Research Article

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Statistical modelling of a tractor tractive performance during ploughing operation on a tropical *Alfisol*

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Abstract: Tractor is the most prominent off-road agricultural machinery that is significant to the global food security. The tractive modelling of tyre–soil interaction and agricultural implement dynamics is a complex phenomenon that require holistic approach. Terramechanics techniques such as empirical, semi-empirical, analytical, and numerical methods such as finite element models and discrete element models have gained traction in tractive performance studies. Some of these approaches are premised on large arrays of variables for modelling tractive performance based on the soil–tyre and tools interactions. In this study, soft computing in R software domain was used to model the tractor tractive performance during ploughing operations on a tropical *Alfisol*. The research farm at the National Centre for Agricultural Mechanization was used for the field experiment. The experimental design was a nested-factorial under a Randomized Complete Block Design having three replications. The input factors were tractor power size, *T*, (60, 65, and 70 hp); tyre inflation pressure, *P*, (83, 124, and 165 kPa); implement configuration, *I*, (2 and 3 bottoms disc plough); and operational speed, *S*, (6.31, 7.90, 9.47, 11.05, and 12.63 km/h). Standard procedures were followed to obtain the measured parameters in the field, which were statistically analysed. Correlation analysis and analysis of variance of the measured parameters at 5% significance level were established. Multiple linear regression was used to develop the model, validated using the 10-fold cross-validation method. The results revealed that the evaluated variables have a range of 1.56–7.79 kN, 5.15–27.20%, 9.10–32.00 cm, 4.50–13.94%, 1.31–1.67 g/cm^3, 95.89–207.78 kPa, and 98.67–295.56 for draught, wheel slip, depth of cut, moisture content, bulk density, cone index (CI), and shear stress, respectively. A positive correlation exists between the towing force (TF) and the measured variables except for the shear stress and CI. The final developed model has seven variables for predicting TF with a 6.5% error and an average of 0.4735 cross validation root mean square error. The model quality of fit achieved an R^2_{Adj} = 0.8754 which satisfactorily described the response variable. The study provides insights into tractive dynamic systems modelling of machine, tractive medium (soil), and agricultural tools anchored on soft computing approach. Its adoption will assist in quality ploughing operation integrating the variables established in the model.

Keywords: tractive modelling, terramechanics, correlation, ANOVA, statistical computing, empirical models

1 Introduction

The advent of tractor in the farming ecosystems has revolutionized the modern farming dynamics. It has brought unique transformation through drudgery reduction, energy resource management and the overall enhancement of farm mechanization objectives [1–3]. A robust field performance delivery from this vital machinery influences the optimum production process and system efficiency. Due to research efforts in tractor and traction dynamics over the years, innovation in farm tractor development has led to the availability of sophisticated and expensive machinery which has cost implications on the budget of farmers. The improper matching of this machinery with the allied implement produces negative impacts on the machine, operator's ergonomics, the working environment such as soil compaction, soil structural

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distortion, pollutants discharge, and the budget of farmer. Accurate prediction of tractor-implement parameters during field work with tillage implements is significant in enhancing the effectiveness of the process [4]. The ability to minimize input resources especially at the production stage is a booster to overall efficiency, productivity, and profitability [5–7].

Tractors are mostly used to perform drawbar activities that involve the movement of force over some distances. Thrust is generated to overcome inherent impediments to motion, thereby achieving useful work. The swiftness to how this important function is achieved is a measure of tractor effectiveness in the field [8–10]. Ideally, a tractor is expected to convert all its chemical energy (fuel) into useful work at the drawbar but this is hardly the case in practice as losses through the drive-train, terrain, and tractive device–soil interaction set in [8,11]. This decimates the gross torque output developed from the power train needed for intermittent operations such as soil tillage. Studies have shown that approximately 20–55% of tractor available energy is wasted at the tractive device–soil interface. The negative effects of these generate lower output and productivity. Factors relating to the machine, operation characteristics, and soil properties influences the power delivery efficiency that can be obtained from a tractor-implement combination [12–14], with the soil properties depicting the most prominent [15]. Ploughing operation as the initial soil manipulation stage is an energy intensive exercise that expend huge force to break soil mass. Draft force depicts the horizontal force required to pull a tillage implement through the soil. This along with other indices are the determining factors in tillage operation efficiency. Accurate draft force predictions are critical for tractor-implement matching which have always been a challenge in the developing economy farming domain. Achieving this will improve machine efficiency, proper machinery selection, production costs reduction, and quality work enhancement [16,17]. Draft force prediction has always been a herculean task because of soil variability and intermittent load that characterized the tillage operations.

