MJ^{-1}, SE = 0.41 MJ kg^{-1}, and NEG = 919,750.28 MJ ha^{-1}. The multivariate model, including interaction and quadratic terms, outperformed the stepwise model (full R^2 = 98.8% vs. 95.7%; 5-fold CV R^2 ≈ 91.0% vs. 92.5%). Key interactions—nitrogen×phosphate (positive), phosphate×micronutrients (negative), and labor×nitrogen (positive)—highlighted balanced nutrient management. Diesel and micronutrients together accounted for >64% of total energy input, stressing the need for better machinery efficiency and targeted micronutrient use. For energy indices, multivariate regression achieved excellent fits (R^2 = 99.54% for ER and EP; 97.66% for SE), with yield, micronutrients, diesel, and nitrogen as the most influential variables. Optimal application ranges for maximizing yield were estimated at 80–90 kg ha^{-1} (phosphate), 60–70 kg ha^{-1} (micronutrients), and 60–70 kg ha^{-1} (nitrogen). These findings offer practical guidance for optimizing energy use, reducing environmental impacts, and promoting sustainable sugar beet production in semi-arid systems.

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1. Introduction

Sugar beet (*Beta vulgaris* L.) supplies 40% of the world's sugar demand, playing a vital role in food security and economic development (Shirvani et al., 2020). Efficient sugar extraction was first achieved by Marggraf in Germany in 1747 (Misra et al., 2022). Global sugar beet production is approximately 48 million tons, with the United States and Germany producing 31.95 and 31.55 million tons, respectively, while Iran produces about 5 million tons (FAOSTAT, 2023).

In Iran, despite a cultivated area of approximately 521,856 hectares (2022–2023) and an average yield of 22.32 t ha^{-1} (Ministry of Jihad-e Agriculture, 2023), sugar beet is considered an appropriate rotational crop in Chaharmahal and Bakhtiari Province due to favorable climatic and soil conditions, offering a suitable option for improving agronomic factors and environmental efficiency (Babaeian et al., 2021). Current cultivation challenges—including climate change, resource constraints, and the need for data-driven management—have been increasingly addressed (İrik et al., 2024).

The average sugar beet yield in Iran (23 kg m^{-2} per year) is 30 kg m^{-2} below international standards. Cultivation involves intensive operations, high energy consumption, and resource management, which can increase domestic yield from 22 to 49 t ha^{-1} (Nikukar, 2020). Energy in agriculture is categorized into direct (e.g., organic fertilizer) and indirect (e.g., energy embedded in fertilizers), both of which are key determinants of sustainable production (Nabavi-Pelesaraei et al., 2014). Given concerns over resource constraints, climate change, and economic costs, assessing environmental footprints and optimizing resource use are essential for sustainable production (Tayyab et al., 2023; Matzen & Demirel, 2016).

As population and food demand increase, water and energy consumption in agriculture continue to rise, making efficient energy use a priority from both economic and environmental perspectives (Ghaderzadeh & Pirmohamadyani, 2019). Reducing energy losses is one strategy for achieving environmental sustainability (Nikukar, 2020). Energy flow analysis can provide solutions to increase production while reducing energy consumption (Lovarelli & Bacenetti, 2017). Indirect inputs—nitrogen, electricity, machinery, seeds, fertilizers, and herbicides—play a key role in energy supply (Imanmehr, 2019). Fertilizer use increases energy consumption and greenhouse gas emissions (Feyz Bakhsh, 2019), while high energy consumption combined with proper soil management can enhance agricultural efficiency (Mello, 2020). In modern agricultural systems, reducing greenhouse gas emissions is increasingly emphasized (Pomoni et al., 2023).

Chaharmahal and Bakhtiari Province, with an average altitude of 2,000 meters and annual precipitation of 350–400 mm, is suitable for sugar beet cultivation despite long-term resource constraints (Babaeian et al., 2021). Yields of 50–60 t ha^{-1} in this region exceed the national average, mainly due to appropriate resource use (Rajaeifar et al., 2014). Energy inputs are broadly categorized as direct (e.g., organic fertilizer and machinery) and indirect (e.g., energy embedded in fertilizers) (Jensen et al., 2025). Climate research in Iran highlights the need to optimize fertilizer use in arid regions, improve energy efficiency, and reduce environmental impacts (Namdari et al., 2025).

Energy indices are important measures for evaluating environmental sustainability in agriculture, including the energy ratio (output/input), energy productivity (yield per unit of energy), specific energy (energy per unit of yield), and net energy gain (output minus input) (Saltuk et al., 2022). The energy ratio reflects the efficiency of the agricultural system, with lower values indicating inefficient energy use and greater environmental impacts (Hosseini-Fashami et al., 2019). Improving the energy ratio by 2050 is essential, given the projected need for 1.5 times the current level of food production

(Willett et al., 2019). For example, wheat energy productivity in Iran is low (0.10–0.15 kg MJ^{-1}), primarily due to inefficient use of chemical fertilizers and machinery (Yousefi et al., 2016).

Climate research in Iran underscores the need to analyze food and energy losses in sugar beet production while promoting sustainability and optimization (Namdari et al., 2025). Regression models are mathematical tools for optimizing inputs and outputs in agricultural systems, including linear, nonlinear, and multiple regression, used to predict outcomes based on key variables such as nitrogen application, water consumption, and machinery hours (Hernández Hernández et al., 2025). Minitab software, equipped with stepwise regression, models crop yield and handles normal and non-normal data, improving regression coefficient accuracy (Minitab Inc., 2023). Regression provides interpretable models for consumption optimization, nitrogen–phosphorus coefficient estimation, and efficiency improvements (Montgomery et al., 2021). Recent studies have advanced the use of regression combined with vegetation indices (e.g., NDVI) to improve sugar beet yield prediction under controlled water conditions (Lu et al., 2020; İrik et al., 2024).

In wheat cultivation, regression analysis demonstrates the need for optimized fertilizer use and reduced mechanical operations to improve energy productivity (Mohammadi & Meysami, 2021). In sugar beet production, models are designed to optimize energy inputs (Nikukar, 2020). Iranian studies show that reducing chemical and organic fertilizer use improves the positive energy balance and energy ratio (Babaeian et al., 2021). Quantitative models such as WOFOST are needed to analyze sugar beet yield with numerical indices (Zhang et al., 2022; İrik et al., 2024). These models predict inputs and optimize "what if" scenarios for input planning (Khoshnevisan et al., 2013; Shamshiri et al., 2024).

In Iran, regression models have been developed to predict local crop yields. For black cumin in Chaharmahal and Bakhtiari Province, stepwise regression incorporating organic fertilizer and seed inputs explained 82% of yield variability. In sugar beet, regression analysis of fertilizer effects has shown that balanced NPK application can increase efficiency by 12% (Koocheki et al., 2009). However, these efforts are often based on simplifying assumptions or long-term average data, and environmental variability is frequently not considered (Soltani et al., 2012).

Given these limitations, this research introduces a practical approach by integrating multivariate and stepwise regression modeling to simultaneously predict sugar beet yield and energy indices under semi-arid conditions. Unlike previous studies that focused on either yield prediction or energy analysis separately, this study develops a dual-objective framework using Minitab to quantify the interactive effects of key inputs (nitrogen, phosphate, and micronutrients) on both agronomic and energy performance. The practical novelty lies in identifying optimal fertilizer application ranges that increase yield while reducing energy losses. Furthermore, the study provides field-ready stepwise regression models for farmers and more comprehensive multivariate models for researchers and policymakers. These contributions offer actionable insights to improve energy efficiency, reduce greenhouse gas emissions, and promote sustainable sugar beet production in regions facing soil nutrient deficiencies and mechanization constraints.

