Predicting the effect of tillage on fuel consumption

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Abstract: Wastage and economic loss in agricultural productivity during tillage operations could be predicted and reduced at the design stages. This study used a factorial experimental design to optimize tractor hourly fuel consumption during ploughing and ridging operations. The research aimed to investigate tillage effect on fuel utilization efficiency for reduction of operational costs and increase agricultural productivity. A 4,480 m^2 research plot split into three blocks of nine treatments with three replicates was adopted for the research. The plot varied from loamy sand to sandy loam, which are good for agricultural productivity. The disc plough and disc ridger were the prominent tillage implements used in the research while the DFM Fuel Flow Meter was used for fuel consumption measurement. Field test parameters (ploughing depth (or ridging height), and tractor onward speed) and fuel use were measured. Using MINITAB 19 software, statistical analyses of the general full factorial design (GFFD) were carried out. These analyses included model fit adequacy, analysis of variance (ANOVA), main and interaction effects, multiple linear regression model, and response optimizer. Normal probability plots showed that the hourly fuel use during ploughing and ridging were approximately normally distributed, satisfying model fitness examination, and was confirmed by the model competence plot of frequency versus residual. The hourly fuel use during ploughing and ridging was shown to be randomly distributed with no discernible structure in the residual versus fitted value plots, supporting the residuals' constant variance requirement. Statistical analysis, and ANOVA in GFFD indicated that a significant difference exists with 95% and 99 % levels of significance on the influence of ploughing depth (or ridge height), tractor onward speed and their effects on tractor hourly fuel consumption during ploughing and ridging operations. Optimized tractor hourly fuel consumption during ploughing and ridging was attained at plough depth and ridge height of 0.10 m respectively, and tractor onward speed of 5 km h^{-1}. This study determined that the minimum fuel consumption per hour for tractor under optimised working circumstances were 2.93 L h^{-1} and 3.30 L h^{-1} for ploughing and ridging operations respectively.

Keywords: fuel, optimization, ploughing, tractor, speed.

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1 Introduction

Tillage operations for sustainable agricultural productivity under the dynamic tropical climatic conditions are gradually becoming an emerging issue of concern. Ploughing and ridging being primary tillage operations involves the use of implements such as ploughs and ridgers for physical and mechanical manipulation of soil for maximizing crop production (Pereira et al., 2024; Topa et al., 2021). Prominent ploughs used in soil operations include harrow ploughs, mould-board ploughs, disc ploughs, and reversible

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mould-board ploughs. The disc plough is widely adopted for soil manipulation due to its use for tillage operation of virgin, stony, and moist soils that roll over the roots and cut through crop residues leading to higher plough efficiency (Ishmuradov and Abdumajidov, 2022; Tukhtakuziev and Ishmuradov, 2024). Tilling of soil with disc plough subsequently leads to nutrients uptake, enhances soil aeration, improves soil health, and soil moisture reservation, which inspires crops development and yield (Wang et al, 2023; Abrougui et al., 2014; Steponavičienė et al., 2024). A tillage procedure called ridging is typically carried out following harrowing and ploughing. Ridging involves piling up tilled soil from two sides to create lengthy mound stripes with a furrow in between, allowing for planting on beds while encouraging mechanisation (Alele et al., 2023; Nkakini and Fubara-Manuel, 2012). Ridging increase surface water storage and prevent runoff, the length is determined by the size and configuration of the field, while its breadth and height are determined by the size and adjustment of the implement that was used (Abie et al., 2024; Zhao et al., 2024). Ridgers, are of various types, with the disc ridgers having ability of constructing beds tailored to the specific size and shape requirements of the soils and crops (Achankeng and Cornelis, 2023; Kabaradin et al., 2023). However, ridgers and ploughs, like other tillage implements, increase fuel consumption during tillage operations due to the tractor's pull and speed (Al-sager et al., 2024; Amer, 2024).

The operational speed, particularly the tractor forward speed, significantly influences soil tillage (Oduma et al, 2023). Soil tillage under diverse conditions, including differing tractor speeds, soil types and depths, implements utilised, and climatic factors, necessitates varied fuel consumption (Janulevičius and Damanauskas, 2023). Increased fuel consumption not only increases the cost of tillage operations but also adversely affects the environment (Kumari and Raheman, 2023). The increment in fuel consumption is also contributed by the type of tillage operation such as increment in ridge height and plough depth, traction power, and interaction of drive wheel and terrain soil which had account for 575 million liters of annual fuel loss in the USA (Md-tahir et al., 2021). Studies have shown that during tillage operations, soil properties such as soil moisture, bulk density, soil texture and shear strength can influence fuel consumption depending on the ploughing depth or ridge height (Zimmermann et al., 2023; Kim et al., 2022). The pursuit of sustainable tillage to reduce fuel consumption and greenhouse gas emissions has prompted the investigation of an optimal ploughing depth or ridge height for enhanced productivity.

In attempts to provide sustainable solutions to fuel consumption during tillage operations, several factors of influence have been identified, including driving strategy, speed, width and depth, plough and ridger type, tractor model, and climatic and soil conditions during ploughing, ideal engine performance (Al-Sager et al., 2024; Nkakini and Ekemube, 2020; Leghari et al., 2016). Further suggestions on strategies to reduction in fuel consumption during ploughing and ridging operations include selecting approximately 70%–80% nominal engine speed, combination of a tractor's implement type, draught force, and adopting shift-up throttle-down techniques (Ekemube et al. 2020; Mamkagh, 2018; Taiwo, 2015). In addition to the quest for sustainable solutions to fuel consumption during ploughing and ridging operations, models including linear, non-linear, artificial neural networksz, and regression models have been developed to monitor and predict fuel consumption (Vahdanjoo et al., 2024; Al-Dosary et al., 2019). Optimizations strategies have been adopted by researchers intending to determine the best possible solutions on fuel consumption, minimize the total present costs and subsequent maximization of total profit, best estimate, ideal design and management, or efficient control (Jensen et al., 2024; Shahakar et al., 2019; Nurmiev et al., 2018; Al-Dosary et al., 2019; Ndirika and Onwualu, 2016). These attempts to achieve sustainable fuel consumption during tillage operations have led to development and modifications on experimental designs including frequently adopted experimental designs such as randomized block designs, single factor designs, and factorial designs; with factorial designs having about 66% adoption when compared with the randomized block designs, and single factor designs which had 45% and 38%, respectively (Ekemube et al., 2023; Al-Dosary et al., 2019; Aboukarima, 2016). This study aims to apply suitable experimental design for sustainable optimization of tractor fuel consumption during ploughing and ridging operations, ensuring sustainable fuel consumption to reduce operational cost, global warming, increase agricultural productivity and profit.

2 Materials and methods

2.1 Experimental site description

The Rivers Institute of Agriculture Research and Teaching (RIART) Farm at Rivers State University, Port Harcourt, Nigeria served as the site of the field experiment. Port Harcourt is located at latitude 4° 49′ 27″ N and longitude 7° 2′ 1″ E. It is 274 mm above mean sea level and experiences 2310.9 mm of annual rainfall on average (Nkakini and Ekemube, 2020). The study was carried out in September, during the late planting season of 2023.