Soil properties, tillage depth, and speed of operation are among the many factors that contribute to the draft force of an implement. The type and condition of the soil significantly influence the resistance encountered during tillage operations [18]. The studies by Okayasu et al. [19] and Kim et al. [20] emphasize the influence of soil properties, such as moisture content (MC) , bulk density (BD), cone index (CI), and soil structure, on the draft force exerted by tillage implements. Understanding these soil characteristics and their effects on draft force can aid in selecting the appropriate equipment for specific soil conditions and tillage requirements [21,22].

In addition to soil properties, tillage depth is another critical factor affecting draft force. Azimi-Nejadian et al. [23] and Kim et al. [20] have investigated the relationship between tillage depth and draft force, affirming the need for accurate predictions to optimize tillage practices. Furthermore, the speed of operation plays a significant role in determining the draft force required. Naderloo et al. [24] emphasized the impact of operating speed on draft force, presenting that higher speeds tend to increase the draft force due to increased soil disturbance. Al-Suhaibani et al. [25] have investigated the relationship between forward speed and ploughing depth, and showed that draft force changed non-linearly in a particular tillage system.

Tractor-implement matching and the dynamic tractive interface depict a complex phenomenon due to the intermittent nature of field operation resulting from varying torque and speed. The complexity in soil–tyre interaction and the tool–soil interaction result from the forces acting on a blade that transverse through soil as witness during ploughing. Notable studies in tractor performance improvement during field operations have been documented over the years [15]. These have led to the emergence of improved tractors and mobile systems with high efficiency and stability. The matching of a tractor with an implement requires information on tractor capacity, the implement, and possible load to be imposed. Draft requirements of an implement is premised on the soil characteristics, implement configuration and machine operational conditions. These define the tractive output from a tractor implement combination. Key indices among others are the soil type and moisture content, width and depth of operation, shape and sharpness of the implement, speed of operation, tyre inflation pressure and previous crop planted [26,27]. Studies in terramechanics have adopted majorly four techniques or approaches for vehicle–terrain interaction modelling, namely, empirical methods, semi-empirical methods, analytical methods, and numerical methods [15]. Due to the complexity of these approaches, researchers have investigated the possibility of using soft computing to model the performance of machinery and traction devices both in the laboratory (*in situ*) and on the field. Software packages such as Microsoft Excel, Visual C++, Statistica, Artificial neural network, machine learning, Adaptive network-based fuzzy inference system have been used for such predictions [4,28,29]. Most often these software are paid access packages and the challenge with user interface interactiveness limit their adoption and usability. The soft computing techniques offer robust approach for solving complex real-world problems that involve approximations, ambiguity, partial truth, and imprecision [30]. These have the capacity to extract insights and identify important variables by unravelling complex relationships among multiple variables [31].

R is a computer language that allows user to program algorithms and also use tools that have been programmed by others known as user-contributed package. It uses functions to perform operations. R software is an open access, versatile package with a wide array of applications. The tool is a powerful modern computation environment for data manipulation, statistical computation, and visualization [32]. Several packages are available in the R project for the most diverse areas. Most of them are demonstrated and described only in the manuals available in the Comprehensive R Archive Network (CRAN) repository. There are several fields of knowledge with detailed scientific documentations using R software packages such as statistics, economics, meteorology, medicine, and medical sciences, bioinformatics, data analytics, engineering, soil science, geology, and earth science [33–39]. The application of R software packages for soft computing in tillage and traction dynamic investigations will be an avenue to widen the knowledge base in terramechanics studies toward enhancing process efficiency, system reliability, and optimum performance. Therefore, this study explores statistical computing using multiple linear regression modelling technique on tractor tractive performance during ploughing operation on a tropical *Alfisol*.

2 Materials and methods

2.1 Research conceptual framework

The need to improve operational efficiency and tractive performance of a tractor-implement combination during the initial soil loosen-up process is the focus of this study. Four input variables were investigated to obtain the measured parameters which were statistically analysed using the R software package. Figure 1 presents the experimental flowchart.