2. Materials and Methods

2.1. Study Area and Climatic and Soil Conditions

This research was conducted in Shahrekord County, Chaharmahal and Bakhtiari Province, Iran, during the crop year 1403–1404. Chaharmahal and Bakhtiari has an area of about 16,500 square kilometers, extending from the highlands and mountains in the north to Isfahan in the east, to Lorestan in the west, and to Khuzestan in the south. Shahrekord, the center of Chaharmahal and Bakhtiari Province, is located at an altitude of

2066 meters above sea level, in the east longitude range 49°22' to 50°49' and the north latitude range 32°20' to 33°31'. This region has a semi-arid climate, with an average annual precipitation of 350 mm (mainly in winter and spring), an average annual temperature of 11°C, a cold winter down to -30°C, and a hot summer up to 38°C. Based on regional soil surveys, the soils are predominantly calcareous (pH 7.5–8.5) with low organic matter and available micronutrients (Babaeian et al., 2021).

2.2. Data Collection

The study of energy consumption and greenhouse gas emissions associated with sugar beet production employs a combination of methods, including imaging data and secondary analyses. Field data were collected through direct observation and measurement in sugar beet cultivation areas. To better understand energy consumption patterns, information on the types and quantities of inputs—such as chemical fertilizers, water, fuel, electricity, and machinery—used at various production stages is required. In the first phase, the general requirements for input and output entities in sugar beet production were measured and recorded in collaboration with local farmers. Subsequently, to estimate greenhouse gas emissions from the models used, emission factors for each entity and production stage were incorporated. These factors were derived using field data and reliable scientific sources.

The statistical population consisted of 78 active farms in the study area, with a total cultivated area of 255 hectares. This information was obtained through observation and interviews with experts from the Chaharmahal sugar factory. To determine the sample size, the Cochran formula was applied to ensure that the sampling procedure was conducted scientifically and in accordance with statistical principles (Nabavi-Pelesaraei et al., 2014):

$$n = \frac{N(s \times t)^2}{(N-1)d^2 + (s \times t)^2} \qquad (1)$$

where *n* is the required sample size, *N* is the number of samples (population of interest), *S* is the standard deviation, *t* is the value at the 95% confidence level, and *d* is the acceptable error (5% tolerance).

To calculate the sample size, a 5% deviation from the population mean and a 95% confidence level were used. Based on this, a cultivated area of 153.51 hectares was determined as the required sample size. However, in the present study, the entire cultivated area of 255 hectares was surveyed. Nevertheless, to ensure the study's comprehensiveness and full accuracy, the entire cultivated area of these farms was surveyed, and all relevant data were collected with high precision.

The sampling method used random sampling across cultivated areas, with a total of 78 data collection points used to calculate factor values (tons per hectare). The inputs considered in this study included nitrogen, agricultural machinery, organic fertilizer, seeds, pest control agents (weeds, insects, fungi), pesticides (herbicides, insecticides, fungicides), electricity, and irrigation water. All data were processed using Microsoft Excel 2021.

Data quality control was performed by cross-checking with local experts. Outliers were identified and handled using the Interquartile Range (IQR) method. Additionally, 10% of the farms were randomly re-visited and re-measured to verify data accuracy. Measurement error for the main variables was estimated to be less than 5%.

2.3. Calculation of Energy Equivalent Inputs

To calculate the total energy consumption, the following formula was used:

$$E_T = \sum_{i=1}^{n} (Q_i \times E_i) \qquad (2)$$

where Q_i is the amount of input, E_i is the energy equivalent corresponding to the input. The energy equivalent for each input was calculated using the following standard coefficients (Firouzi et al., 2022; Babaeian et al., 2021):

Table 1. Equivalent coefficients of agricultural inputs.

Item	Unit	Energy Coefficient (MJ/unit)	Reference
A) Inputs			
Human labor	h	1.960	(Mohammadshirazi et al., 2012)
Machinery	kg	142.700	(Kaltsas et al., 2007)
Diesel fuel	kg	56.310	(Ghasemi-Mobtaker et al., 2020)
Chemical fertilizers			
Nitrogen	kg	66.140	(Namdari et al., 2011)
Phosphate	kg	12.440	(Namdari et al., 2011)
Potassium	kg	11.150	(Namdari et al., 2011)
Micronutrients	kg	120	(Banaeian et al., 2011)
Herbicides	kg	238	(Ghaderzadeh & Pirmohamadyani, 2019)
Insecticides	kg	101.200	(Ghaderzadeh & Pirmohamadyani, 2019)
Fungicides	kg	115	(Ghaderzadeh & Pirmohamadyani, 2019)
Irrigation water	m³	1.020	(Khoshnevisan et al., 2013)
Electricity	kWh	12	(Mohseni et al., 2018)
Seeds	kg	50	(Šarauskis et al., 2018)
B) Outputs			
Sugar beet yield	kg	16.800	(Šarauskis et al., 2018)

2.4. Calculation of Energy Indices

2.4.1. Energy Ratio

The most important indicator for evaluating energy systems in agriculture is the energy output-to-input ratio, calculated by dividing the total energy output by the total energy input. Energy ratio (ER) is typically expressed in megajoules per hectare (MJ ha⁻¹), enabling farmers to assess the efficiency of their energy systems more effectively. The higher the ratio, the higher the energy efficiency and sustainability in the production process (Saidi et al., 2020).

$$ER = \frac{E_O}{E_I} \tag{3}$$

where EO represents the output energy (MJ ha⁻¹), and EI denotes the input energy (MJ ha⁻¹).

2.4.2. Energy Productivity

Energy productivity (EP) refers to how much energy is used to produce one kilogram of sugar beet crop. It is the ratio of crop yield per unit area to total energy input, expressed in megajoules per hectare. Energy productivity is expressed in kilograms per hectare (Meysami & Jalali, 2020):

$$EP = \frac{Y_{sb}}{E_I} \tag{4}$$

where Y_{sb} is sugar beet root yield (kg ha^{-1}) and E_I is the input energy (MJ ha^{-1}).

2.4.3. Specific Energy

Specific energy (SE) in agriculture refers to the optimal utilization of energy resources in agricultural and livestock activities, encompassing the energy required for planting, harvesting, transporting, and processing agricultural products. Effective use of SE can not only reduce costs but also help decrease pollutants and conserve natural resources. Consequently, the adoption of modern technologies and sustainable agricultural methods provides a suitable platform for achieving higher productivity. The ratio of total farm energy input to sugar beet yield per unit area is defined as SE. This indicator effectively represents the energy consumed per kilogram of product produced (Mousavi, 2021):

$$SE = \frac{E_I}{Y_{sb}} \tag{5}$$

2.4.4. Net Energy Gain

Net energy gain (NET) refers to the change in total energy within a system, expressed as a positive or negative value depending on whether energy increases or decreases. This concept is particularly important in various scientific applications, including physics and engineering, as it helps analyze system efficiency. It is calculated as the difference between total energy output and total energy input (Hosseini & Sadeghi, 2024):

$$NET = E_O - E_I \quad (6)$$

2.5. Regression Modeling

Regression modeling was performed to predict yield and energy indices. This method, assuming the existence of linear or nonlinear relationships among variables, allowed examination of the impact of each input on the dependent variables. In this study, two methods were employed to evaluate the validity of the results and to model sugar beet yield: multivariate regression and stepwise regression. Multivariate regression allows all variables to be entered into the model simultaneously and calculates the collective effect of all input variables on crop yield. Furthermore, it can accurately estimate the variance–covariance matrix for sugar beet yield. In contrast, stepwise regression uses an automatic variable selection procedure to identify the most important predictors, thereby avoiding unnecessary model complexity.

