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ANALYZING THE INFLUENCE OF LABOR INPUT SPENT ON SUGARCANE PRODUCTIVITY: A CASE STUDY OF URIRI SUB-COUNTY, MIGORI COUNTY, KENYA

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ABSTRACT

Sugarcane farming remains an important economic activity for smallholder farmers in Kenya, especially in labor-intensive regions such as Uriri Sub-County, Migori County. Despite its importance, productivity levels remain significantly below potential, largely due to inefficient labor utilization. This study investigates the effect of labor input, measured in man-days per acre, on sugarcane productivity (yield in tonnes per acre). A cross-sectional survey and multistage sampling technique were used to choose a sample of 297 respondents and a semi-structured questionnaire were used to gather primary data. A multiple linear regression model was employed to estimate the relationship between labor spent on specific farm operations during planting, fertilizer application, weeding, and harvesting and average sugarcane productivity. The results of the study found out that each additional man-day per acre spent on planting was associated with a 0.40-tonne increase in sugarcane productivity ($p < 0.001$), while fertilizer application showed a 0.34-tonne increase in sugarcane productivity per acre ($p = 0.035$). Labor input on weeding had a positive effect of 0.46 tonnes per man-day increase in sugarcane productivity ($p < 0.001$), and harvesting demonstrated the strongest influence, with a 0.79-tonne increase in sugarcane productivity per acre ($p < 0.001$). The model intercept was 11.87, indicating the estimated sugarcane productivity per acre in the absence of the specified labor inputs, though such a scenario is theoretical. The model exhibited strong explanatory power, with an R^2 of 0.761 suggesting that approximately 76% of the variability in sugarcane productivity could be explained by the labor inputs considered. These findings confirm a significant and positive relationship between labor input and sugarcane productivity, emphasizing the need for timely and adequate labor allocation in key operations to maximize productivity. The study underscores the importance of addressing labor inefficiencies and supports policy efforts to enhance labor management strategies, promote mechanization, and mitigate labor shortages in the sugarcane sector.

KEYWORDS: *Sugarcane productivity, Labor input, Regression analysis, Agricultural efficiency.*

1. INTRODUCTION

1.1 Background of the study

Sugarcane (Saccharum officinarum) is a major cash crop cultivated worldwide, providing raw materials for sugar production and other related industries (Hartemink & Kuniata, 1996; Kuniata et al., 2001). The productivity of sugarcane is influenced by various factors, including labor input, which plays an important role in its cultivation, maintenance, and harvesting (Amukoya et al., 2023; AFA, 2024). Labor is a significant determinant of efficiency in sugarcane farming, particularly in smallholder farms where manual labor is the predominant mode of operation (Ouko et al., 2022).

In Kenya, sugarcane farming is largely dominated by smallholder farmers, who rely heavily on manual labor for production activities (AFA, 2024). Sugarcane farming is labor-intensive, requiring significant human effort in land preparation, planting, weeding, fertilizer application, and harvesting due to the crop's long growing cycle and the need for continuous field management (Kombo, 2023; Bundeh, 2022). The industry relies heavily on smallholder farmers, who contribute about 94% of the total sugarcane production, with most cultivation being done manually (AFA, 2024).

The labor spent in sugarcane production varies across different zones, depending on farm size, availability of mechanization, and socioeconomic factors affecting labor supply (Anino, 2024). Despite the high demand for labor, many farmers face challenges such as delays in major farming activities such as harvesting and weeding due to labor shortages, increasing wages, and delays in important farm operations, which negatively impact productivity and economic losses for farmers (Kombo *et al.,* 2022).

In the South Nyanza Sugar Belt, including Migori County, labor constraints have been a major challenge in sugarcane farming (CGM, 2023). The reliance on manual labor in activities such as weeding and cane cutting has contributed to inefficiencies in production. The high cost of labor and limited availability of skilled farm workers further impact productivity, resulting in lower yields (Kombo et al., 2022; AFA, 2024). In Uriri sub-county, sugarcane productivity levels have remained low, with yields ranging between 25-40 tons per acre in 2023, significantly lower than the potential yield of 70 tons per acre (Bundeh, 2022). This decline has been attributed to labor inefficiencies, many farmers experience difficulties in timely field operations due to labor constraints, leading to delayed planting, poor weeding practices, and untimely harvesting, all of which reduce sugarcane productivity (Anino, 2024).