2.2 Experimental design

The two factors at three levels (3^2) full factorial design in triplicates were carried out to investigate its impact on the tractor fuel use during ploughing and ridging operations. The adopted two factors were the ploughing depth (0.10, 0.20 and 0.30 m) and the tractor forward speed (5, 7 and 9 km h^{-1}). The analyzed response was the tactor hourly fuel use during ploughing and ridging operations, which was achieved by slitting the fields into blocks. Block 1, 2, and 3 for depth levels of 0.10 m, 0.20 m and 0.30 m depth levels respectively. The 4,480 m^2 experimental plot was equally split into nine (9) experimental treatments with three blocks as explained in Table 1. Each subplot was 100 m^2 with 1m alley between each plot and 4 m alley between blocks. In this study randomization was achieved using MINITAB 19 software program (Minitab Inc, State College, PA, USA).

2.3 Tractor and implement specifications

A Swaraj 978FE tractor (weight, 3015 kg; engine horsepower, 53.7 kW; and lifting power of 2200 kg) was used for the ploughing and ridging operations. Front and the rear tyres were 7.5 –16, 8 ply and 16.9 – 28, 12 radials respectively. For the experiments, two instruments were used: a 2500 mm frame width mounted-type disc ridger with a disc diameter of 711.20 mm and a 1180 mm frame width mounted-type disc plough with a disc diameter of 300 mm (Baldan implementos agricolas, Brazil) with a 3-disc bottom mounted on a gauge wheel (Figure 1).

Table 1 Treatment distribution through blocks

Std order	Run order	Blocks	Depth (or height), d (m)	Speed, V (km h^{-1})
22	1	3	0.2	5
23	2	3	0.2	7
26	3	3	0.3	7
20	4	3	0.1	7
21	5	3	0.1	9
19	6	3	0.1	5
25	7	3	0.3	5
27	8	3	0.3	9
24	9	3	0.2	9
13	10	2	0.2	5
15	11	2	0.2	9
18	12	2	0.3	9
17	13	2	0.3	7
11	14	2	0.1	7
12	15	2	0.1	9
16	16	2	0.3	5
14	17	2	0.2	7
10	18	2	0.1	5
9	19	1	0.3	9
4	20	1	0.2	5
3	21	1	0.1	9
5	22	1	0.2	7
6	23	1	0.2	9
1	24	1	0.1	5
2	25	1	0.1	7
7	26	1	0.3	5
8	27	1	0.3	7

2.4 Fuel flow meter specifications

In the experiment, a DFM 100CD fuel flow metre (Technoton Engineering, Belarus) was used. It had the following specifications: minimum kinematic viscosity of 1.5 mm^2 s^{-1}, maximum kinematic viscosity of 6.0 mm^2 s^{-1}, minimum supply voltage of 10 V, and maximum supply voltage of 45 V (Figure 2).

2.5 Experimental procedures and soil characterization

The particle size distribution analysis was carried out using the hydrometer method modified by Juo

(1979). The percentage of sand, silt and clay were determined based on gravitational sedimentation as governed by stokes law. The percentage proportion of the soils were simulated, and the soil class was determined. The soil texture was also established using soil textural triangle according to United State Department of Agriculture (USDA). Table 2 illustrates, the soil texture grades at various depths denoted by A, B, and C.

Figure 1 Disc plough and disc ridger (Baldan implementos agricolas, Brazil)

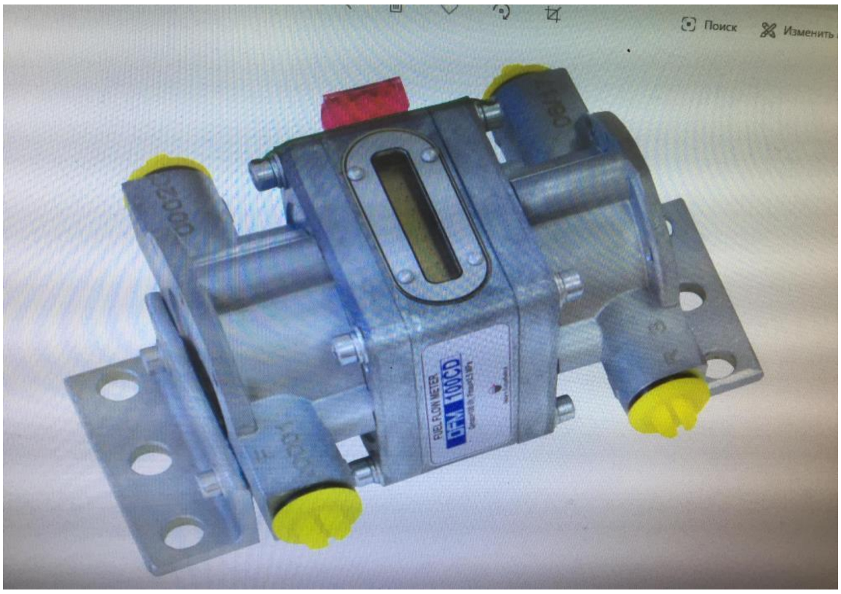


Figure 2 DFM 100CD fuel flow meter (Technoton Engineering, Belarus)

Prior to tillage operation, the tractor's top links were used to level the disc plough before the ploughing operation, this aided in lessening the effects of parasitic pressures. The lifting mechanism's level control (the three-point linkage height) was adjusted to lower the disc plough to the appropriate ploughed depths, which allowed for the determination of the ploughing depths. A stopwatch that was reset to zero before each operation was used to calculate the operation time and measure the ploughing depth. A similar operation was carried out on the ridger to reduce parasitic forces. To calculate tractor fuel usage, the digital fuel measurement technique was utilized. Fuel use was measured during this procedure using a DFM fuel flow meter. Using Equation 1, the hourly fuel usage was determined (Shafaei et al., 2018).

$$FC_h = \frac{T_{fc}}{h} \quad (1)$$

Where: FC_h = Fuel use per hour (L h^{-1}); T_{fc} = Tractor fuel use, L; h = time (hour, h).

Table 2 Soil textural class (particle size distribution)

		Percentage, % by mass			Textural class
Sample	Depth, *d* (cm)	Clay	Silt	Sand	(USDA)
A	0 – 10	9.60	6.80	83.60	Loamy sand
B	11 – 20	8.60	9.80	81.60	Loamy sand
C	21 – 30	12.60	6.80	80.60	Sandy loam

2.6 Model fitness adequacy

Before conducting any statistical analysis, the model fitness adequacy for tractor hourly fuel use for the tillage activities was tested. This was done to validate various residual assumptions. According to Ekemube et al. (2020), residual is often defined in statistics as the difference between the measured and expected response value. The experimental run yielded the measured tractor hourly fuel consumption (actual response) figures used in this investigation, which are shown in Table 1. Three assumptions about the residuals are governed by fitness adequacy: (1) the residuals' normality assumption; (2) the residuals' constant variance; and (3) the residuals' independent assumption. Given the fitness of these hypotheses, it can be concluded that Equation 2, the regression model that was developed, provides a typically accurate representation of the measured data. Numerous statistical residual plots, including the Pareto chart of the standardized effects, the plot of residuals in observation order, the plot of residuals versus fitted or predicted values, the histogram of frequency versus residuals, and the plot of residuals in normal probability all supported these three hypotheses.

2.7 Statistical analysis

Analysis of variance (ANOVA), normal probability plot, residual versus fits plot, interaction plot, and response optimizer were the statistical studies performed. To find statistically significant changes between the treatment means, a two-way ANOVA was used. MINITAB 19 software (Minitab Inc., State College, PA, USA) was used to perform statistical analyses at a 95% and 99% confidence level ($p < 0.05$ and $p < 0.01$ significance levels).