In this method, variables are progressively entered into or removed from the model based on statistical criteria. Multivariate regression is typically used to test hypotheses about prespecified variables, whereas stepwise regression is better suited to identifying the variables that exert the greatest influence on sugar beet yield. The model derived from stepwise regression is considerably simpler than that obtained from multivariate regression (Smith & Moore, 2020). These regression models were executed in Minitab software to validate the results statistically. Nonlinear linear regression was also incorporated by considering quadratic and interactive effects in the multivariate model to cover more complex relationships. The general equation for multi-variable linear regression is as follows (Montgomery et al., 2021):

$$\mathrm{Y_i} = a_0 + \sum a\mathrm{Xi} + \sum a_{\mathrm{ij}}\,\mathrm{X_i X_j} + \sum a_{\mathrm{ii}}\,\mathrm{X_i^2} + \varepsilon \quad (7)$$

where Yi is the dependent variable (Y_1 - Y_5), α_0 is the intercept (line slope), α_i is the linear coefficient of independent variables, α_{ij} is the interaction coefficients, α_{ii} is the quadratic coefficients and ε is the random error.

All regression analyses were performed using Minitab Statistical Software version 22.2.1. For the stepwise regression model, the Forward Selection method was applied with Alpha-to-Enter = 0.15 and Alpha-to-Remove = 0.15. Default software settings were used for other parameters.

To ensure the robustness of the regression models and address potential issues of multicollinearity and overfitting, two additional statistical checks were performed. First, the Variance Inflation Factor (VIF) was calculated for all independent variables. Most variables had VIF values below 5, indicating acceptable multicollinearity among the energy inputs. Second, to evaluate the generalizability of the models, 5-fold cross-validation was conducted. The cross-validated coefficient of determination (CV R^2) for the multivariate model was approximately 0.91 for sugar beet yield and above 0.96 for the energy indices. These results confirm that while the models show excellent fit on the full dataset, they maintain reasonable predictive performance on unseen data, supporting their applicability under semi-arid field conditions.

2.6. Evaluation of models

Two indicators, including mean square error (MSE) and coefficient of determination (R^2), were used to evaluate model performance. The analysis focused on removing unnecessary variables using forward selection. Model selection was performed using a stepwise method to eliminate redundant variables. The final model was selected based on MSE and R^2 criteria to balance accuracy and complexity. Nonlinear regression was also employed, incorporating interaction and quadratic effects, to improve accuracy and reduce unnecessary complexity through modeling and optimization.

Model performance was further assessed using 5-fold cross-validation and VIF analysis to mitigate concerns about overfitting and multicollinearity, as recommended in regression studies with moderate-sized agricultural datasets.

3. Results and Discussion

3.1. Energy equivalent of inputs

Table 2 presents the average input consumption and their corresponding energy equivalents for the evaluated sugar beet farms. In the present study, the average sugar beet yield across 83 farms in Shahrekord County, Chaharmahal and Bakhtiari Province, was estimated at 56,108.43 kg ha^{-1} (56.1 t ha^{-1}). This value exceeds the averages reported in several previous studies and ranks highly on a national scale. Tayyab et al. (2023) reported yields between 68 and 106 t ha^{-1} under tropical conditions. Firouzi et al. (2022) reported a yield of 46.44 t ha^{-1}, Babaeian et al. (2021) reported 48.45 t ha^{-1}, and Shirvani et al. (2020) reported 47 t ha^{-1} in Borujen—all lower than the average obtained in the present study. However, the yield observed in this study is lower than the values reported by Baran & Gokdogan (2016) at 68 t ha^{-1}, Hua et al. (2016) Hua et al. (2016) at 85 t ha^{-1} in China, and Mrini et al. (2002)) at 48.86 t ha^{-1}.

The higher yield observed in the present study may be attributed to better utilization of high-quality seeds and effective monitoring of pest and weed control. Conversely, the lower yields reported by Firouzi et al. (2022) and Shirvani et al. (2020) could be due to water constraints in their respective study regions as well as lower input management, particularly concerning micronutrients.

Table 2. Equivalent energy values of inputs in the studied farms.

Input	Unit	Mean ± SD	Minimum	Maximum	Energy Equivalent (MJ ha^{-1})
Human labor	h ha^{-1}	199.36 ± 18.2	193.65	212.74	390.76
Machinery	MJ ha^{-1}	3,114.32 ± 34.57	3,012.04	3,179.71	3,114.32
Diesel fuel	L ha^{-1}	152.035 ± 7.60	135.10	171.00	8,561.09
Nitrogen	kg ha^{-1}	46.93 ± 11.41	21.00	70.00	3,104.26
Phosphate	kg ha^{-1}	69.25 ± 11.04	41.76	92.72	861.52
Potassium	kg ha^{-1}	49.62 ± 9.41	35.50	67.11	553.28
Micronutrients	kg ha^{-1}	51.14 ± 13.07	30.20	82.00	6,136.80
Fungicides	kg ha^{-1}	0.20 ± 0.03	0.13	0.40	23.31
Seeds	kg ha^{-1}	2.52 ± 0.11	2.30	3.00	126.02
Yield	kg ha^{-1}	56,108.43 ± 10,694.21	38,000	74,000	942,621.69

Diesel fuel, with an average value of 8,561.09 MJ ha^{-1}, and micronutrients, at 6,136.80 MJ ha^{-1}, represent the highest shares of energy inputs. The high diesel consumption is attributed to the prolonged use of heavy machinery for operations such as plowing, harvesting, loading, and transportation. The substantial use of micronutrients is due to the high prevalence of element deficiencies in the region's soils, necessitating foliar application to compensate.

Compared with the studies by Soleymani et al. (2023), Babaeian et al. (2021), and Firouzi et al. (2022), the share of diesel fuel in the present study is lower, which can be attributed to improved transportation management or the use of more efficient machinery. In contrast, the share of micronutrients in this study is higher than that reported in most studies. It is consistent with the findings of Shirvani et al. (2020) and Azizpanah & Namdari (2020), who also reported high micronutrient consumption in similar regions. This pattern underscores the need for precise management of micronutrient application in the region to enhance productivity while reducing energy consumption.

Figure 1 presents the percentage share of each input in the total energy input to the farms. This grph clearly shows that more than 64% of the total farm input energy is attributable to two inputs: diesel fuel and micronutrients. This pattern indicates a high dependence of the production system on fossil fuels and chemical fertilizers. Such strong dependence has also been reported in numerous studies conducted in Iran (Asgharipour et al., 2012; Firouzi et al., 2022; Soleymani et al., 2023; Babaeian et al., 2021).

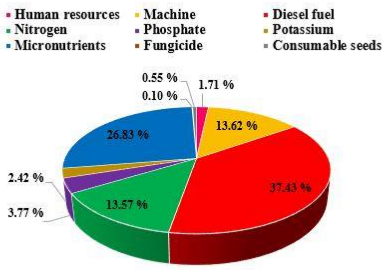


Figure 1. Contribution of inputs to total energy input in sugar beet farms.

The high micronutrient share in the present study exceeded that reported in most previous studies. It was consistent with the findings of Shirvani et al. (2020) and Azizpanah & Namdari (2020), who also observed high consumption of these fertilizers in similar regions. This pattern underscores the need for more precise management of micronutrient application in the area to enhance productivity while reducing energy consumption. Table 3 presents the calculated energy indices for sugar beet production on farms in Shahrekord County. The energy ratio in the present study was 40.89, which is substantially higher than those reported in other studies. Soleymani et al. (2023) and Shirvani et al. (2020) reported energy ratios of 7.08 and 20.99, respectively. This difference is primarily attributable to the higher yield (56.1 t ha^{-1}) observed in the study region, which significantly influences the energy ratio calculation. Energy productivity was 2.43 kg MJ^{-1}, also exceeding the values reported by Soleymani et al. (2023) at 1.83 kg MJ^{-1} and Shirvani et al. (2020) at 1.24 kg MJ^{-1}. These findings indicate better local efficiency per unit of energy consumption, resulting from improved input management and higher yield.