2.2 Soil properties and description of the study area

The research farm of National Centre for Agricultural Mechanization, Ilorin was used for the study under real working conditions. The location is 370 m above sea level, longitude 4°30′E and latitude 8°26′N along Ilorin-Lokoja highway, Idofian, Kwara State, Nigeria. It is found under

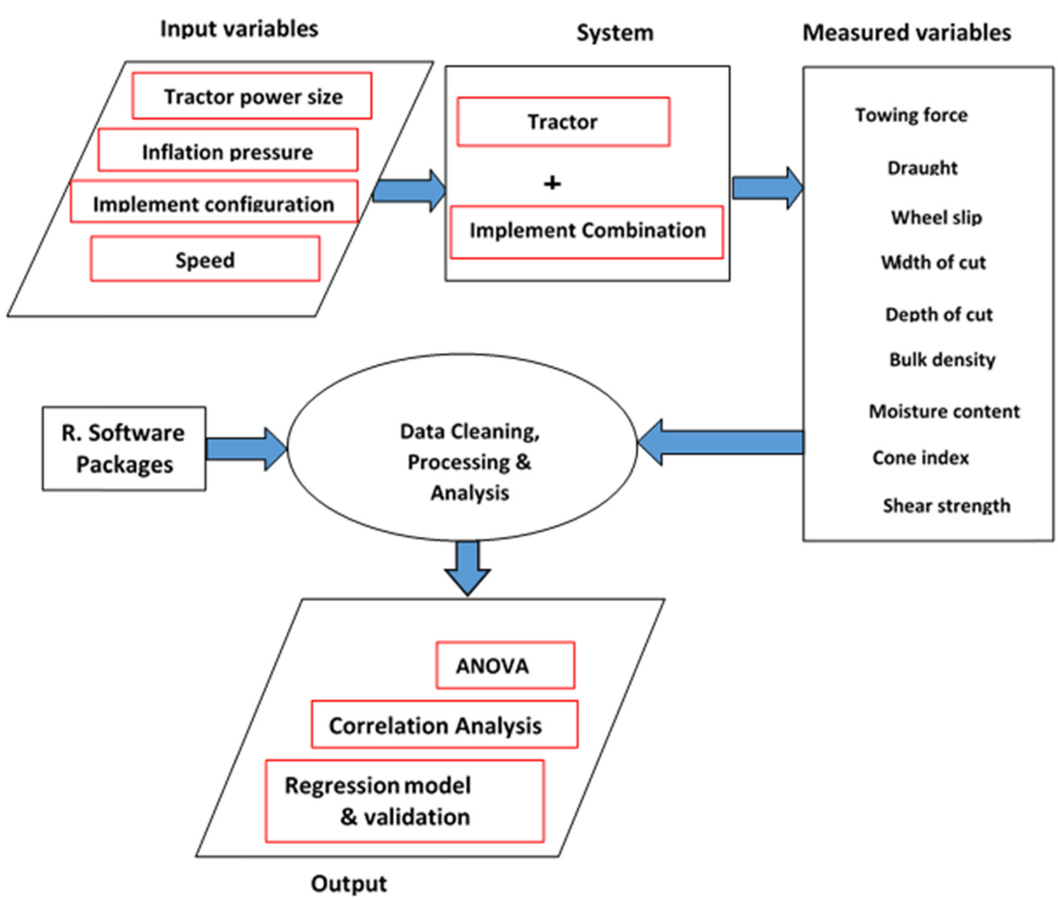

Figure 1: Research procedural approach.

the southern Guinea Savannah agro-ecological zone characterized by a tropical climate with distinct wet and dry seasons, mean annual rainfall of about 1,000 mm, and daily temperature range of 20–35°C [40]

The dominant soil type is a tropical sandy loam classified as *Alfisol* developed on parent material from the basement complex made up of gneisses and granite. The texture of the ploughed layer (0–21 cm) was established to contain 67% sand, 16% silt, and 17% clay with 0.21% organic matter (OM). Experimental site topography is relatively flat and confirmed to be fallow land as it has not been used for any intensive farming for two farming seasons.

2.3 Machine specifications and experimental equipment

Process parameters for the investigation were measured and recorded following standard procedures [41,42]. The tractors used for the research were TS 604 (60 hp), John Deere 5503 (65 hp), and Shuhe SH750 (70 hp) while JS-800 (80 hp) was the auxiliary tractor. The choice was premised on availability and wide acceptability of these power ranges among the farmers and stakeholders in tractor hiring services. The corresponding implements attachment were tractor mounted 3-bottom and Mex Rav, 2-bottom disc ploughs. The specifications of the tractors and the matching implements are presented in Tables 1 and 2. Other equipment used were digital dynamometer, digital pressure gauge, digital weighing balance, cone penetrometer, shear vane apparatus, Memmert electrical oven, toolbox, measuring tape, metre rule, ranging pole, chain, tray, airtight polythene material, cutlass, rope, and pegs.