Moreover, labor challenges in sugarcane farming extend to socio-economic factors such as the migration of young laborers to urban areas, leaving an aging workforce to handle demanding farm tasks (FAO, 2023; Wambasi, 2024). This has led to increased labor costs, making it more expensive for smallholder farmers to maintain their farms (Kombo et al., 2022). Delays in harvesting and transportation further contribute to yield losses, as mature cane left unharvested for extended periods deteriorates in quality (AFA, 2024). The delayed payment of wages and lack of mechanization in key farming activities have also contributed to inefficiencies in labor utilization (Oduor, 2019).

To enhance sugarcane productivity, addressing labor-related constraints is essential. Improving access to affordable mechanization, providing incentives to attract farm labor, and adopting efficient farm management practices can help optimize labor input (AFA, 2024; Onyuro, 2020). This study aims to examine the impact of labor spent on sugarcane productivity, focusing on how labor input influences yield and identifying strategies to enhance efficiency in sugarcane farming.

1.2 Problem statement

Sugarcane farming is labor-intensive, requiring significant labor input in major production activities. However, inefficiencies in labor utilization, labor shortages, and increasing costs have negatively impacted productivity, particularly among smallholder farmers. In Kenya, sugarcane productivity has declined from an average of 63 t/ha in 2022 to 54.95 t/ha in 2023, far below the potential yield of 120 t/ha under good agronomic practices (Ambetsa et al., 2021; Okumu, 2023; AFA, 2024). This decline has adversely affected farmers' financial stability, forcing some to withdraw from sugarcane production and contributing to increased sugar imports into the country. In Uriri sub-county, sugarcane productivity ranges between 20-40 t/ac, significantly lower than the 70 t/ac recorded in the South Nyanza Sugar Belt (Kombo et al., 2022; Ouko et al., 2022; SSC, 2023). The major factor contributing to this low productivity is inefficient labor use. Farmers in the region experience delays in important farm activities due to inadequate labor supply and rising wages, leading to poor crop management and yield losses. Despite the essential role of labor in sugarcane farming, limited empirical studies has been conducted to analyze its effect on productivity. Understanding how labor input influences sugarcane productivity is important for formulating strategies to optimize labor use, improve farm efficiency, and enhance economic sustainability for farmers.

1.3 Research Hypothesis

H_0: There is no significant effect of labor input spent on sugarcane productivity.
H_1: There is a significant effect of labor input spent on sugarcane productivity.

1.4 Significance of the Study

This study is significant as it examines the impact of labor input on sugarcane productivity, helping stakeholders optimize labor use and improve efficiency. Farmers can reduce inefficiencies, policymakers can develop labor-supportive interventions, and agribusiness firms can enhance labor management strategies. Additionally, researchers can expand knowledge on labor economics in agriculture, while improved labor efficiency can boost production, stabilize sugar supply, and strengthen the agricultural sector.

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2. LITERATURE REVIEW

2.1 Theoretical Framework

Production theory, particularly the Cobb-Douglas production function, developed by Charles W. Cobb and Paul H. Douglas between 1927 and 1947. This theory models the technological relationship between input factors most notably labor and capital and the output level of a production process. In the context of sugarcane farming, labor is a fundamental input, measured in terms of man-hours or labor days, which directly contributes to activities such as land preparation, planting, weeding, fertilization, and harvesting. The Cobb-Douglas production function, typically expressed as: $Q = AL^{\alpha}K^{\beta}$,

where Q represents sugarcane output, L is labor input, K is capital input (e.g., machinery, fertilizer), A is total factor productivity, and α and β are the respective output elasticities. This model is instrumental in estimating the responsiveness of sugarcane output to changes in labor input. A positive and significant α implies that increased labor effort contributes meaningfully to higher productivity.

Empirical applications by Mandla and Maker (2012) and Jamil *et al.* (2014) demonstrate the model's suitability for evaluating agricultural production systems, highlighting its effectiveness in regression analysis to determine input-output relationships. These studies support the argument that labor remains a key driver of productivity in labor-intensive agricultural systems like sugarcane farming.

However, critiques of the Cobb-Douglas model note its simplifying assumptions. Scholars such as Colther and Doussoulin (2024), and da Silva (2023) argue that the model neglects complex engineering processes and assumes perfect divisibility of inputs—a condition often violated in real-world agricultural settings. Moreover, the model's assumption of constant returns to scale may not hold where labor efficiency varies due to socio-economic constraints, such as education, skill levels, or seasonal labor shortages (Khaemba *et al.,* 2021; Bohr *et al.,* 2024). However, studies such as Pokharel *et al.* (2019) and Ambetsa *et al.* (2020) reaffirm the Cobb-Douglas function's utility in agricultural contexts. These studies emphasize that while the model may overlook complex interactions among variables, it provides a reliable basis for assessing how labor input influences productivity under varying farm-level conditions.