The specific energy value was 0.41 MJ kg^{-1}, indicating lower energy consumption per unit of local production. This value was lower than that reported by Soleymani et al. (2023) of 0.54 MJ kg^{-1}, reflecting a higher efficiency per kilogram of locally produced sugar beet. The net energy gain was calculated as 919,750.28 MJ ha^{-1}, confirming a positive and high energy balance in the system (Erdal et al., 2007). This value is considerably higher than those reported in similar previous studies (Firouzi et al., 2022; Soleymani et al., 2023).

Table 3. Energy index values for sugar beet production.

Title	Unit	Value
Input energy	MJ ha^{-1}	22,871.40
Output energy	MJ ha^{-1}	942,621.69
Energy ratio	-	40.89
Energy productivity	kg MJ^{-1}	2.43
Specific energy	MJ kg^{-1}	0.41
Net energy gain	MJ ha^{-1}	919,750.28

The obtained energy indices in this study were as follows: energy ratio of 40.89, energy productivity of 2.43 kg MJ^{-1}, specific energy of 0.41 MJ kg^{-1}, and net energy gain of 919,750 MJ ha^{-1}. These values are considerably higher than those reported in previous studies (Shirvani et al., 2020; Babaeian et al., 2021; Soleymani et al., 2023; Firouzi et al., 2022). Based on response surface analysis, the optimal application ranges for maximizing sugar beet yield under local conditions are: phosphate 80–90 kg ha^{-1}, micronutrients 60–70 kg ha^{-1}, and nitrogen 60–70 kg ha^{-1}.

3.2. Sugar Beet Yield Analysis

3.2.1. Multivariate Regression

The analysis of variance (ANOVA) for the multivariate regression model of sugar beet yield is presented in Table 4. The overall model was highly significant ($F = 50.06$, $p < 0.001$), indicating that the independent variables collectively explain a substantial portion of the variability in sugar beet yield. The model accounted for a substantial proportion of the total sum of squares, underscoring its robustness in predicting yield from the selected input variables. Among the linear effects, the overall contribution was statistically significant ($p = 0.032$), suggesting that individual input variables exert meaningful linear influences on yield.

Specifically, the quadratic term for potassium (Potassium × Potassium) was significant at the threshold of $p = 0.050$, indicating a nonlinear (curvilinear) relationship between potassium application and sugar beet yield. This finding implies that beyond an optimal level, additional potassium may not proportionally increase yield, consistent with the law of diminishing returns commonly observed in crop production. The interaction effects, considered collectively, approached but did not reach conventional statistical significance ($p = 0.086$). However, several specific two-way interactions were significant, revealing complex interdependencies among inputs. The interaction between human labor and nitrogen was significant ($p = 0.031$), suggesting that the effectiveness of nitrogen application depends on the level of human labor input, likely reflecting management quality and timing of application. Similarly, the interaction between human labor and micronutrients was significant ($p = 0.023$), indicating that the yield response to micronutrient application is modulated by labor input, possibly through improved application precision and timing.

The most pronounced interaction was observed between nitrogen and phosphate ($p = 0.004$), highlighting a synergistic effect whereby the combined application of these two macronutrients enhances yield more than either input alone. This finding aligns with established agronomic knowledge regarding the complementary roles of nitrogen and phosphorus in plant metabolism. Furthermore, the interaction between phosphate and micronutrients was also significant ($p = 0.025$), suggesting that phosphorus availability may influence the uptake and utilization efficiency of micronutrients. Collectively, these results demonstrate that both linear and nonlinear (quadratic) effects, as well as specific input interactions, play important roles in determining sugar beet yield. The significant interactions involving human labor underscore the importance of management practices alongside material inputs. These findings provide valuable guidance for optimizing input combinations to maximize yield while potentially reducing unnecessary applications.

Table 4. Analysis of variance (ANOVA) for the multivariate regression model of sugar beet yield.

Source	DF	SS	MS	F	Sig
Model	51	9,265,513,176	181,676,729	50.06	0.000
Linear effects	9	79,233,507	8,803,723	2.43	0.032
Potassium × Potassium	1	15,117,630	15,117,630	4.17	0.050
Interactions	33	196,054,856	5,941,056	1.64	0.086
Human labor × Nitrogen	1	18,485,299	18,485,299	5.09	0.031
Human labor × Micronutrients	1	20,643,128	20,643,128	5.69	0.023
Nitrogen × Phosphate	1	36,045,939	36,045,939	9.93	0.004
Phosphate × Micronutrients	1	20,221,541	20,221,541	5.57	0.025
Error	31	112,510,921	3,929,385	-	-
Total	82	9,378,024,096	-	-	-

Before interpreting the regression coefficients, multicollinearity among the independent variables was assessed using the Variance Inflation Factor (VIF). All variables had VIF values below 5.3, except for diesel fuel (VIF = 12.67), which is expected given its strong correlation with machinery hours (R = 0.82). While VIF > 10 indicates high collinearity, it inflates standard errors but does not bias coefficient estimates. Given that diesel fuel is a key management variable in sugar beet production, it was retained in the model. The VIF values for other variables (nitrogen: 4.81, micronutrients: 5.23, phosphate: 3.95, potassium: 2.68, human labor: 1.85) were within acceptable limits.

Table 5 presents the results of the multivariate regression analysis for sugar beet yield modeling, based on the interactions among input variables across the studied farms. The strongest and most statistically significant interaction effect ($p=0.004$) was observed between nitrogen and phosphate fertilizers, indicating a strong influence on sugar beet yield. The interaction effect between human labor and nitrogen fertilizer, with a regression coefficient of 57,840 and a significance level of 0.031, also shows a notable effect on sugar beet yield. However, its relatively high standard error and associated t-statistic reduce the precision of yield estimation. Despite this, it ranks second among interaction effects by significance level. Among the variable interactions examined, the interaction between human labor and micronutrients, with a larger negative coefficient and a significance level of 0.023, was found to be highly significant and ranked third in effect magnitude, compared to the interaction between phosphate and micronutrients.

Nevertheless, the interaction between phosphate and micronutrients exhibits a lower standard error, making its estimation more reliable and precise than that of the human labor–micronutrients interaction. The nonlinear (quadratic) effect of potassium demonstrated the weakest influence on sugar beet yield among the evaluated effects, with a significance level of 0.050. However, due to its low standard error (1568), it enhances the overall accuracy of sugar beet yield estimation.

Table 5. Coefficients of the multiple regression model for sugar beet yield.

Variable	Coefficient	Standard Error	T	Sig
Potassium × Potassium	-3200	1568	-2.04	0.050
Human labor × Nitrogen	57840	25629	2.26	0.031
Human labor × Micronutrients	-41181	17267	-2.38	0.023
Nitrogen × Phosphate	48462	15378	3.15	0.004
Phosphate × Micronutrients	-31256	13242	-2.36	0.025

The interaction between nitrogen and phosphate, with a positive coefficient of 48,462 and $p = 0.004$, underscores the importance of balanced application of these two fertilizers to enhance sugar beet yield.