Table 2: Specifications of matching implements

Item	Disc plough	
	3-Bottom	**2-Bottom**
Implement type	Mounted	Mounted
Disc diameter (mm)	635	550
Type of disc blade	Plane concave	Plane concave
Spacing of discs (mm)	540	545
Average implement draught (D) (kN)	5.02	3.96

2.4 Field layout, experimental structure, and procedures

A 5 ha fallow parcel of land was used for the fieldwork under real-time conditions. Preliminary field preparations and marking out of 270 sample plots were done. Each experimental plot measured 35 m × 4 m considering the plough width. The 35 m length was partitioned into 15 and 20 m. The measured variables were taken in the 20 m portion while the 15 m length was for the tractor speed pick up and stability maintenance. Each tractor was prepared before the fieldwork and the required pressures, 83, 124, and 165 kPa were put into the tractor rear wheel being the traction wheel using a digital pressure gauge, while the front wheels were maintained at the manufacturer's recommended pressures. The tractor-implement combination was investigated at five levels of speed, 6.3, 7.9, 9.5, 11.1, and 12.6 km/h at gear 2 H using the hand throttle.

2.4.1 Experimental measurements of variables

Dillon EDXtreme precision dynamometer (capacity 5,000 lbs/2,000 kgf, accuracy within ±0.1% functional

Table 1: Tractors' specifications used for the fieldwork

Item	Tested tractors, tractor make, and model auxiliary			
	TS 604	**JD 5504**	**Shuhe SH750**	**JS 800**
Effective output (hp)	60	65	70	80
Type of fuel	Diesel	Diesel	Diesel	Diesel
Type of steering system	Hydrostatic	Hydraulic	Hydrostatic	Power steering
Number of cylinders	4	4	4	4
Engine rated speed (rpm)	2,300	2,300	2,200	2,300
Type of cooling system	Water-cooled	Water-cooled	Water-cooled	Water-cooled
Front tyre size	8.3–20	11.2–24	6.50–20	7.50–20
Rear tyre size	13.6–28	16.9–30	14.9–30	16.9–34

specification of the machine, resolution 1 part in 5,000 enhanced and up to 7:1 safety factor) was used to measure the D based on availability. This was connected to the front of the lower size tractor being pulled, on which the plough was mounted using chains. Another tractor of higher capacity tractor called auxiliary tractor (JS 800, 80 hp) was used to pull the plough-mounted tractor through the dynamometer. The auxiliary tractor pulls the plough-mounted tractor with the light tractor in neutral gear, first with the plough raised off the ground to measure the towing force (TF) at no load using dynamometer and theoretical time using a digital stop watch. The same process was repeated for the plough in working condition to obtain the TF under load and actual time. All required measurements were taken within the 20 m portion of the experimental plot. The D was the difference between the TF in neutral gear without implements in tillage operation and TF when the implement was engaged in tillage operations [43].

The shear strength (SS) was measured at three random points within the 20 m sub-plots using vane shear test apparatus, Geonor 05903 model [44]. The measuring meter permits the reading of the actual value of torque with ±0.5% range accuracy of torque. The process involves driving the vane to the desired soil depths, namely, 0–7, 7–14, and 14–21 cm, and then turned using the handle. The obtained results were measured prior to the ploughing operations. This same procedure was used to measure the soil CI at 0–7, 7–14, and 14–21 cm depths using a recording soil cone penetrometer (penetrologger ART.NR. 06.15.01; accuracy of 1%). This device complied with ASABE Standard S313.3 having 12.7 mm diameter 30° conical tip [44]. The CI values represent the force required to push the penetrologger into the soil [45].

Soil MC was measured just prior to tillage, using a manual soil auger at 7, 14, and 21 cm depths, at three random points within each experimental plot. The cylindrical soil auger was driven into the soil until the outer end of the ring assumes the same level with the soil surface. The ring was then pulled out carefully. The excess soil sample was cut out with a knife to the same level of the cylinder rim. The content of the soil auger was gently emptied into a polythene bag that was tight to prevent moisture loss and labelled accordingly. This was weighed and recorded prior to oven drying to affirm the moisture condition of the freshly sampled wet soil using a Tianfu electronic weighing scale (W_1 and W_c) with 0.01 g accuracy. The sample was dried in an open container using a Memmert electrical oven at a controlled constant temperature of 105°C for 24 h to obtain the dry mass (W_2) of the soil to calculate MC and BD using equations (1) and (2) [46]. The direct method of core sampling was used for the BD (g/cm^3) which consist of drying and weighing of soil sample, the volume of which is known [47,48]. The oven-dried soil mass to the volume of the cylindrical soil auger (167 cm^3) gave the soil BD.

$$W = \frac{w_1 - w_2}{w_2 - w_c}, \tag{1}$$

where W = MC (%); W_1 = mass of container + moist soil (g); W_2 = mass of container + oven dry soil (g); and W_c = mass of container (g).

$$\rho_b = \frac{M}{V}, \tag{2}$$

where ρ_b = soil BD (g/cm^3); M = mass of oven-dried soil (g); and V = volume of wet soil, (cm^3)

The theoretical and actual field speeds were measured using a digital stopwatch to record the time taken by the tractor to travel the 20 m specified distance with the specific implement raised up or working in the field, respectively, at the desired speed achieved using the hand throttle and 2 H gear ratio.