2.2 Empirical Review

Fatah *et al.* (2022), conducted a study on the Analysis of labor efficiency on sugarcane cultivation through mechanization application, focusing on sugarcane fields in Java, Indonesia. The study aimed to assess the potential of mechanization in increasing labor efficiency in sugarcane farming. Using a survey design, data were collected from smallholder farmers. The findings revealed that labor input used by the farmers increased sugarcane production. The study recommended promoting mechanization to boost farmers' income and support sustainable sugarcane development.

Ali *et al.* (2020), conducted a study on the technical efficiency of growing sugarcane crop in Khyber Pakhtunkhwa, Pakistan, focusing on the technical efficiency and factors affecting sugarcane productivity in three key sugarcane-growing districts: D.I. Khan, Malakand, and Charsadda. The study analyzed the effects of various inputs, including labor, on sugarcane productivity. Using a Stochastic Frontier Approach (SFA) and a cross-sectional research design, data were gathered through structured questionnaires from a sample of 299 sugarcane growers, selected through a purposive sampling procedure. Labor input was found to be statistically significant in influencing productivity, suggesting that increased labor utilization could enhance yields. However, the study did not address the diminishing return of more labor input on productivity after a given period of time, which presents a gap for future.

Edriss *et al.,* (2014) examined the impact of labor market liberalization on maize Productivity and Rural Poverty in Malawi. The study aimed to quantify how labor market reforms affected maize production efficiency. Utilizing a frontier production function and Divisia Index, the researchers analyzed data to assess changes in productivity. They found that labor input declined by 6.7% following market liberalization, leading to significant decreases in maize productivity. The study recommended addressing labor allocation issues and enhancing wage levels to improve food security and reduce rural poverty.

2.3 Conceptual Framework

The conceptual framework illustrates the direct relationship between labor input, measured in man-days per acre, and sugarcane productivity, measured in yield per acre. Labor input representing the human effort invested in major sugarcane

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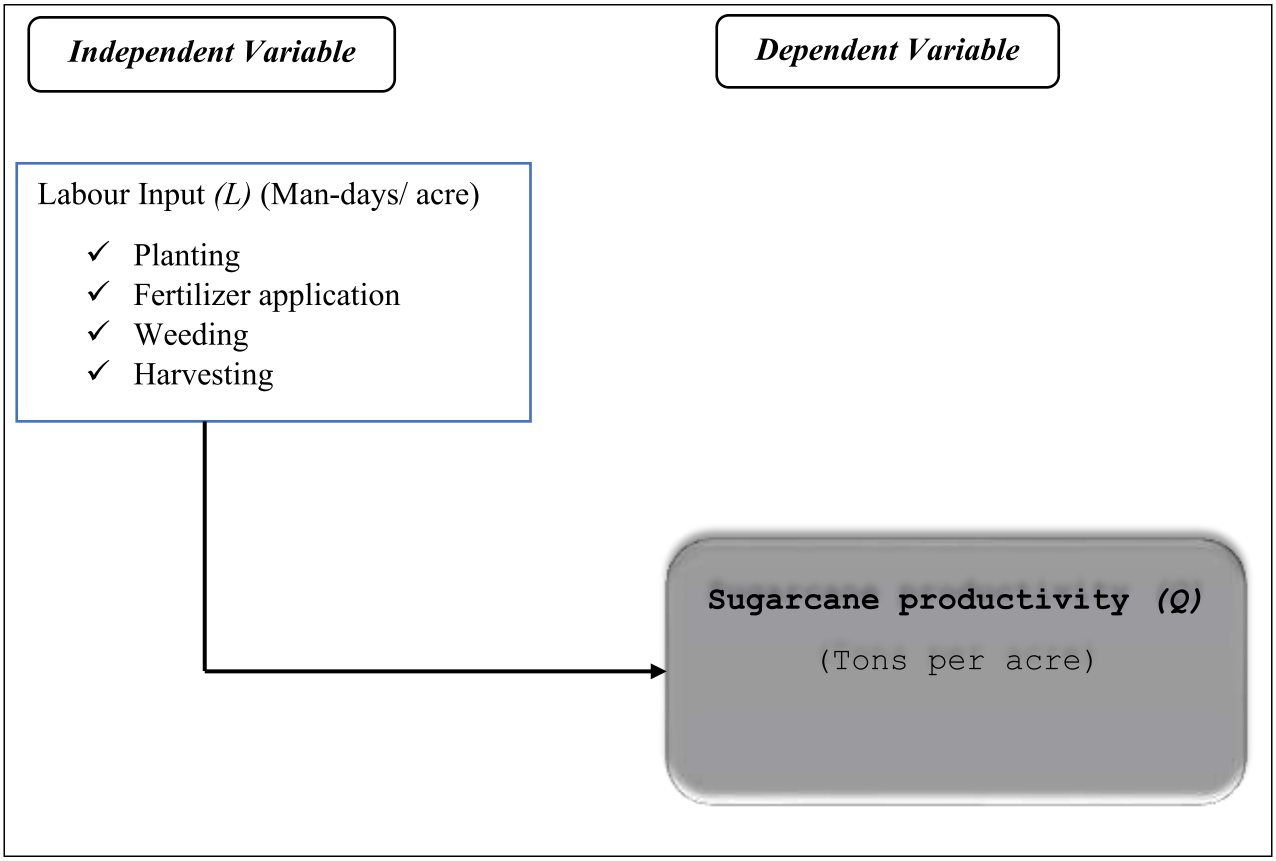
farming activities such as land preparation, planting, weeding, fertilization, and harvesting. Sugarcane productivity reflects the output level resulting from this input. The framework posits that an increase in labor input, when applied efficiently, can lead to higher productivity by ensuring timely and effective execution of agronomic practices. By focusing on input-output relationship, the framework provides a clear basis for analyzing how variations in labor effort affect sugarcane productivity, thereby guiding resource allocation and labor management decisions in sugarcane farming.