Analysis of variance (ANOVA) was conducted to evaluate the statistical significance of operating factors to responses of a particular developed product or application (Abdel-Ghani et al., 2009; L'Hocine and Pitre, 2016; Mohammed Razzaq et al., 2020). In this study, ANOVA was used to showed the significance of the effects of tillage depth (d) or height (h), and tractor forward speed (V) on the responses, such as tractor hourly fuel consumption during ploughing and ridging were determined, by observing F value at 5% and 1% significance levels and probability value, also commonly known as 'p-value' of the analysis. Generally, the null hypothesis (H_0) of ANOVA states that one or more than one operating factor do not cause a significant difference in means of any responses; H_0: $\mu 1 = \mu 2 = \ldots = \mu a$ (Anderson, 2001; Montgomery, 2013). The p-value has to be equal or less than 0.05 for the operating factors to be statistically significant for the investigated response (Prakash et al., 2008; Abdel-Ghani et al., 2009; Saadat and Karimi-Jashni, 2011; Mutuk and Mesci, 2014; Salleh et al., 2015; L'Hocine and Pitre, 2016; Mohammed Razzaq et al., 2020).

2.8 Prediction equations

The multiple linear regression model representing hourly fuel use of the tractor during ploughing and ridging operations was expressed as a function of depth and forward speed being the input variable of tractor hourly fuel use (response). To find the response equation, d_1, d_2, d_3 are assigned to depths (for both ploughed depth and ridge depth) and V_1, V_2, V_3 assigned to tractor forward speed respectively. The multiple linear regression models with two variables (d and V) with their interaction terms can be expressed as in Equation 2. Thus, the estimated linear regression models are:

$$FC_h = \alpha + \beta_1 d_1 + \beta_2 d_2 + \beta_3 d_3 + \beta_4 V_1 + \beta_5 V_2 + \beta_6 V_3 + \beta_{11} d_1 V_1 + \beta_{12} d_1 V_2 + \beta_{13} d_1 V_3 + \beta_{21} d_2 V_1 + \beta_{22} d_2 V_2 + \beta_{23} d_2 V_3 + \beta_{31} d_3 V_1 + \beta_{32} d_2 V_2 + \beta_{33} d_3 V_3 \quad (2)$$

Where: FC_h = Hourly fuel consumption, L h^{-1};α = Intercept (Average value of the result); β_1, β_2, β_3, β_4, β_5, β_{11}, β_{12}, β_{13}, β_{21}, β_{22}, β_{23}, β_{31}, β_{32}, and β_{33}, = Interactions' coefficients; $d_{12,3}$ = depths, m; $V_{1,2,3}$ = velocity, km h^{-1}.

The multiple linear regression models were formulated by Minitab 19 interactive statistical data analysis tool for factoring designs.

2.9 Validation of the multiple linear regression model

The developed multiple linear regression models were verified by utilising the model to simulate the experimental data and then use standard error to compare the experimental and predicted data. To determine if the measured and forecasted findings have a good agreement and to assess its validity, the 95% confidence interval and prediction interval, coefficient of determination (r^2), adjusted r^2 (Adj r^2), and predicted r^2 [r^2 (Pred)] were utilised. The computer programme Minitab-19 (Minitab Inc., State College, PA, USA) was used for this.

The coefficient of determination (r^2) as a global statistic to assess the fit of the model was determined using Equation 3 (Montgomery and Runger, 2014; Montgomery, 2017):

$$r^2 = \frac{SS_{model}}{SS_T} \tag{3}$$

SS_{model} was computed using Equation 4 (Montgomery and Runger, 2014; Montgomery 2017):

$$SS_{model} = SS_d + SS_V + SS_{dV} \tag{4}$$

The adjusted r^2 (r^2_{Adj}) was computed using Equation 5 (Montgomery and Runger, 2014; Montgomery, 2017):

$$r^2_{Adj} = 1 - \frac{SS_E/(n-p)}{SS_T/(n-1)} \tag{5}$$

The predicted r^2 (r^2_{Pred}) was computed using Equation 6 (Montgomery and Runger, 2014; Montgomery 2017):

$$r^2_{Prediction} = 1 - \frac{PRESS}{SS_T} \tag{6}$$

Where: $PRESS$ = Prediction error sum of squares.

The PRESS statistic is defined as the sum of squares of the n PRESS residuals, and it was calculated using Equation 7 (Montgomery and Runger, 2014; Montgomery, 2017):

$$PRESS = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} \left[Y_i - \hat{Y}_{(I)}\right]^2 \tag{7}$$

Where: e_i = Prediction error (ith PRESS residual); Y_i = Predicted data; $\hat{Y}_{(I)}$ = Mean of predicted data.

2.10 Optimization of the tractor fuel consumption

This study was based upon the optimization of tractor hourly fuel consumption. The optimization was carried out by varying two factors: different ploughing depths or ridge height, and tractor forward speeds. Three different depths or heights (0.10, 0.20, and 0.30 m), as well as three tractor forward speeds of 5, 7, and 9 km h^{-1} were used. ANOVA and optimization graph were employed for the optimization of the response variables (tractor hourly fuel consumption) within the 95% confidence and prediction intervals. The desirable point for the response optimizer was achieved at the best corresponding minimum tractor hourly fuel consumption with the combination of operating conditions (ploughing depth and tractor forward speed).

Composite desirability was computed using Equation 8 (Minitab 18 Support, 2019):

$$D = \left[n\left(d_i^{w_i}\right)\right]^{\frac{1}{W}} \tag{8}$$

Where: D = Desirability; d_i = Individual desirability for the ith response; w_i = Importance of the ith response; W = Summation of w_i; n = Number of responses.

In addition, Individual desirability (d_i) for the minimization ith response was computed as represented in Equation 9 (Minitab 18 Support, 2019b):

$$d_i = \left[\left(U_i - \hat{Y}_i\right)/\left(U_i - T_i\right)\right]^{r_i} \tag{9}$$

Where: $\hat{Y}_i$ = Predicted value of ith response; U_i = Highest acceptable value of ith response; T_i = Targeted value of ith response; r_i = Weight of desirability function of ith response.

The optimization process was performed with Minitab-19 (Minitab Inc, State College, PA, USA).

This subsequently led to having the optimization regression model to be:

$$FC_h = \alpha + \beta_1 d_1 + \beta_2 d_2 + \beta_3 d_3 + \beta_4 V_1 + \beta_5 V_2 + \beta_6 V_3 + \beta_{11} d_1 V_1 + \beta_{12} d_1 V_2 + \beta_{13} d_1 V_3 + \beta_{21} d_2 V_1 + \beta_{22} d_2 V_2 + \beta_{23} d_2 V_3 + \beta_{31} d_3 V_1 + \beta_{32} d_2 V_2 + \beta_{33} d_3 V_3 \tag{10}$$

3 Results and discussion

3.1 Soil textural classification

Prior to each of the tillage procedures under study, the air-dried soil's particle size distribution (PSD) revealed the relative amounts of different-sized soil particles, including sand, silt, and clay (Table 2). The soil texture was classified as sandy loam at depths of 20–30 cm and as loamy sand at depths of 0–10 cm and 10–20 cm, respectively, using the United States

Department of Agriculture's (USDA) system.