The tractor wheel slippage was calculated as a percentage loss of forward speed of the tractor at various levels of the variables considered and their combinations as expressed in equation (3) [49]:

$$\text{Slippage} = \frac{\text{Theoretical speed} - \text{Actual speed}}{\text{Theoretical speed}} \times 100. \tag{3}$$

The width of cut (WC) was measured with a measuring tape while a steel rule was used for the depth of cut (DC). The maximum width and deepest depth were obtained at three points within the 20 m ploughed portion.

2.5 Statistical analysis and algorithmic approach

Analysis of Variance (ANOVA) at 95% confidence level was used to examine which of the measured variables contributed significantly to the response variable. Multiple linear regression analysis provided regression coefficient estimation, t-test, and F-test values. These analyses helped to establish the linear relationship existing between the response variable (TF) and the predictors using the R software package. The experimental design used for data collection has both nested and factorial factors of a linear model structure equation (4).

$$y_{ijkl} = \mu + \alpha_i + \beta_j + \gamma_{k(j)} + (\alpha\beta)_{ij} + (\alpha\gamma)_{ik(j)} + \epsilon_{(ijk)l}, \tag{4}$$

for $\begin{cases} i = 1, 2, 3, 4, 5 \\ j = 1, 2, 3 \\ k = 1, 2 \\ l = 1, 2, 3 \end{cases}$, where y_{ijkl} = tractive force measurement arising from ith speed, jth tractor type with kth implement attached at lth inflation pressure (replicate), μ = overall mean tractive force, α_i = ith speed effect, β_j = jth tractor hp effect, $\gamma_{k(j)}$ = effect of the kth implement within the jth tractor level, $(\alpha\beta)_{ij}$ = speed and tractor hp interaction, $(\alpha\gamma)_{ik(l)}$ = speed and implement within inflation pressure level interaction, and $\epsilon_{(ijk)l}$ = random error term.

Regression analysis help to infer causal relationships between the predictors and response variable. The relationship existing between the TF and the other variables identified to influence tractor tractive performance during ploughing operation was established using the multiple linear regression technique. This is a supervised statistical learning process where both input and output variables were observed and the best mathematical equation that describes the existing relationship was established. Using the least regression approach [50], the mathematical form of the multiple linear regression models in terms of the variables is as follows:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_{3i} X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 X_{6i} + \beta_7 X_{7i} + \beta_8 X_{8i} + \epsilon_i, \tag{5}$$

where Y = TF (kN) of ith tractor, X_1 = D (kN) of ith tractor, X_2 = WS (%) of ith tractor, X_3 = DC (cm) of ith tractor, X_4 = WC (cm) of ith tractor, X_5 = MC (%) of ith tractor, X_6 = BD (g/cm^3) of ith tractor, X_7 = CI (kPa) of ith tractor, X_8 = SS (kPa) of ith tractor, ϵ = random error term; and β_0, β_1, β_2, β_3, β_4, β_5, β_6, β_7, and β_8 are the regression coefficients.

2.5.1 Parameter estimation and hypothesis testing

The estimation of all model parameters was done using the *stats* library of the R software. The research hypotheses adopted were the test adequacy of the fitted models for the data set (F-test) and the significance of the inputs effects in predicting the TF during ploughing operation (t-test). To establish the relationship between the response variable and the predictors, both null and alternative hypotheses were tested with a decision rule that at $\alpha = 0.05$ critical rejection region, there is enough data evidence to reject (H_0) in favour of H_1 if p-value $\le \alpha$, otherwise, there is not enough data evidence to reject H_0.

Null hypothesis ($\boldsymbol{H}_0$): $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = 0$.

Alternative hypothesis H_1: at least one β_j is non-zero.