3. METHODOLOGY

3.1 Research Design and Sampling

3.1.1 Research Design

The study adopted a cross-sectional survey design to collect data at a single point in time. This design was appropriate for examining the relationship between labor spending and productivity across a diverse population of sugarcane farmers (Ambetsa, 2020; Maier *et al.,* 2024; Vadakedath & Kandi, 2024).

3.1.2 Sampling Frame and Procedure

The sampling frame consisted of all sugarcane farmers in Uriri Sub-County, totaling 1,158 farmers distributed across five wards. A multistage sampling technique was employed, beginning with stratification by ward to create homogeneous subgroups, followed by proportional random sampling within each ward based on the number of farmers. This approach ensured fair representation from each ward and enhanced the reliability of the findings (Kothari *et al.,* 2005; Cooper & Schindler, 2014).

3.2 Data Collection and Analysis

3.2.1 Data Collection

Primary data were collected using a semi-structured questionnaire administered via face-to-face interviews by trained enumerators. Both open and closed-ended questions captured demographic, farm-level, and input cost data, focusing on labor spending and sugarcane productivity.

3.2.2 Data Analysis.

Multiple linear regression was used to determine linear relationship between independent variable and dependent variable. Regression analysis was done to estimate the parameters. The goodness of fit test was used to test the adequacy of the model. Hypothesis testing was used to test the significance of a parameter; each parameter in the model represents a specific relationship between variables. The relationship between the output (Y_i) and the independent variable in its stochastic form can be expressed by the function as:

$$Y_i=\beta_0\times(Labr^2_{(P)})^{\beta 1}\times(Labr^2_{(FA)})^{\beta 2}\times(Labr^2_{(W)})^{\beta 3}\times(Labr^2_{(H)})^{\beta 4}\times e^{\mu i} \quad (3.1)$$

Where Y_i = dependent variable Y for observation i^{th},
β_0 = The intercept;
$\beta_1, \beta_2 ..., \beta_4$, = Partial regression coefficients for the independent variables;
$Labr^2_{(P)}$ = Labor input spent during planting.
$Labr^2_{(FA)}$ = Labor input spent during fertilizer application.
$Labr^2_{(W)}$ = Labor input spent during weeding.
$Labr^2_{(H)}$ = Labor input spent during harvesting.
μ_i = Stochastic disturbance term for the i^{th} observation.