Table 3 Ploughing fuel consumption model prediction

Block	d (m)	V (km h^{-1})	FCh (m) (L h^{-1})	FCh (p) (L h^{-1})	PSE
1	0.1	5	2.93	2.93	0.002222
1	0.1	7	4.14	4.14	0.002222
1	0.1	9	4.24	4.23333	0.002222
1	0.2	5	4.25	4.25	0.002222
1	0.2	7	5.98	5.98	0.002222
1	0.2	9	6.15	6.15	0.002222
1	0.3	5	6.36	6.36	0.002222
1	0.3	7	8.95	8.95	0.002222
1	0.3	9	9.19	9.19	0.002222
2	0.1	5	2.91	2.93	0.002222
2	0.1	7	4.12	4.14	0.002222
2	0.1	9	4.22	4.23333	0.002222
2	0.2	5	4.23	4.25	0.002222
2	0.2	7	5.96	5.98	0.002222
2	0.2	9	6.13	6.15	0.002222
2	0.3	5	6.34	6.36	0.002222
2	0.3	7	8.93	8.95	0.002222
2	0.3	9	9.17	9.19	0.002222
3	0.1	5	2.95	2.93	0.002222
3	0.1	7	4.16	4.14	0.002222
3	0.1	9	4.24	4.23333	0.002222
3	0.2	5	4.27	4.25	0.002222
3	0.2	7	6	5.98	0.002222
3	0.2	9	6.17	6.15	0.002222
3	0.3	5	6.38	6.36	0.002222
3	0.3	7	8.97	8.95	0.002222
3	0.3	9	9.21	9.19	0.002222

Note: d = ploughing depth, V = tractor forward speed, FC_h = hourly fuel consumption, PSE = pseudo standard error.

Table 4 Ridging fuel consumption model prediction

Block	Height, h (m)	Speed, V (km h^{-1})	Hourly Fuel Consumption, FC_h (L h^{-1})	FC_h (p) (L h^{-1})	PSE
1	0.1	5	3.3	3.3	0.005774
1	0.1	7	4.25	4.27	0.005774
1	0.1	9	4.36	4.36	0.005774
1	0.2	5	4.76	4.76	0.005774
1	0.2	7	6.09	6.11	0.005774
1	0.2	9	6.24	6.26	0.005774
1	0.3	5	7.13	7.15	0.005774
1	0.3	7	8.84	8.86	0.005774
1	0.3	9	9.38	9.4	0.005774
2	0.1	5	3.28	3.3	0.005774
2	0.1	7	4.27	4.27	0.005774
2	0.1	9	4.34	4.36	0.005774
2	0.2	5	4.74	4.76	0.005774
2	0.2	7	6.11	6.11	0.005774
2	0.2	9	6.26	6.26	0.005774
2	0.3	5	7.15	7.15	0.005774
2	0.3	7	8.86	8.86	0.005774
2	0.3	9	9.4	9.4	0.005774
3	0.1	5	3.32	3.3	0.005774
3	0.1	7	4.29	4.27	0.005774
3	0.1	9	4.38	4.36	0.005774
3	0.2	5	4.78	4.76	0.005774
3	0.2	7	6.13	6.11	0.005774
3	0.2	9	6.28	6.26	0.005774
3	0.3	5	7.17	7.15	0.005774
3	0.3	7	8.88	8.86	0.005774
3	0.3	9	9.42	9.4	0.005774

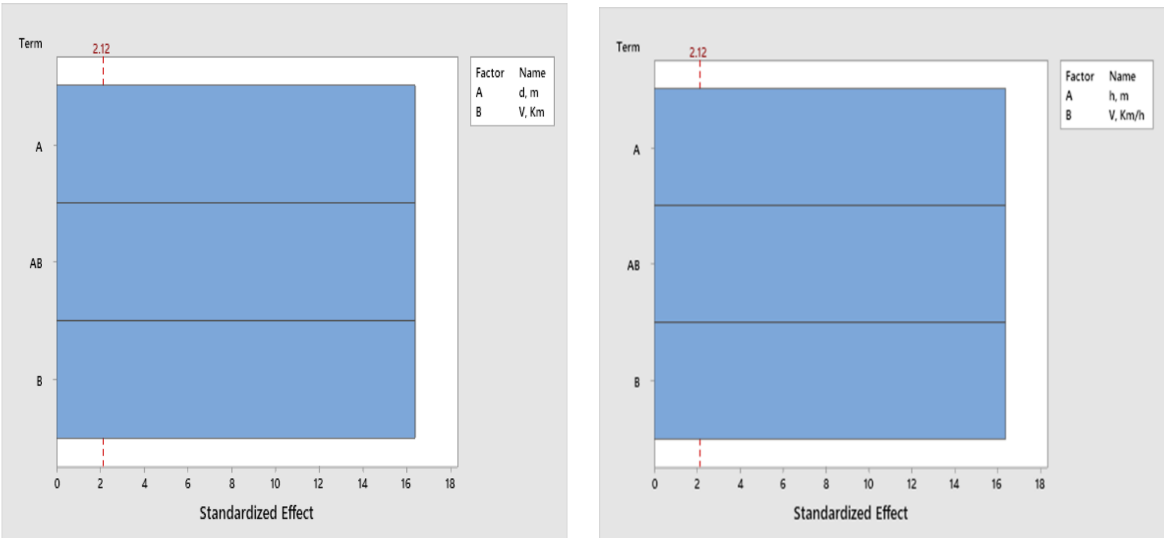
Note: h = ridge height, V = tractor forward speed, FC_h = hourly fuel consumption, PSE = pseudo standard error.

3.2 Ploughing and ridging fuel consumption

The predictions of fuel consumption, plough depth (or ridge height), and tractor forward during ploughing and ridging operations were shown in Table 3 and 4 respectively. Table 3 showed that the increase in ploughing depth and forward speed led to a corresponding increase in the fuel consumption. This result corroborates with the findings of Shafaei et al. (2018), Nkakini and Ekemube (2020), and Ekemube et al. (2021) on depth of ploughing in sandy soils. From Tables 4, the increase in ridging heights and forward speed correspondingly increased the tractor hourly fuel consumption. This corroborates with the findings of Igoni et al. (2020) on the ridging of agricultural soils.

3.3 Tractor fuel consumption model fitness adequacy

The Pareto chart of the standardised impacts on the hourly fuel use of the tractor during the investigated ploughing and ridging activities is shown in Figure 3. According to Shafaei et al. (2018), the Pareto chart of the standardised effects helps determine the size and significance of an effect. A Pareto chart, where t is the (1 - α/2) quantile of a t-distribution with degrees of freedom equal to the degrees of freedom (24) for the error term, illustrates the absolute value of the effects and draws a reference line at the t-value limit (Kukreja et al., 2011). A statistically significant effect is one that lies behind the reference line; a statistically insignificant effect is one that falls within the reference line. A, B, and AB (which suggested d (depth for a plough (Figure 3, a) or height for a ridge (Figure 3, b)), *V* (tractor speed), and *dV*) are statistically significant, according to the chart in Figure 3 (i and ii). The components with the biggest standardised effect on the hourly fuel usage were d, V, and dV (Figure 3).



(a) Ploughing chart (b) Ridging chart

Figure 3 Standard effect of ploughing and ridging on fuel consumption

Note: $\alpha = 0.05$

The hourly consumption residual plots from the ploughing operation are shown in Figure 4. From the normal probability plots (Figure 4), it was observed that the residual points are scattered randomly on both sides of the straight line. This suggests that the hourly fuel use data during ploughing was approximately normally distributed, which satisfies the first condition of model fitness examination. The histogram plot (Figure 4), which showed an approximately normal distribution and the high model prediction of ploughing operations, corroborated this fact. Additionally, the data points for hourly fuel use data during ploughing are distributed randomly without substantial structure, as shown by the residual data versus fitted value plots (Figure 4), supporting the constant variance condition of the residuals. The residual points are entirely random regardless of the observation order, as demonstrated by the plot of residual versus observation order (Figure 4), which suggested that the residuals were independent of one another. The regression model (Equation 10) could accurately represent the experimental data for tractor hourly and tilled area fuel use during ploughing operation after considering all the residuals' assumptions.