Test statistic: $F^* = \frac{\text{Regression | Mean | Square}}{\text{Error | Mean | Squares}} = \frac{(\text{TSS} - \text{RSS})/p}{\text{RSS}/(n-p-1)}$,

where,

$$\text{TSS} = \sum (y_i - \bar{y})^2 \text{ and } \text{RSS} = \sum (y_i - \hat{y}_i)^2.$$

Similarly, to test whether a certain subset q of the coefficients is zero, both null and alternative hypotheses were used.

Null hypothesis (H_0): $\beta_{p-q+1} = \beta_{p-q+2} = \cdots = 0$.

Alternative hypothesis H_1: $\beta_{p-q+1} \neq \beta_{p-q+2} \neq \cdots \neq 0$.

Test statistic: $F^* = \frac{(\text{RSS}_0 - \text{RSS})/q}{\text{RSS}/(n-p-1)}$,

where RSS_0 is the residual sum of squares for a model fit that uses all the input variables except those last q, n is the number of ploughing operational runs included in the data, and p is the number of ploughing input variables included in the data. The decision rule was based on the p-value relative to the set α critical region.

Variable selection, a process that help to pick the most relevant variables to include in the model was performed. This help to determine those variable associated with TF to fit a single model containing only those significant inputs whether traction inputs or their subset. This help to avoid over fitting and improve model performance [50,51]. This involved attempting different possible combinations of models, each having a different subset of the predictors using the forward selection method [50] in the *regsubselect* function included in version 1.0 of the ISLR library of the R software [52]. The quality of final models was judged based on forward selection by making a good choice of statistics such as Mallow's C_p, Akaike information criterion (AIC), Bayesian information criterion (BIC), and adjusted R^2, equations (6)–(9) [50,53–55].

$$c_\text{p} = \frac{1}{n}(\text{RSS} + 2d\hat{\sigma}^2), \tag{6}$$

$$\text{AIC} = \frac{1}{n\hat{\sigma}^2}(\text{RSS} + 2d\hat{\sigma}^2), \tag{7}$$

$$\text{BIC} = \frac{1}{n}(\text{RSS} + \log(n)d\hat{\sigma}^2), \tag{8}$$

$$\text{Adjusted } R^2 = 1 - \frac{\text{RSS}/(n-d-1)}{\text{TSS}/(n-1)}, \tag{9}$$

where d is the number of predictors in the model.

The measurement of the final models quality of fit was obtained using the Regression standard error (RSE) and the fraction of explained variance (R^2) [50] as expressed in equations (10) and (11).

$$\text{RSE} = \sqrt{\frac{1}{n-p-1}\text{RSS}}, \tag{10}$$

$$R^2 = \frac{\text{SSR}}{\text{SST}} = 1 - \frac{\text{SSE}}{\text{SST}}. \tag{11}$$

2.6 Model validation

This is to affirm model usefulness and real-life applicability [56]. It was done using a 10-fold cross-validation structure as provided in the DAAG library and the cv.glm function of ISLR library of the R software [50]. This validation structure randomly divides dataset into approximately ten equal subsets or size. At each run, nine subsets were used to construct the model while the remaining subset was used for validation. The average accuracy for ten iterations was recorded as the final measurement [57]. The first fold was treated as a validation set, and the least squares regression was fitted on the remaining folds (ten less one). The Mean square error (MSE) was then computed on the observations in the held-out folds. This procedure was repeated ten times, and each time, a different group of observations was treated as a validation (test) set. The output is in ten estimates of the test errors, MSE_1, MSE_2, …, MSE_{10}. The 10-fold cross-validation (CV) estimate was computed based on the average of these values equation (12).

$$CV_{10} = \frac{1}{10}\sum_{1}^{10} MSE_i, \tag{12}$$

This validation method is an extremely flexible, powerful, and widely used technique in validation work for estimating prediction error. The measure of error for cross-validation is the MSE for a quantitative response [57].

2.7 Multi-collinearity effect estimation

To avoid multi-collinearity effect in the predictors, only models whose variance inflation factor (VIF) is smaller than 10 were retained [51,58,59]. VIF defined the ratio of the variance of $\hat{\beta}_j$ when fitting the full model divided by the variance of $\hat{\beta}_j$ if fit on its own equation (13). This has been reported to be a better technique to evaluate multi-collinearity in regression models [50],

$$VIF(\hat{\beta}_j) = \frac{1}{1 - R^2_{X_j|X_{-j}}}, \tag{13}$$

where $R^2_{X_j|X_{-j}} - R^2$ from a regression of X_j onto all of the other predictors. Estimation having $R^2_{X_j|X_{-j}}$ value close to 1 indicates the presence of multi-collinearity, and hence, a large VIF.