Equation 3.2 below is a semi-logarithmic regression model where the dependent variable *Yi* and the independent variables, are log-transformed. The regression coefficients, β0, β1, ….., β4, are generally estimated by least squares. Since the variables are measured in different units, it is preferred to use the natural logarithm of the variable (Zulu *et al.,* 2019). The logarithmic transformation helped to linearize the relationship between variables that are non-linear in their original form. This makes it easier to model and interpret the relationship using linear regression techniques in terms of elasticities. Hence, the equation can be expressed by log-transforming the dependent variable and the independent variables on both sides can be expressed as:

$$LnY_i=ln\beta_0+\beta_1ln(Labr^2_{(P)})+\beta_2ln(Labr^2_{(FA)})+\beta_3ln(Labr^2_{(W)})+\beta_4ln(Labr^2_{(H)})+\mu_i \quad (3.2)$$

Equation (3.3) was obtained to make interpretation of the parameters easy; this was done by letting Ln β0 = α0. The subsequent functional econometric model was as follows.

$$LnY_i=\alpha_0+\alpha_1ln(Labr^2_{(P)})+\alpha_2ln(Labr^2_{(FA)})+\alpha_3ln(Labr^2_{(W)})+\alpha_4ln(Labr^2_{(H)})+\mu_i \quad (3.3)$$

The study included squared terms for labor use in the regression model to capture the non-linear relationship between the input and productivity. Initially, increasing use of labor during cane production activities leads to higher productivity. However, beyond a certain point, adding more labor results in marginal increase in productivity returns (Law of Diminishing Marginal Returns) leading to inefficiencies, resulting in a decline in productivity levels. According to Samuelson and Nordhaus (2001), Barkley and Barkley (2013), Erickson (2014) law of diminishing returns states that in productive processes, increasing a single unit of input, while holding all other production factors constant, will at some point return a lower unit of output per incremental unit of input.

4. RESULTS AND DISCUSSIONS

4.1 Labor Spent and Sugarcane Productivity

The main activities involved in sugarcane production include planting, fertilizer application, weeding, and harvesting. Allocation of labor to these activities, as detailed in Table 4.3, highlights the average number of man-days per acre required for each activity.

Table 4.3: Labor Allocation in Cane Production Activities per Acre

Labor activity per acre	Mean	Min	Max	Std. Dev
Number of Man days used in planting per acre	4	1	24	3.89
Number of Man days used in fertilizer application per acre	3	0	11	2.04
Number of Man days used for weeding per acre	5	0	18	3.58
Number of Man days used for harvesting per acre	7	1	36	5.02

Min- *Minimum,* ***Max***- *Maximum,* ***Std. Dev***- *Standard deviation*
Source: *Research Data, 2024*

From Table 4.3 above, on average, planting requires 4 man/days per acre, and ranges from 1 to 24 man/day per acre. Fertilizer application is less labor-intensive, requiring an average of 3 man/days per acre, with a maximum of up to 11 man/day per acre. Weeding requires a little more, averaging 5 man/days per acre and with a maximum of 18 man/day per acre. Harvesting consumes the most labor, with an average requirement of 7 man/days per acre, ranging from a minimum of 1 to a maximum of 36 man/days per acre. Differences in labor requirements can be attributed to the complexity of each activity. Planting and weeding require more attention, but harvesting is more labor-intensive due to the need for careful handling and processing of the crop to avoid damage and losses. Fertilizer application generally requires less labor because it can often be done quickly and efficiently. However, variability in farm size and technology use contributes to a wider range of labor inputs across all activities.

4.2 Sugarcane Productivity

Sugarcane productivity varies significantly across crop cycles and is influenced by several factors, including the intensity and timing of labor inputs. The data indicates that productivity during the plant crop stage averages 22.7 tons per acre, with yields ranging from 10 to 73 tons per acre. This stage typically requires the highest labor input, particularly for land preparation, planting, and weed management. The improved productivity observed in the first ratoon crop, averaging 25.7 tons per acre (range: 9 to 79 tons), may be attributed to reduced land preparation costs and more focused labor input on crop maintenance, such as fertilization and weeding.

However, a noticeable decline in productivity occurs in the second ratoon, with an average of 19.3 tons per acre and yields ranging between 7 and 46 tons per acre. This reduction suggests a decline in labor efficiency or intensity, possibly due to diminishing returns on effort, poor crop stand management, or less investment in weeding and fertilizer application during later crop cycles. The average productivity across all cane cycles is 22.6 tons per acre, further highlighting the role labor plays not just in yield, but in sustaining it over multiple cycles. Variations in productivity are also affected by climate and soil fertility, but the data supports the argument that timely and adequate labor input is a key determinant of yield performance, especially during the more productive early crop phases.