From Figure 5, the residual points were scattered randomly on both sides of the straight line which implied that the hourly fuel use during ridging operations were approximately normally distributed and satisfied the first condition of model fitness. The histogram plot (Figure 5) displayed an approximately normal distribution, which further supported the usual distribution of the tractor hourly fuel use. The hourly fuel use during ridging was randomly distributed in the residual versus fitted value plots (Figure 5), supporting the constant variance criteria of the residuals. The residual points were totally randomised, as demonstrated by the residual versus observation order plot (Figure 5), suggesting that the residuals were independent of one another. The regression model (Equation 10) was able to forecast the tractor hourly fuel use during ridging operations with a high degree of reliability after observing all the residuals' assumptions.

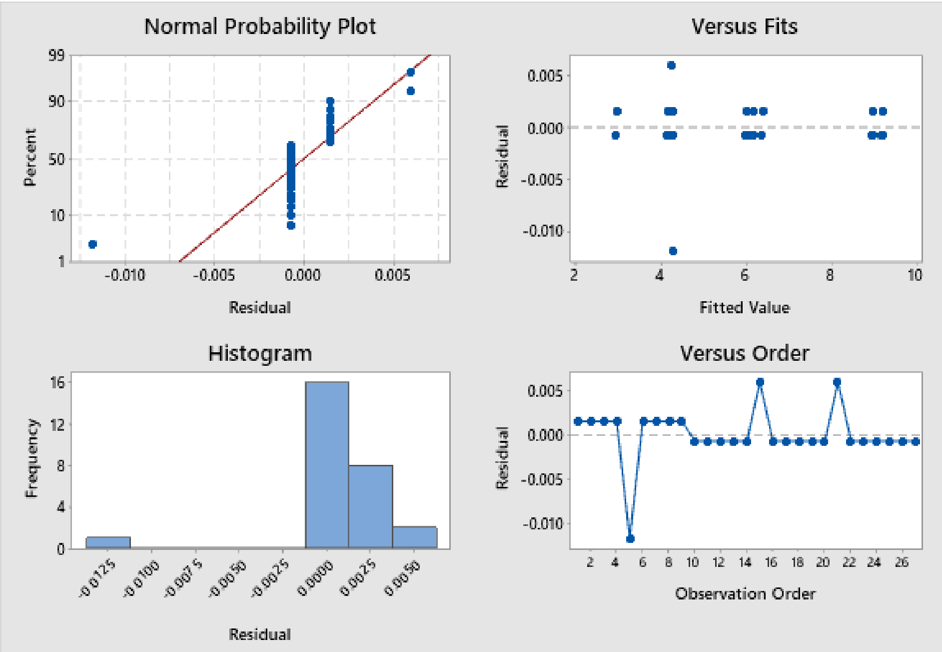


Figure 4 Model competence for tractor fuel consumption during ploughing

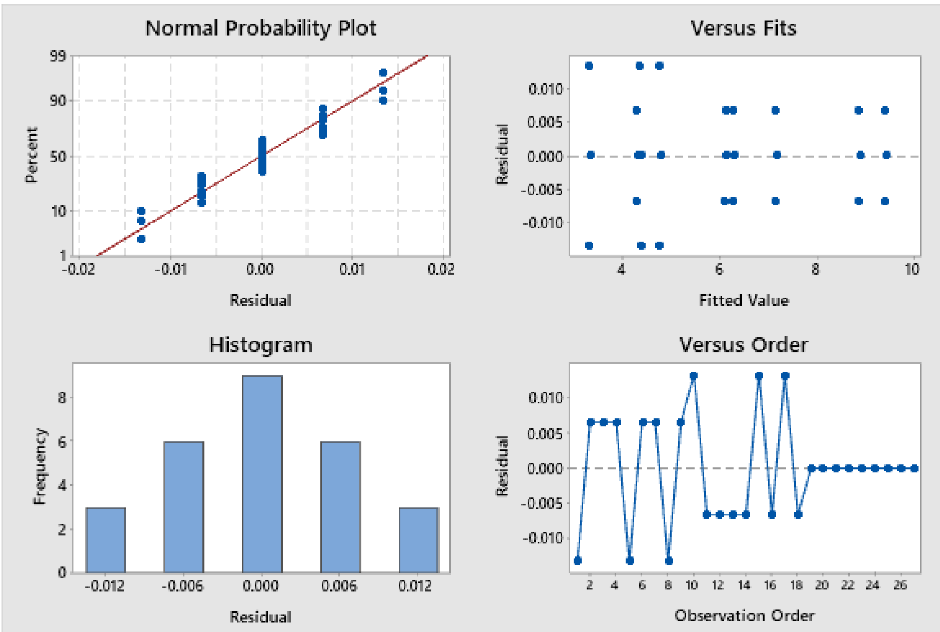


Figure 5 Model competence for tractor fuel consumption during ridging

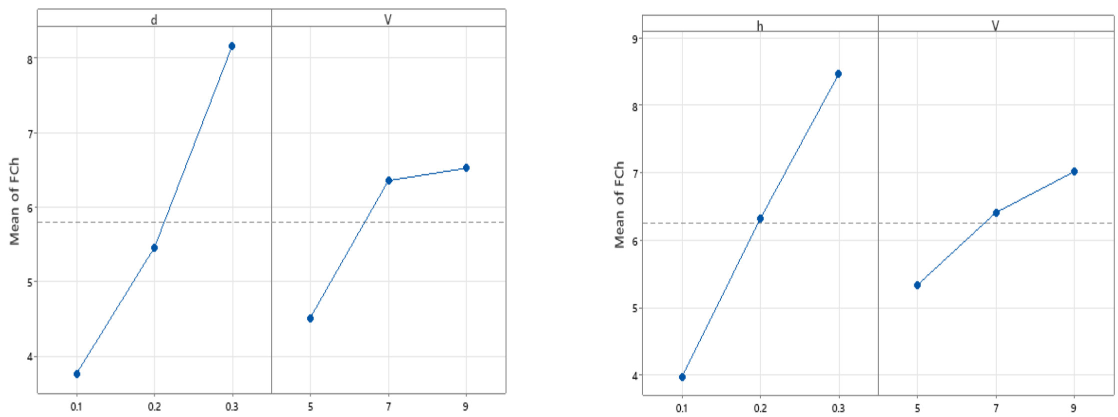
3.4 Effect of tillage depth and tractor forward speed on tractor fuel efficiency

The main and interaction plots (Figures 6 and 7) illustrated the single and the combination effects of tillage depth and forward speed (at three different levels) to the response of hourly fuel use during ploughing. The slope of the plots indicated the relative strength for the effect of the factors (tillage depth or height, and tractor forward speed). Inclusion of center point to the design indicated that a curvature was detected between the levels. In Figure 6a, 2.93 L h^{-1} was detected as minimum hourly fuel consumption, which was achieved at a plough depth of 0.10 m and tractor forward speed of 5 km h^{-1}. The results also showed 54% hourly fuel use (L h^{-1}) increase from ploughing at depth of 0.1 m to 0.3 m at forward speed of 5 to 9 km h^{-1} respectively. This finding corroborates with the suggestion of Aboukarima (2016) on fuel use in tillage operations where the researcher suggested that increased speed in tillage operations may lead to increased fuel use. From the interaction plots (Figure 6), it was observed that by reducing the ploughing depth and forward speed, hourly fuel consumption was correspondingly reduced. Conversely, the interaction plots (Figure 7) showed that the lines are unparalleled to each other, which implied that there was interaction between the factors such as ploughing depth and forward speed. These results agreed with the findings of Adewoyin and Ajav (2013) and Shafaei et al. (2018) on tractor forward speed in tillage operations.