The positive and significant nitrogen × phosphate interaction ($p = 0.004$) is one of the most important findings of this study. Scientifically, this interaction reflects the complementary roles of the two nutrients. Nitrogen is essential for protein synthesis, chlorophyll production, and vegetative growth, while phosphorus is critical for energy transfer and storage, root development, and carbohydrate metabolism. Phosphorus enhances the activity of nitrate reductase and the expression of high-affinity nitrate transporters, thereby improving nitrogen use efficiency (Noshad et al., 2012; Hergert, 2010). The combined application of both elements increases their uptake and utilization efficiency, ultimately improving sugar beet yield.

Similarly, the positive coefficient for the interaction between human labor and nitrogen suggests that increased labor input, when combined with nitrogen fertilizer, enhances productivity. In contrast, the negative coefficients observed for the interactions between human labor and micronutrients, and between phosphate and micronutrients, likely indicate saturation effects or nutrient imbalances when these inputs are applied at excessive levels.

According to equation (8), where Y represents the dependent variable (sugar beet yield) and X_1, X_4, X_5, X_6, and X_7 represent the input variables —namely human labor, nitrogen, phosphate, potassium, and micronutrients, respectively— the results indicated that the coefficient of determination (R^2) for yield was 98.80%. This finding demonstrates that the model has good accuracy in predicting sugar beet yield in the studied fields. The obtained regression equation is as follows:

$$\begin{aligned} Y = {} & -66578535 + 247(X_1 \times X_4) \\ & -166.600(X_1 \times X_7) + 77.600(X_4 \times X_5) \\ & -47.400(X_5 \times X_7) - 12.810(X_6)^2 \end{aligned} \quad (8)$$

where Y is the dependent variable representing local sugar beet yield, and X_1, X_4, X_5, X_6, X_7 are respectively, human labor, nitrogen, phosphate, potassium, and micronutrients.

3.2.2. Stepwise Regression

Table 6 presents the results of the analysis of variance for the input variables affecting sugar beet yield using a stepwise regression model. This approach led to selecting the best regression model based on a higher coefficient of determination for modeling and predicting sugar beet yield. The resulting model was statistically significant, as shown in the first row of Table 6. The stepwise regression model was highly significant ($F = 433.92$, $p < 0.001$). The linear effects were strongly significant ($p < 0.001$), with nitrogen exhibiting the highest F-value (151.00). The observed nonlinear effect ($p < 0.001$) was attributed to the quadratic term of micronutrients.

Regarding the linear effects of the independent variables, the significance levels indicated that among the four types of fertilizers applied in the fields, nitrogen, phosphate, and micronutrients significantly influenced sugar beet yield. Based on the F-statistic and significance levels, nitrogen fertilizer had the greatest impact on yield, followed by micronutrients and phosphate, ranking second and third, respectively, as the most influential inputs. Among the nonlinear effects, only the quadratic effect of micronutrients contributed significantly to model performance. The appropriateness of the model fit was confirmed by comparing the degrees of freedom and the sum of squared errors with the total value.

The stepwise regression model is simpler than the multivariate regression model, with 4 degrees of freedom, whereas the multivariate regression model has 51 degrees of freedom, reflecting greater complexity. However, a comparison of the sum of squared errors between the two models indicated that the stepwise regression model has lower predictive accuracy than the multivariate regression model. Furthermore, based on the coefficients of determination presented in Tables 5-7, it can be concluded that the independent variables in the multivariate regression model possess a greater ability to explain sugar beet yield. Due to the smaller number of variables and the inclusion of only those variables with the most substantial effects on yield modeling, the F-statistic in the stepwise regression was higher than that in the multivariate regression. This difference is due to the fact that stepwise regression includes only linear and a single nonlinear effect, whereas multivariate regression accounts for two-way interaction effects among inputs and quadratic effects. Although stepwise regression is simpler due to its automatic variable selection, it omits several important effects, such as the interaction between nitrogen and phosphate fertilizers.

Equation (9) for sugar beet yield, derived from stepwise regression, includes three input variables—X_4 (nitrogen), X_5 (phosphate), and X_7 (micronutrients). The results indicated that the coefficient of determination (R^2) for yield was 95.70%, as shown in Table 4 8. This finding demonstrates that the model has good accuracy in predicting sugar beet yield in the studied fields. The stepwise regression equation for sugar beet yield is as follows:

$$Y = -6718 + 601.800(X_4) - 105.800(X_5) + 843(X_7) - 5.690(X_7)^2 \quad (9)$$

Table 6. Analysis of variance (ANOVA) for the stepwise regression model of sugar beet yield

Source	DF	SS	MS	F	Sig
Model	4	8,974,707,096	2,243,676,774	433.92	0.000
Linear effects	3	8,530,717,327	2,843,572,442	549.94	0.000
Nitrogen	1	780,804,738	780,804,738	151.00	0.000
Phosphate	1	31,521,183	31,521,183	6.10	0.016
Micronutrients	1	107,553,278	107,553,278	20.80	0.000
Nonlinear effects	1	79,830,410	79,830,410	15.44	0.000
Micronutrients × Micronutrients	1	79,830,410	79,830,410	15.44	0.000
Error	78	403,317,000	5,170,731	-	-
Total	82	9,378,024,096	-	-	-

3.2.3. Comparison of Stepwise and Multiple Linear Regression Models for Predicting Sugar Beet Yield

Table 7 compares the performance criteria of the stepwise and multivariate regression models. The multiple regression model, with a coefficient of determination (R^2) of 98.8%, demonstrated higher accuracy, and its lower residual standard deviation (1,905.09) indicates better predictive performance compared to the stepwise model (2,773.92). Nevertheless, the stepwise model, owing to its lower complexity and comparable performance, represents a more practical option for field applications. The multivariate regression model, with an R^2 of 98.8% and a root mean square error (RMSE) of 1,905.09, explains nearly all the variability in sugar beet yield and exhibits strong predictive power for new data. The CV R^2 values were 92.5% for the stepwise model and 91.0% for the multivariate model. Although the multivariate model shows a higher full dataset R^2, the stepwise model is preferred for field applications due to its simplicity and comparable cross-validated performance.

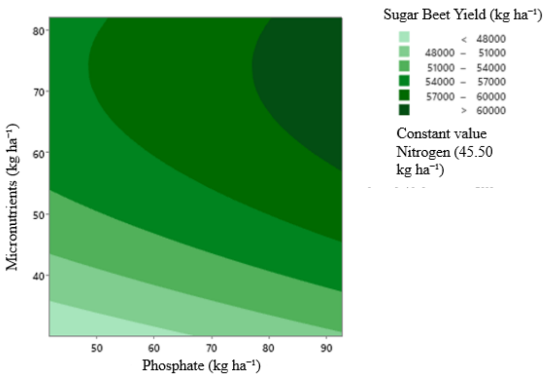
Table 7. Comparison of performance criteria for the stepwise and multivariate regression models.

Model	RMSE	R^2 (%)	Adjusted R^2 (%)	Prediction R^2 (%)	5-fold CV R^2 (%)	CV RMSE (kg ha⁻¹)
Stepwise	2,273.92	95.70	95.48	93.55	92.50	2800
Multivariate	1,905.09	98.80	98.30	-	91.00	2600

3.2.4. Crop Yield Response to Changes in Input Variables

Figure 2 illustrates the simultaneous effects of micronutrient and phosphate fertilizers on sugar beet yield, with nitrogen fertilizer held constant at 45.50 kg ha^{-1}. As shown in the figure, increasing phosphate application from 40 to 100 kg ha^{-1} alongside increasing micronutrient application from 30 to 80 kg ha^{-1} resulted in an increase in sugar beet yield from approximately 45,000 to over 60,000 kg ha^{-1}. In the intermediate range of fertilizer application, yield increased uniformly. The highest sugar beet yield was observed within the range of 90–95 kg ha^{-1} for phosphate fertilizer and 65–75 kg ha^{-1} for micronutrient fertilizer. However, at application rates below 90 kg ha^{-1} for phosphate and below 70 kg ha^{-1} for micronutrients, the slope of the yield curve decreased significantly, and even a slight reduction in yield was observed. This phenomenon—characteristic of the saturation and diminishing returns phase—is likely attributable to competitive interactions among nutrients, toxicity resulting from excessive micronutrient accumulation in root tissues, or disruption of the cation–anion balance in the soil solution. This finding is consistent with previous studies reporting reduced phosphorus use efficiency at high application levels (Abdou et al., 2008; Abdou et al., 2014).