4.3 Regression Analysis

4.3.1 Determinants of Sugarcane Productivity

The presented linear regression model investigates the effect of labor input, measured in man-days per acre, on the average yield of sugarcane (in tonnes per acre). The analysis draws on data from 206 observations and incorporates four key labor-related predictors: the number of man-days used in planting, fertilizer application, weeding, and harvesting. These predictors reflect core farm operations that are expected to influence productivity.

The study applied the following regression formula:
$Ln(Y_i)=\alpha_0+\alpha_1 ln(Labr^2{}_{(P)})+\alpha_2 ln(Labr^2{}_{(FA)})+\alpha_3 ln(Labr^2{}_{(W)})+\alpha_4 ln(Labr^2{}_{(H)})+\mu_i$
The estimated model findings for the study were:
$Ln(Y_i)=11.87+0.40(Labr^2{}_{(P)})+0.34(Labr^2{}_{(FA)})+0.46(Labr^2{}_{(W)})+0.79(Labr^2{}_{(H)})$
The intercept value of 11.87 *($p < 0.001$)* represents the expected average yield in tonnes per acre when no labor is applied in the specified activities. While this is not practically feasible in real farming scenarios, the intercept serves as a reference point in the model. Each of the four predictors has a positive and statistically significant effect on productivity.

Labor input in planting shows a coefficient of 0.40 *($p<0.001$)*, indicating that an additional man-day per acre spent on planting is associated with an increase of 0.40 tonnes in yield, all else being equal. Fertilizer application has a coefficient of 0.34 *($p=0.035$)*, suggesting a modest but significant contribution to yield from labor allocated to this activity. Although the effect is smaller compared to other activities, it remains statistically significant at the 5% level.

Weeding showed a stronger effect, with a coefficient of 0.46 *($p<0.001$)*. This implies that each additional man-day per acre spent on weeding leads to a 0.46 ton increase in yield, highlighting the importance of timely and adequate weed control. Among all predictors, harvesting exhibits the highest impact, with a coefficient of 0.79 *($p<0.001$)*. This finding suggests that labor intensity during the harvesting phase plays an important role in enhancing sugarcane productivity, likely due to the need for prompt and efficient harvesting to prevent losses. In terms of model fit, the R-squared value of 0.761 indicates that approximately 76.1% of the variability in sugarcane yield is explained by the model. The adjusted R-squared value of 0.756, which accounts for the number of predictors, confirms that the model is well-specified and robust. Furthermore, the Akaike

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Information Criterion (AIC) value of 1133.417 provides a basis for model comparison, with lower values indicating better model performance.

	Average Yield in Tones per Acres			
Predictors	*Estimates*	*std. Error*	*Statistic*	*p-value*
(Intercept)	11.87	0.53	22.39	**<0.001**
No. of Man /Days used in Planting per Acres	0.40	0.10	3.99	**<0.001**
No. of Man Days used in Fertilizer Application per Acres	0.34	0.16	2.13	**0.035**
No. of Man Days used for Weeding per Acres	0.46	0.10	4.70	**<0.001**
No. of Man Days used for Harvesting per Acres	0.79	0.07	11.49	**<0.001**
Observations	206			
R^2 / R^2 adjusted	0.761 / 0.756			
AIC	1133.417			

**** denotes significant at the 0.05 level (2-tailed)*
Source: *Research data, 2024*

5. CONCLUSION AND RECOMMANDATIONS

5.1 Conclusion of the study

The objective of the study was to estimate whether labor input affects sugarcane productivity. The findings revealed that labor input at different stages of sugarcane production has a varying effect on productivity. Increased labor during plantation, weeding, and harvesting directly affect sugarcane productivity, as each additional man-day increases productivity per acre. This conclusion supports the hypothesis that labor input influences sugarcane productivity. However, beyond an optimal level, additional labor creates inefficiencies. This inefficiency brings down overall yield despite an increase in labor.

5.2 Recommendations of the study

To increase sugarcane productivity, the government should provide targeted training programs to farmers to increase productivity by focusing on best practices for managing labor, such as workshops on efficient labor use during important stages such as planting, weeding, and harvesting to maximize yield. Farmers should optimize their labor input by ensuring a sufficient workforce during the important stages. By adopting these practices leads to higher overall productivity.

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