In Figures 6 and 8 plots of main and interaction effects consisting of mean response (hourly fuel use for ridging) values at different levels of factors (ridging height and forward speeds). The slope of the plots (Figures 6b and 8) indicated the relationship between the effect of the factors (that is ridging height and forward speed) and the center point which revealed the curvature detected between the levels. From Figure 6b, the optimum hourly fuel consumption (L h^{-1}) was achieved at 3.30 l h^{-1} for a ridge height of 0.10 m and forward speed of 5 km h^{-1}. The hourly fuel consumption (ln h^{-1}) increased by 53.5% from ridge height of 0.1 m to 0.3 m at forward speed of 5 to 9 km h^{-1}. This result agreed with the findings of Igoni et al. (2020) on maximalizing fuel use. The interaction plots (Figure 8) showed unparallel plots (implying various levels of interactions between factors) which indicated that reducing ridge height and tractor forward speed could subsequently reduce hourly fuel consumption.

Comparing the mean of the treatments with the main effects (plough depth and forward speed) during ploughing, the ANOVA findings (Table 5) revealed significant impacts. Additionally, the calculated "*F*" value (36553.00) for the interactions between d and V was greater than the table "F" value (3.63), which indicated a significant difference at the 5% and 1% levels of significance. For all responses, the p-value for the "*d*" and "*V*" linear factors as well as the "*dV*" interaction factor is zero (0.000), suggesting a stronger significant effect. This result corroborates with the findings of Prakash et al. (2008). From Table 5, it can be inferred that both plough depth (d) and forward speed (V) significantly influenced the hourly fuel use during ploughing.

The main effects of ridge height and forward speed during ridging were the subject of an ANOVA, shown in Table 6. The calculated "*F*" values (462181.33 and 66642.33) are greater than the table "F" values (3.63 and 6.23, respectively), indicating a significant difference between the means at the 5% and 1% levels of significance. There is a substantial difference between the means at the 5 and 1 percent significance levels, as indicated by the interactions of h and V with calculated "F" value (2793.33) greater than table "F" value (3.63). For all responses, the p-value for the "*h*," "*V*," and "*hV*" interaction factor was zero (0.000), which is less than the probability level ($p < 0.05$). This implied that both ridge height (h) and tractor forward speed (V) operating factors significantly influenced the tractor hourly fuel consumption during ridging. Prakash et al. (2008) stated that when the p-value is less than 0.05, the factor is regarded to have a higher significant effect on the response.



(a) Plot of main effects on FCh for ploughing (b) Plot of main effects on FCh for ridging

Figure 6 Effect of ploughing and ridging depth and tractor forward speed on fuel consumption

Note: FCh, d, and V are measured in L h^{-1}, m, and km h^{-1} respectively.

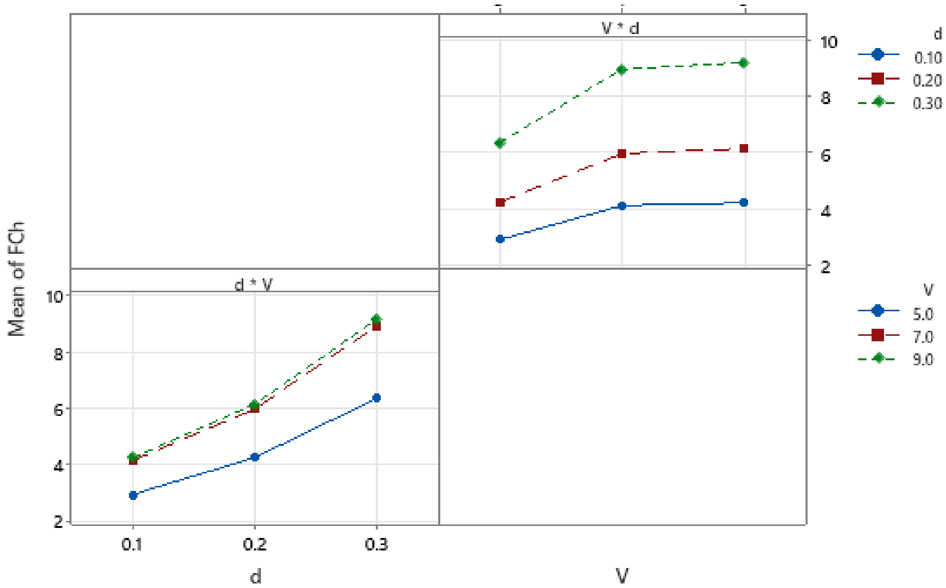


Figure 7 Effect of ploughing depth and tractor forward speed on fuel consumption

Note: FCh, d, and V are measured in L h^{-1}, m, and km h^{-1} respectively.

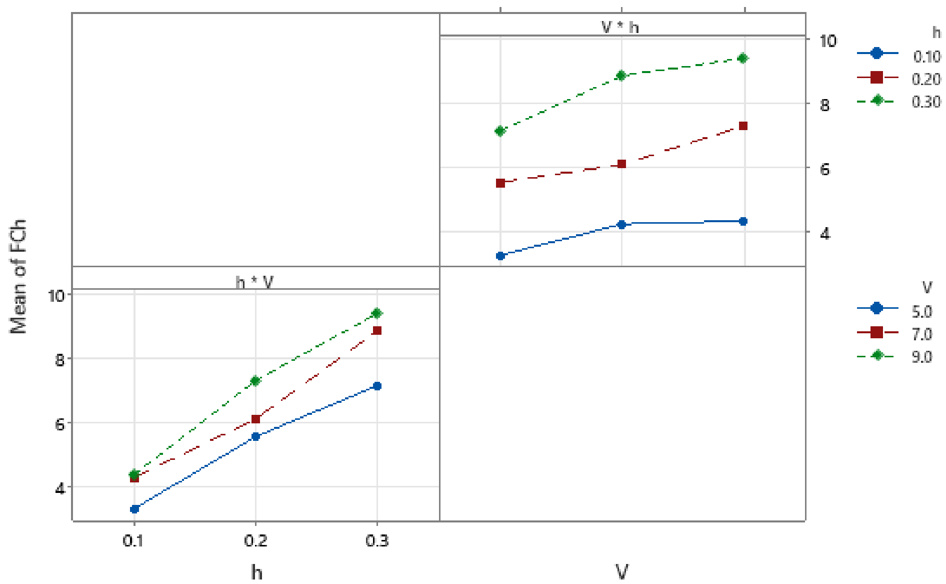


Figure 8 Effect of ridging height and tractor forward speed on fuel consumption

Note: FCh, d, and V are measured in L h^{-1}, m, and km h^{-1} respectively.