Based on the findings presented, it can be concluded that the application of phosphate and micronutrient fertilizers enhances sugar beet yield only up to a certain threshold in the studied farms. Excessive application of these fertilizers does not further increase yield and may, in fact, have a detrimental effect on sugar beet yield. The optimal fertilizer application range for achieving maximum sugar beet yield is estimated to be 80–90 kg ha⁻¹ for phosphate fertilizer and 60–70 kg ha⁻¹ for micronutrient fertilizer.



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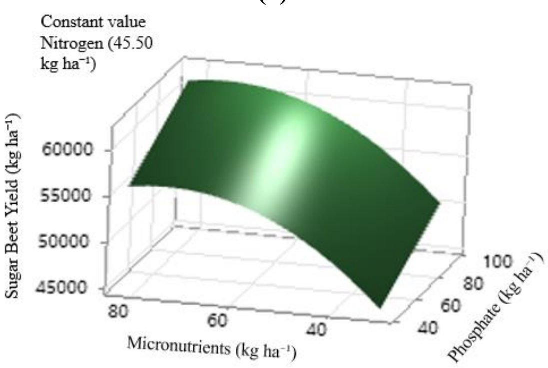
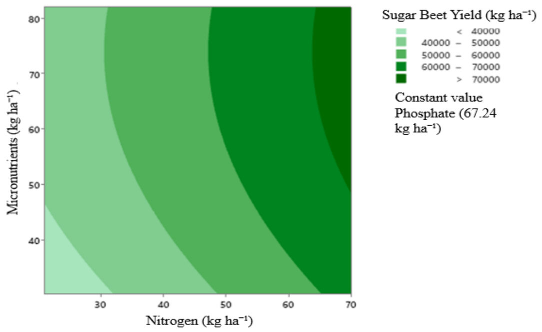


(b)

Figure 2. Interaction effects of phosphate and micronutrients on sugar beet yield: (a) two-dimensional representation; (b) response surface.

Figure 3 shows the interaction effects of nitrogen × micronutrients on sugar beet yield with fixed phosphate fertilizer. Simultaneous increases in nitrogen and micronutrient fertilizers generally enhanced crop yield. The maximum yield increase—from 30,000 to 70,000 kg ha⁻¹—occurred when nitrogen application rose from 30 to over 60 kg ha⁻¹ and micronutrient application increased from 40 to 70 kg ha⁻¹. This significant increase indicates strong synergism between nitrogen and micronutrients. Micronutrients, particularly zinc and manganese, play a key role in activating nitrate reductase and nitrogen-fixing enzymes; their deficiency severely reduces nitrogen use efficiency (Noshad et al., 2012). In areas with high nitrogen consumption (>60 kg) and micronutrients (>70 kg), the yield increase slope decreased noticeably, and the plant approached saturation phase. This behavior reflects physiological limitations in the plant's ability to absorb and utilize excess nitrogen, potentially leading to nitrate accumulation in the root and reduced crop quality (Hergert, 2010).



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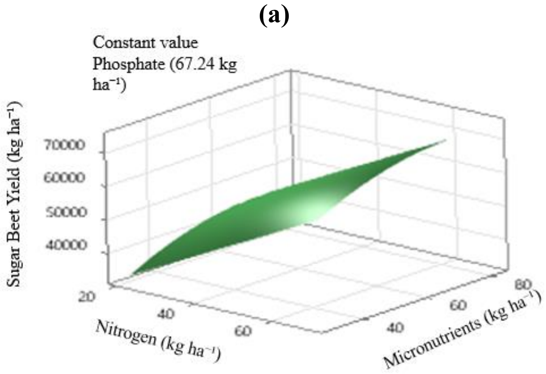


(b)

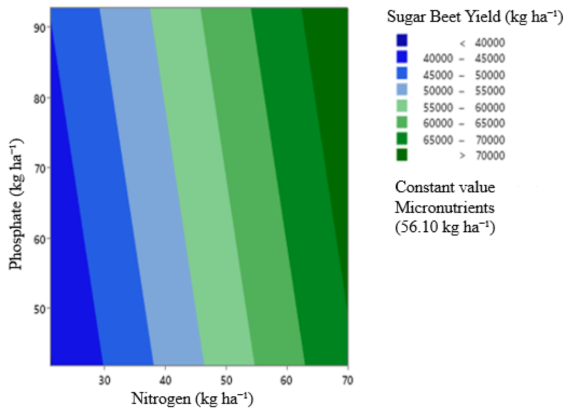
Figure 3. Interaction effects of nitrogen and micronutrients on sugar beet yield: (a) two-dimensional representation; (b) response surface.

Figure 4 shows the interaction between nitrogen and phosphate with micronutrients fixed at the mean value of 51.14 kg ha^{-1}. As nitrogen application increased from 30 to 70 kg ha^{-1} and phosphate from 50 to 90 kg ha^{-1}, the local yield increased from approximately 40,000 to 70,000 kg ha^{-1}. In contrast to the nonlinear responses shown in Figure 2 (phosphate × micronutrients) and Figure 3 (nitrogen × micronutrients), the nitrogen × phosphate response is linear and positive across the range, indicating no saturation at the observed application levels (Hergert, 2010; Noshad et al., 2012). The nitrogen–phosphate interaction shows a positive, significant linear relationship, indicating that increasing both elements together enhances yield.

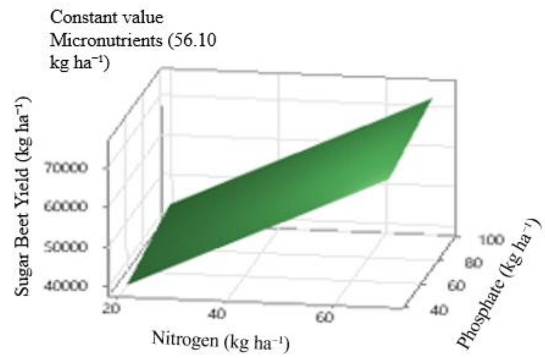
However, at higher application rates, this practice may lead to environmental concerns such as nitrate leaching and eutrophication. The optimal application range for achieving high yield is estimated to be 60–70 kg ha^{-1} for nitrogen and 80–90 kg ha^{-1} for phosphate. While this range enhances local productivity, it should be considered alongside micronutrient intake to avoid nutritional imbalances.

The phosphate–micronutrient and nitrogen–micronutrient interactions display nonlinear patterns and saturation at high consumption levels, whereas the nitrogen–phosphate interaction is linear and exhibits no saturation, albeit with potential environmental risks at elevated levels. These differences underscore that micronutrient application in the presence of macronutrients is critical and can lead to saturation or negative effects when applied excessively. The highest consumption rates were observed for organic fertilizer (37.44%) and micronutrients (26.83%), underscoring the need for effective management of these inputs. The modeling results indicate that the phosphorus–micronutrient and nitrogen–micronutrient interactions exhibit positive effects at high consumption levels, whereas the nitrogen–phosphate interaction demonstrates negative effects.