3 Results and discussion

Field data from the experiment were analysed using descriptive and inferential statistics. This resulted in the development of empirical equations for predicting TF of tractor implement combination during ploughing operations on a tropical *Alfisol*.

3.1 Experimental site soil textural properties

This established the soil conditions for the tractor-implement working environment, a principal factor that influences machine field performance. Soil data collected included soil grain, BD, MC, cone penetrometer (CI), and SS. The values obtained are indicators to affirm the suitability of the experimental site for the study because agricultural field machines perform well within certain soil properties or conditions [60]. Textural characteristic of the experimental site was found to be sandy loam based on United States Department of Agriculture (USDA) classification (Table 3).

These soil properties affect traction and tyre performance, tractor fuel efficiency, *e*, wheel slip (WS), tillage energy, and soil morphology [37,61,62].

3.2 Collected experimental field data characteristics

Descriptive statistics of the field data revealed the minimum, maximum, mean value, and standard deviation of the 270 treatments obtained from the fieldwork (Table 4). These variables have a direct impact on tractor performance in the field.

Quantitative output from these indices have impact on the soil, machine, and operational characteristics. Soil BD (ρ_b) has a direct effect on soil properties such as porosity, soil moisture availability, and hydraulic conductivity, with an indirect effect on root growth and crop yield [61,62]. A BD greater than 1.2 mg/m^3 (clayey soil), 1.6 mg/m^3 (loam soil), and 1.8 mg/m^3 (sandy loam soil) may adversely affect paddy root growth [60]. Most tillage exercise for crop sowing are usually done at depths of 10–30 cm because average depths of roots penetration for food crops are within this range. The mean DC for the investigations was 20.51 cm which implies a favourable condition for

Table 3: Experimental site soil characteristics

Soil properties	Values
Clay (%)	17.00
Silt (%)	16.00
Sand (%)	67.00
USDA textural class	Tropical *Alfisol (*Sandy loam)
BD (g/cm^3)	1.31–1.67
MC (%, d.b)	5.95–12.70
CI (kPa)	85.00–202.00
SS (kPa)	105.00–285.15

d.b - dry basis.

Table 4: Descriptive statistics overview of the experimental filed data

Measured parameters	Minimum	Maximum	Mean value	Std. Dev
TF (kN)	3.38	10.91	7.30	1.37
D (kN)	1.56	7.79	4.49	1.21
WS (%)	5.15	27.20	14.21	4.37
DC (cm)	9.10	32.00	20.51	4.20
WC (cm)	123.00	298.00	202.40	30.00
MC (%)	4.50	13.94	8.66	1.49
BD (g/cm^3)	1.31	1.67	1.52	0.09
CI (kPa)	95.89	207.78	161.56	23.17
SS (kPa)	98.67	295.56	171.93	85.76

(TF- Towing force; D- Draught; WS- Wheel slip; DC- Depth of cut; WC- Width of cut; MC- Moisture content; BD- Bulk density; CI- Cone index; SS- Shear strength).

the exercise as the deeper DC has effect on tractive performance indices such as the D, WS, and speed of operation. A CI of 246 kPa was considered a soft soil condition and a CI of 492 kPa was considered a firm soil [63]. Overall, these are pertinent to good traction force and tractor efficiency during field operations.

3.3 Data pre-processing of experimental results for predictive analysis and inference

Based on standard established procedures followed in parametric model assumptions checking and data inspection for the anomaly that may impact the reliability of the predictive inference on the study data, the dataset was checked for missing observations and correlation between the response variable and among the predictors, using version 3.5.1 of the R software for statistical computing and graphics. The dataset run for all the observations produced no missing reading or value. A check for bivariate (Pearson) linear correlation between the variables is as shown in Table 5. Clearly, D, WS, and WC have a significantly strong relationship with tractor TF. The other predictors show no enough data evidence to reject null hypothesis of no significant correlation with tractor TF in ploughing operation. Significant correlations among predictors may suggest multi-collinearity which can be checked only when classical test for multi-collinearity on fitted models is performed.

3.4 Multiple linear regression modelling of TF in ploughing operation

To predict TF in the 270 runs included in the study datasets with the eight traction inputs, model was fitted into the data using the lm() function in the R software [64]. Data indications in Table 6 reveal that only least squares estimate of model parameters D, WC, MC, BD, and CI, respectively, are non-zero since their p-values are much smaller than the $\alpha = 0.05$ rejection region. Hence, a clear statistical relationship exists between them and the response variable. The variables with value greater than p-values as observed for the intercept, WS, DC, and SS indicate that the least squares estimate for them should be zero. This confirmed the suitability of regression through the origin for the data and that WS, DC, and SS do not have significant predictive relationship with the TF. The fitted least squares regression model is

$$\begin{aligned} y_i = {} & -0.0837 + 1.0216x_1 + 0.01210x_2 - 0.0024x_3 \\ & + 0.0026x_4 - 0.0490x_5 + 1.2747x_6 + 0.0035x_7 \\ & + 0.0003x_8, \end{aligned} \tag{14}$$

Based on equation (14), average TF (kN) is −0.0837 when zero unit of D (X_1), WS (X_2), DC (X_3), WC (X_4), MC (X_5), BD (X_6), CI (X_7), and SS (X_8) are applied.