Table 5 2-Way analysis of variance for *FCh* during ploughing

Source	DF	Adj SS	Adj MS	Computed F-Value	Tabular F-Value		P-Value
					5%	1%	
Model	10	113.204	11.3204	764126.80**	2.49	2.69	0.000
Blocks	2	0.006	0.0032	217.00**	3.63	6.23	0.000
Linear	4	111.031	27.7579	1873655.50**	3.01	4.77	0.000
D	2	88.620	44.3098	2990913.25**	3.63	6.23	0.000
V	2	22.412	11.2059	756397.75**	3.63	6.23	0.000
2-Way Interactions	4	2.166	0.5415	36553.00**	3.01	4.77	0.000
dV	4	2.166	0.5415	36553.00**	3.01	4.77	0.000
Error	16	0.000	0.0000				
Total	26	113.204					

Note: *Significant, **Highly significant, ns non-significant

Table 6 2-Way analysis of variance for *FCh* during ridging

Source	DF	Adj SS	Adj MS	Computed F-Value	Tabular F-Value		P-Value
					5%	1%	
Model	10	106.888	10.6888	106887.67**	2.49	2.69	0.000
Blocks	2	0.006	0.0028	28.00**	3.63	6.23	0.000
Linear	4	105.765	26.4412	264411.83**	3.01	4.77	0.000
h	2	92.436	46.2181	462181.33**	3.63	6.23	0.000
V	2	13.328	6.6642	66642.33**	3.63	6.23	0.000
2-Way Interactions	4	1.117	0.2793	2793.33**	3.01	4.77	0.000
hV	4	1.117	0.2793	2793.33**	3.01	4.77	0.000
Error	16	0.002	0.0001				
Total	26	106.889					

Table 7 Estimated coefficient of fuel consumption multiple linear regression model during ploughing

Term				
Blocks	Symbol	Coefficient	SE Coefficient	P-Value
Constant	α	5.79815	0.00074	0.000
D				
0.1	β_1	-2.03037	0.00105	0.000
0.2	β_2	-0.33815	0.00105	0.000
0.3	β_3	2.36815	0.00105	0.000
V				
5	β_4	-1.28481	0.00105	0.000
7	β_5	0.55852	0.00105	0.000
9	β_6	0.72630	0.00105	0.000
dXV				
0.1X5	β_{11}	0.44704	0.00148	0.000
0.1X7	β_{12}	-0.18630	0.00148	0.000
0.1X9	β_{13}	-0.26074	0.00148	0.000
0.2X5	β_{21}	0.07481	0.00148	0.000
0.2X7	β_{22}	-0.03852	0.00148	0.000
0.2X9	β_{23}	-0.03630	0.00148	0.000
0.3X5	β_{31}	-0.52185	0.00148	0.000
0.3X7	β_{32}	0.22481	0.00148	0.000
0.3X9	β_{33}	0.29704	0.00148	0.000

Note: r^2 = 100%, Adj r^2 = 100%, r^2(Pred) = 100%

3.5 Effect of tillage depth and tractor forward speed on tractor fuel efficiency parameters using numerical approach

Irrespective of main and interaction effects plots, there is an available alternative for the expression of the effect of operating factors on specific responses using numerical approach, which may well be accomplished by means of regression model analysis (Montgomery, 2013; Montgomery, 2017; Javed et al., 2020), shown in Table 7 and 8. This regression analysis comprises coefficient of determination (r^2), coefficient of each factor (d (or h), V and dV), standard error (SE) coefficient, values of constant, p-value and regression equation. The comprehensive details of each factor's coefficient, values of constant and p-value are displayed in Tables 7 and 8. The significance of this constant and regression coefficient in the developed multiple linear regression model (Equation 10) was indicated by p-value.

Table 7 showed the calculated coefficients for the hourly fuel usage during ploughing operations and the multiple linear regression model. With a p-value of zero (0.000) and a constant value of 5.79815 for the hourly fuel use throughout ploughing operations, the multiple linear regression model indicated significant significance. The interaction terms (*dV*) (all combinations) had a p-value of 0.00, while the coefficients of factors d (tillage depth) and *V* (tractor forward speeds) had p-values of 0.00 and 0.0.00, respectively. The adoption of established multiple regression analysis revealed that the coefficient of factors (*d* and *V*) and their interaction terms (for hourly fuel use during ploughing) had a p-value of 0.00. Similarly, the coefficient of determination (r^2) value of the multiple linear regression model that has been built determines the significant level of the multiple linear regression equation. The regression analysis yielded the correlation coefficient (r^2) between the expected response (derived from the multiple linear regression model) and the measured response (obtained from the experimental run). Accordingly, the better the precision level of the generated regression model, the closer the r^2 value is to 100% (Al-Hassani et al., 2014). Stated otherwise, the multiple linear regression model may serve as an effective means of representing the measured data. The hourly fuel usage multiple linear regression equation's r^2 value, as determined by Table 7, was 100%. This indicates that 100% of variation in the hourly fuel consumption experimental data could be well explained by the Equation 10 multiple linear regression model. Similarly, the r^2 value (Table 8: for ridging operations) for the hourly fuel consumption multiple linear regression equation was 100%. Solaiman et al. (2016), stated that experimental data could be well explained when r^2 of the regression model is 100%.

Table 8 Estimated coefficients for FC_h multiple linear regression model during ridging

Term				
Blocks	Symbol	Coefficient	SE Coefficient	*p*-value
Constant	α	6.05222	0.00192	0.000
h				
0.1	β_1	-0.01333	0.00272	0.000
0.2	β_2	-0.00667	0.00272	0.000
0.3	β_3	2.41778	0.00272	0.000
V				
5	β_4	-0.98222	0.00272	0.000
7	β_5	0.36111	0.00272	0.000
9	β_6	0.62111	0.00272	0.000
h*V				
0.1*5	β_{11}	0.30556	0.00385	0.000
0.1*7	β_{12}	-0.06778	0.00385	0.000
0.1*9	β_{13}	-0.23778	0.00385	0.000
0.2*5	β_{21}	0.03222	0.00385	0.000
0.2*7	β_{22}	0.03889	0.00385	0.000
0.2*9	β_{23}	-0.07111	0.00385	0.000
0.3*5	β_{31}	-0.33778	0.00385	0.000
0.3*7	β_{32}	0.02889	0.00385	0.000
0.3*9	β_{33}	0.30889	0.00385	0.000

Note: r^2 = 100%, Adj r^2 = 100%, r^2(Pred) = 100%

Another criterion to evaluate the degree of accuracy of a regression model is the adjusted r^2 (Adj r^2) (Mutuk and Mesci, 2014). This is the correction of r^2 in view of sample size and number of terms in the regression equation (Javed et al., 2020). From the analysis (Table 7 and 8), the hourly fuel consumption multiple linear regression model during ploughing had Adj r^2 value of 100%, which implied that the accuracy of the model is 100%. This model could well represent the actual measurement data of hourly fuel consumption during ploughing and ridging. In addition, predicted r^2 or r^2(pred.) of the hourly fuel consumption during ploughing and ridging were 100%. This indicated that 100% of the hourly fuel consumption data during ploughing and ridging could be predicted by the multiple linear regression model (Equation 10). According to Palkar and Shilapuram (2015), a highly reliable regression model would be produced if the difference between r^2(adj.) and r^2(pred.) was less than 20. The results of this investigation showed that there as no difference between r^2(adj.) and r^2(pred.) for the hourly fuel consumption used for ridging and ploughing. As can be seen from Tables 7 and 8, the generated multiple linear regression model (Equation 10) for the tractor hourly fuel consumption was highly significant based on the p-value, r^2, r^2(adj.), and r^2(pred.) criteria. This implied that the estimated multiple linear regression model created for the tractor's hourly fuel usage during ploughing and ridging accounted for all of the variability in the dataset.