This difference can be attributed to the role of micronutrients in enhancing nutrient uptake (e.g., phosphorus and nitrogen) and increasing enzymatic activity. In contrast, the combined application of nitrogen and phosphate at elevated levels may lead to competitive interactions or environmental issues. The findings of this study emphasize the need for integrated nutrient management (Integrated Nutrient Management) to increase efficiency. Using a combination of chemical and organic fertilizers (such as 10-15% organic fertilizers with soil testing) and technologies such as drip irrigation or machinery can improve energy productivity and reduce unnecessary consumption (Rezania, 2020). This approach not only increases local output but also helps reduce environmental pollution and greenhouse gas emissions.



(a)



(b)

Figure 4. Interaction effects of nitrogen and phosphate on sugar beet yield: (a) two-dimensional representation; (b) response surface.

3.3. Energy Indices Analysis

3.3.1. Energy Ratio

Table 8 presents the analysis of variance (ANOVA) for the multivariate regression on the energy ratio in sugar beet production. The multivariate regression model was significant at the 1% level (F = 2,622.550, P < 0.001), and all model variance was accounted for by the linear effects of the independent variables. The sugar beet yield variable, with an F-statistic of 3,187.030 and the dominant share in the sum of squares, was the most important factor explaining the variance in the energy ratio. This result indicates that in the studied farms, increasing crop yield (as energy output) has a direct and very strong impact on improving the energy ratio. This is primarily due to the nutritional deficiencies in the region's soil, which make the plant highly dependent on proper input management to achieve high yield. Therefore, any increase in yield (even with energy-intensive inputs) significantly improves the energy ratio, given the crop's high efficiency.

Following yield, micronutrient fertilizers had the greatest impact with F = 1,425.720. This is related to severe micronutrient deficiencies (especially zinc, iron, and manganese) in the region's soils, which cause a sharp reduction in the absorption efficiency of major elements; thus, micronutrient application simultaneously improves yield and the energy ratio. Diesel fuel (F = 106.570) and nitrogen fertilizer (F = 100.470) also have significant impacts. High diesel fuel consumption is mainly due to the obsolescence of agricultural machinery and the complete mechanization of planting, maintenance, and harvesting operations for sugar beet. High nitrogen consumption is also due to severe leaching of the element in the region's light soils and to sugar beet's high nitrogen requirement for vegetative growth and sugar storage. The results of the energy ratio analysis in sugar beet production from the present study are in substantial agreement with the findings of previous research. In a study conducted on sugar beet farms in Isfahan Province, inputs such as nitrogen fertilizer and diesel fuel had the greatest impact on the energy ratio, and their optimal use enhanced energy efficiency (Houshyar et al., 2015).

This finding aligns with the results of the present study, which identified nitrogen fertilizer, micronutrients, and diesel fuel as among the most important factors influencing the energy ratio. The results are also fully consistent with the studies of Erdal et al. (2007) and Gundoshmian et al. (2018), which emphasized the dominant role of energy-intensive inputs in sugar beet production systems. A study conducted in the Xinjiang region of China demonstrated that effective input management, particularly fertilizer and fuel, plays a key role in improving the energy ratio (Hua et al., 2016). The findings of this study align with the report by Zhang et al. (2022) on the positive impact of integrated input management on the energy ratio and with the recommendations of Laufer et al. (2016) regarding nitrogen management.

Table 8. ANOVA of Multivariate Regression on Energy Ratio in Sugar Beet Production.

Source	DF	Sum of Squares	Mean Square	F	Sig
Model	6	1371.290	228.548	2622.550	0.000
Linear Effects	6	1371.290	228.548	2622.550	0.000
Diesel Fuel	1	9.290	9.286	106.570	0.000
Nitrogen	1	8.760	8.755	100.470	0.000
Phosphate	1	2.210	2.209	25.340	0.000
Potassium	1	1.000	1.001	11.480	0.001
Micronutrients	1	124.240	124.236	1425.720	0.000
Sugar Beet Yield	1	277.720	277.716	3187.030	0.000
Error	76	6.290	0.087	-	-
Total	82	1377.570	-	-	-

The relatively lower impact of phosphate and potassium in the regression models is likely due to phosphorus fixation as insoluble calcium phosphate compounds and to the relative accumulation of these nutrients in the region's calcareous soils, which have high pH. In calcareous soils (pH 7.6–8.2), phosphate precipitates as calcium phosphates, and potassium is fixed in the interlayers of illitic clays, reducing their immediate availability and explaining their lower marginal impact on energy indices (Marschner, 2011; Malakouti & Homaii, 2004).

3.3.2. Energy Productivity

Table 9 presents the analysis of variance (ANOVA) for the multivariate regression model of energy productivity in sugar beet production. The overall model was highly significant ($p < 0.001$), and the ranking of variable impacts was similar to that observed for the energy ratio. Sugar beet yield, with an F-value of 3,187.030, emerged as the most important factor, indicating that increasing yield—driven by inherent soil nutrient deficiencies and the high nutritional demands of the crop—directly enhances energy productivity (kg of product per unit of energy consumed). This finding suggests that under nutrient-deficient conditions, even high-energy-consuming investments can substantially improve energy productivity by increasing crop efficiency.

Micronutrients (F = 1,425.720) exhibited a very strong impact, attributable to their severe deficiency in the region's soils. Diesel fuel and nitrogen also demonstrated significant effects. The high diesel fuel consumption is due to the use of obsolete tractors and machinery, as well as the complete mechanization of field operations. The high nitrogen consumption, in turn, results from severe leaching losses and the crop's substantial requirement for this element to support vegetative growth and sugar accumulation.

Previous research demonstrated that combining chemical and organic fertilizers (e.g., 10–15% organic fertilizers with soil testing) with technologies such as drip irrigation or efficient machinery can improve energy productivity, reduce greenhouse gas emissions, and minimize unnecessary input use (Rezania, 2020).

3.3.3. Specific energy

Table 10 presents the analysis of variance (ANOVA) for the multivariate regression model of specific energy in sugar beet production. The model was significant at the 1% level ($F = 600.88$, $p < 0.001$) and explained 97.66% of the variance in specific energy (energy consumed per unit of product). Sugar beet yield ($F = 569.58$) was the most important factor in reducing specific energy; that is, higher yields were associated with lower energy consumption per kilogram of product. This finding indicates that, under the nutrient-deficient conditions prevailing in the region, increasing yield—even with energy-intensive inputs—effectively reduces specific energy use.

Micronutrients ($F = 263.76$) had a very strong impact on reducing specific energy, attributable to their severe soil deficiencies. Diesel fuel and nitrogen also demonstrated significant effects. The high diesel fuel consumption is due to the use of obsolete machinery and the complete mechanization of field operations. In contrast, the high nitrogen consumption results from severe leaching losses and the crop's substantial requirement for this element.

3.3.4. Comparison of Stepwise and Multiple Linear Regression Models for Predicting Energy Indices

Following the modeling of sugar beet yield using multivariate regression and stepwise methods, the energy indices—namely, energy ratio, energy productivity, and specific energy—were calculated and modeled according to the relationships described in the Materials and Methods section (Equations 3–5).

Table 9. Analysis of variance (ANOVA) for the multivariate regression of energy productivity in sugar beet production

Source	DF	Sum of Squares	Mean Square	F	Sig
Model	6	4.8585	0.8098	2622.290	0.000
Linear Effects	6	4.8585	0.8098	2622.290	0.000
Diesel Fuel	1	0.0329	0.0329	106.570	0.000
Nitrogen	1	0.0310	0.0310	100.470	0.000
Phosphate	1	0.0078	0.0078	25.340	0.000
Potassium	1	0.0035	0.0035	11.480	0.001
Micronutrients	1	0.4402	0.4402	1425.720	0.000
Sugar Beet Yield	1	0.9840	0.9840	3187.030	0.000
Error	76	0.0223	0.0003	-	-
Total	82	4.8809	-	-	-

Table 10. Analysis of variance (ANOVA) for the multivariate regression of specific energy in sugar beet production.

Source	DF	Sum of Squares	Mean Square	F	Sig
Model	5	0.1549	0.03097	600.88	0.000
Linear Effects	5	0.1549	0.03097	600.88	0.000
Diesel Fuel	1	0.0012	0.00120	23.08	0.000
Nitrogen	1	0.0005	0.00050	10.25	0.002
Phosphate	1	0.0004	0.00040	8.17	0.006
Micronutrients	1	0.0136	0.01360	263.76	0.000
Sugar Beet Yield	1	0.0293	0.02930	569.58	0.000
Error	77	0.0037	0.00005	-	-
Total	82	0.1586	-	-	-

A comparison of the two regression methods revealed that the multivariate model, owing to its very high coefficient of determination (exceeding 97% for all indices), low residual standard deviation, and superior explanatory power, provides better accuracy and fit than the stepwise model. Consequently, the multivariate regression model was selected for the final modeling of the energy indices. The multivariate regression models for the energy indices—energy ratio, energy productivity, and specific energy—are presented in Equations (10), (11), and (12), respectively:

$$Y = 39.74 - 0.001618X_3 - 0.001666X_4 - 0.002439X_5 - 0.001615X_6 - 0.002026X_7 + 0.000046X_{10} \tag{10}$$

$$Y = 2.365 - 0.000100X_3 - 0.000099X_4 - 0.000145X_5 - 0.000096X_6 - 0.000121X_7 + 0.000003X_{10} \tag{11}$$

$$Y = 0.433 + 0.000019X_3 + 0.000013X_4 + 0.000034X_5 + 0.000021X_7 - 0.00000047X_{10} \tag{12}$$

In these equations, Y is the dependent variable representing the energy indices. The independent variables used in these equations are denoted X3, X4, X5, X6, X7, and X10, respectively representing diesel fuel consumption, nitrogen fertilizer, phosphate fertilizer, potassium fertilizer, micronutrient fertilizers, and sugar beet yield.

The performance evaluation of the multivariate regression models for each energy index is presented in Table 11, which displays the fit criteria for the three models corresponding to energy ratio, energy productivity, and specific energy. The coefficient of determination (R^2) for the energy ratio and energy productivity models was equally 99.54%, while for the specific energy model it was 97.66%, indicating an excellent fit of the models to the observed data. The adjusted coefficient of determination (Adjusted R^2) was very close to the unadjusted R^2 for all three models—99.48% for the first two indices and 97.34% for specific energy. Similarly, the predicted coefficient of determination (R^2 Prediction) was 99.39% and 97.00%, respectively. These high values indicate that the models not only explain the observed data well but also possess accurate predictive capability for new data.

Table 11. Performance criteria of multivariate regression model for energy indices in sugar beet production.

Criterion Name	Energy Ratio	Energy Productivity	Specific Energy
Standard Deviation of Residuals	0.296	0.0176	0.0072
Coefficient of Determination (%)	99.540	99.540	97.660
Adjusted Coefficient of Determination (%)	99.480	99.480	97.340
Prediction Coefficient of Determination (%)	99.390	99.390	97.000

According to Table 11, the root mean square errors (RMSEs) were very low for the energy ratio (0.296) and energy productivity (0.0176) models, and even lower for the specific energy model (0.0072), indicating high predictive accuracy and negligible model error. The slight difference in R^2 between the specific energy model and the other two indices is attributed to the exclusion of the potassium variable from the specific energy model, as it had a lesser influence on this index. This finding confirms that crop yield, micronutrients, diesel fuel, and nitrogen play key roles in all indices, whereas phosphate and potassium exhibit more limited impacts. The very high coefficient of determination (99%) for the first two indices indicates that nearly all the variability in energy indices across the studied farms is explained by these variables, reflecting the strong dependence of the region's sugar beet production system on precise management of energy-intensive inputs, particularly crop yield. These results underscore the need to focus on improving yield through optimal nutrition and reducing energy consumption through machinery modernization to achieve sustainable, energy-efficient production.

4. Conclusion

This study successfully developed and compared multivariate and stepwise regression models for predicting sugar beet yield and energy indices under semi-arid conditions in Chaharmahal and Bakhtiari Province, Iran. The multivariate model, incorporating interaction and quadratic effects (e.g., positive nitrogen × phosphate interaction, quadratic effect of micronutrients), showed superior explanatory power ($R^2 = 98.8\%$), while the stepwise model ($R^2 = 95.7\%$) proved sufficiently accurate and more practical for rapid field-level fertilizer recommendations due to its simplicity and automatic selection of significant variables.

Key yield-related findings include the positive interaction between nitrogen and phosphate, the nonlinear response of yield to micronutrients, and the identification of diesel fuel and micronutrients as the dominant energy inputs (together accounting for >64% of total input energy). Optimal application ranges for maximizing yield were estimated at 80–90 kg ha^{-1} (phosphate), 60–70 kg ha^{-1} (micronutrients), and 60–70 kg ha^{-1} (nitrogen). These ranges can potentially increase yield to 70 t ha^{-1} without excessive input use.

For energy indices, multivariate regression achieved an excellent fit ($R^2 > 97\%$ for all indices). Crop yield, micronutrients, diesel fuel, and nitrogen were identified as the most influential variables. Crop yield emerged as the most important factor, indicating that increasing crop efficiency—even with energy-intensive inputs—significantly improves the energy ratio and energy productivity while reducing specific energy, particularly under conditions of inherent soil nutrient deficiencies.

High diesel fuel consumption was attributed to obsolete machinery and full mechanization of field operations, while high nitrogen use reflected severe leaching in light-textured soils. These findings suggest that without machinery modernization and precise nitrogen management, achieving high energy efficiency will remain challenging. Achieving sustainable and energy-efficient sugar beet production in this region requires two simultaneous approaches: (1) improving yield through precise nutrient management (especially micronutrients), and (2) reducing energy consumption through machinery modernization and optimized diesel fuel and nitrogen use. These measures can enhance energy efficiency while reducing greenhouse gas emissions and production costs.

This study has several inherent limitations that also represent opportunities for future research. The cross-sectional design captured only one growing season; inter annual variability should be examined in longitudinal studies. The moderate sample size ($n = 83$) limited the complexity of models that could be reliably validated; larger datasets would allow more robust interaction testing. Soil properties were not directly measured at each farm, and energy coefficients were derived from literature rather than local measurements. These are not weaknesses but natural boundaries that define clear pathways for subsequent research—particularly the need for field-specific soil testing and locally calibrated energy inventories. Despite these limitations, the robust cross-validation results (over 91% for both models) support the applicability of our findings to similar semi-arid sugar beet production systems.

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Author Contributions

First Author: Investigation, Methodology, Writing–Original Draft, Visualization.

Second Author (Corresponding Author): Supervision, Conceptualization, Data Curation, Resources, Writing – Review & Editing, Supervision, Project administration, Funding acquisition.

Data Availability Statement

Not applicable.

Ethical Considerations

No ethical approval was required for this study. The authors confirm that all ethical standards of scientific research were strictly adhered to, including the avoidance of data fabrication, falsification, plagiarism, and other forms of research misconduct.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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