Table 9 Optimization simulation result for FC_h during ploughing

Solution	d, m	V, km h^{-1}	FC_h (m), L h^{-1}	FC_h, L h^{-1} Fit	Composite Desirability
1	0.1	5	2.93	2.93000	0.996825
2	0.1	7	4.14	4.14000	0.804762
3	0.1	9	4.24	4.23333	0.789947
4	0.2	5	4.25	4.25000	0.787302
5	0.2	7	5.98	5.98000	0.512698
6	0.2	9	6.15	6.15000	0.485714
7	0.3	5	6.36	6.36000	0.452381
8	0.3	7	8.95	8.95000	0.041270
9	0.3	9	9.19	9.19000	0.003175

Table 10 Optimization simulation result for FC_h during ridging

Solution	h, m	V, km h^{-1}	FC_h, L h^{-1} (m)	FC_h, L h^{-1} Fit	Composite desirability
1	0.1	5	3.30	3.30	0.996743
2	0.1	7	4.25	4.27	0.838762
3	0.1	9	4.36	4.36	0.824104
4	0.2	5	4.76	4.76	0.758958
5	0.2	7	6.09	6.11	0.539088
6	0.2	9	6.24	6.26	0.514658
7	0.3	5	7.13	7.15	0.369707
8	0.3	7	8.84	8.86	0.091205
9	0.3	9	9.38	9.40	0.003257

3.6 Optimal response (tractor fuel efficiency parameters) for tillage

Based on the multiple linear regression model developed, the optimal condition of controlled factors or variables might be determined to achieve desired operating conditions for tractor fuel efficiency parameters during the studied tillage operations, using responses optimizer in MINITAB 19. Table 9 and 10, and Figure 9 and 10, showed the optimization plot and the optimal solution for the desired responses (hourly fuel consumption during ploughing and ridging). From the analysis, the minimum hourly fuel consumption during ploughing was 2.93 L h^{-1} at 0.10 m plough depth and 5 km h^{-1} tractor forward speed with composite desirability (D) of 0.996825 which was greater than 0.90 and closer to 1.00 (Table 9 and Figure 9). Similarly, the minimum hourly fuel consumption during ridging was 3.30 l h^{-1} at 0.10 m ridge height and 5 km.h^{-1} tractor forward speed with composite desirability (D) of 0.996743 which was also greater than 0.90 and closer to 1.00 (Table 10 and Figure 10). A statistical measure to confirm the accuracy of the optimisation plot is the composite desirability (D) (Ciopec et al., 2012). Chang et al. (2015) have demonstrated that when the composite desirability (D) is closer to 1.00, the optimisation of factors and answers derived from the statistical analysis is very accurate and dependable. As a result, the optimal solution outcomes in Tables 9 and 10 and the optimal circumstances suggested in the optimisation plot (Figures 9 and 10) were both entirely consistent with the multiple linear regression model that was built and very dependable.

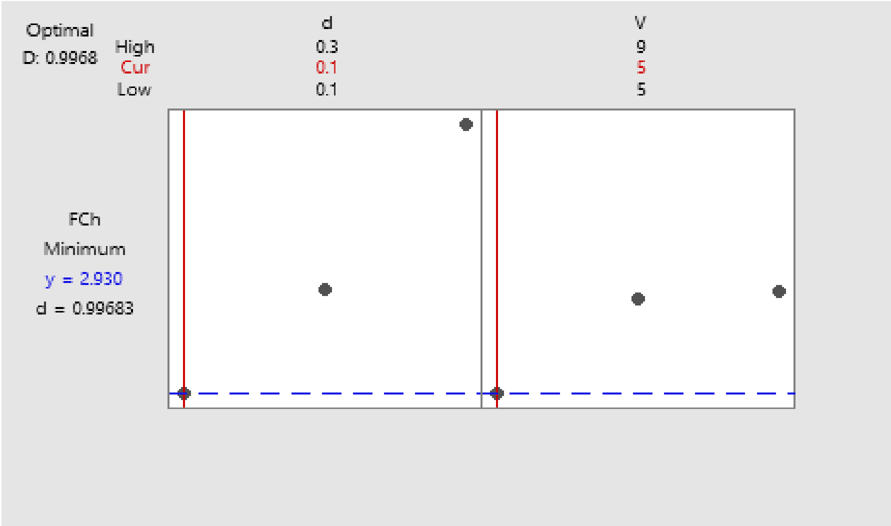


Figure 9 Fuel consumption optimization for ploughing

Note: FCh, d, and V are measured in L h^{-1}, m, and km h^{-1} respectively.

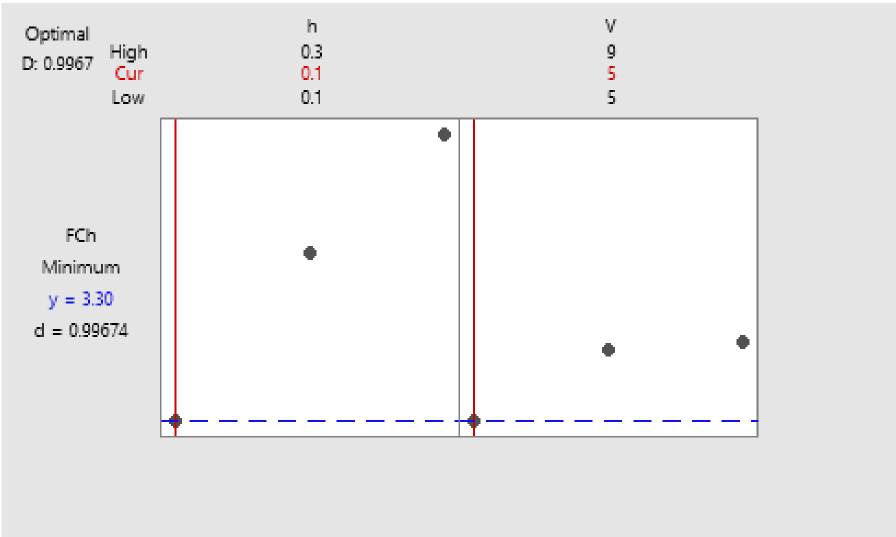


Figure 10 Fuel consumption optimization for ridging

Note: FCh, d, and V are measured in L h^{-1}, m, and km h^{-1} respectively.

4 Conclusion

The factorial experimental design approach successfully optimized tractor hourly fuel use parameters during ploughing and ridging operations. From this study it was established that tillage depth (d) or height (h), forward speed (V), and the interaction of d, V, and dV are statistically significant on the hourly fuel use during the ploughing and ridging operations. The residual versus fitted value plots illustrated that the data points for hourly fuel use data during ploughing and ridging are distributed randomly, confirming the constant variance criterion of the residuals. These results supported the conclusion that the multiple linear regression model generated predicted the experimental data for tractor hourly fuel consumptions during ploughing and ridging. Changes in ploughing depths of 0.10, 0.20 and 0.30 m impacted fuel consumption during ploughing and ridging operations. Similarly, the change in tractor forward speed of 5, 7 and 9 km h^{-1} influenced tractor fuel use during ploughing and ridging operations. The interactions effects of ploughing depth and tractor forward speed had significant effects at $p<0.05$, and $p<0.01$.

Multiple linear regression models for the effects of tillage depth and tractor forward speed on tractor hourly fuel consumption using numerical approach were developed, with the model predicting 100% of the experimental value. This indicates that the model is reliable and can be adopted for predicting ploughing, and ridging operations in various soils for optimal crop production. The optimized tractor hourly fuel consumption (2.93 L h^{-1} for ploughing and 3.30 L h^{-1} for ridging) was achieved at ploughing depth of 0.10 m and tractor forward speed of 5 km h^{-1}. These optimized conditions had minimal negative impacts on the soil and its environment while yielding the most suitable conditions for sustainable farming.

Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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