Table 5: Correlation matrix for study data

	TF	D	WS	DC	WC	MC	BD	CI	SS
TF	1.00								
D	0.93	1.00							
WS	0.44	0.45	1.00						
DC	0.10	0.13	0.16	1.00					
WC	0.48	0.47	0.24	0.05	1.00				
MC	0.07	0.12	−0.01	−0.03	0.17	1.00			
BD	0.03	0.00	−0.24	−0.05	−0.16	0.07	1.00		
Ave. CI	−0.02	−0.05	0.01	−0.02	0.20	0.03	−0.48	1.00	
Ave. SS	−0.02	−0.04	−0.05	−0.02	−0.03	−0.01	0.00	−0.07	1.00

Table 6: Least squares coefficient estimates of the fitted model

Parameters	Estimate	Std. error	*t*-value	*P*-value
Intercept	−0.0836808	0.8192317	−0.102	0.91872
D	1.0215985	0.0307407	33.233	$<2 \times 10^{-16}$
WS	0.0129824	0.0079402	1.635	0.10325
DC	−0.0024087	0.0025934	−0.929	0.35386
WC	0.002614	0.0011572	2.261	0.02459**
MC	−0.0490483	0.0201739	−2.431	0.01572**
BD	1.2746912	0.4081898	3.123	0.00199*
Ave. CI	0.0034808	0.0014936	2.331	0.02054**
Ave. SS	0.0003165	0.003447	0.918	0.35942

Residual standard error: 0.4823 on 261 degrees of freedom (DF).
Multiple *R*-square: 0.8798, Adjusted *R*-square: 0.8761.
F-statistic: 238.8 on 8 and 261 DF, *p*-value: <2.2 × 10−16.
* and ** Represent significant at 1 and 5%, respectively.

The positive least squares estimate for D, WS, WC, BD, CI, and SS, respectively, implies that they have a direct relationship with TF of tractors in ploughing operations. Similarly, the DC and MC are negatively correlated depicting an inverse relationship with the response variable in ploughing operations.

3.5 ANOVA for the fitted regression model

To investigate marginal effects of the individual traction input variables, the ANOVA was obtained and the summary is presented in Table 7. This is to test the null hypothesis of non-dependence of TF (y) on individual traction inputs at the 5% critical rejection region. Data evidence in Table 7 reveals that traction input variables WS, DC, and SS may not have a significant marginal effect on tractor TF in ploughing operation.

Table 7: ANOVA table for fitted regression model

Parameters	DF	Sum of squares	Means squares	*F*-value	*P*-value
D	1	439.13	439.13	1887.9800	$<2 \times 10^{-16}$*
WS	1	0.19	0.19	0.8307	0.36291
DC	1	0.24	0.24	1.0385	0.30912
WC	1	1.02	1.02	4.3676	0.03760**
MC	1	1.09	1.09	4.6865	0.03131**
BD	1	1.21	1.21	5.2065	0.02331**
CI	1	1.19	1.19	5.1116	0.02459**
SS	1	0.20	0.20	0.8429	0.35942
Residuals	261	60.71	0.23	—	—

* and ** Represent significant at 1 and 5%, respectively.

3.6 Variable selection to identify the best model for TF prediction

To determine which subset of these predictors and their interactions are significantly associated with the response, variable selection using a forward stepwise selection algorithm was performed to ascertain the best model for predicting TF, based on the Residual sum of squares (RSS), and AIC criterion [64,65],. In Table 8, all asterisked inputs and interaction terms are said to have marginal significant effects on tractor TF in ploughing operation. They are, therefore, said to be important in the final model.

Based on obtained minimum average AIC, the final model includes D, WC, MC, WS, D:MC interaction, and WC:BD interaction, respectively. The final model produces significant improvement by deleting the intercept term to include CI (Table 9). The no-intercept term model also known as regression-through-the-origin is pronounced in engineering and science phenomena depicting input defines the output. Having intercept in the model signify that when all inputs are zero, the output will assume the intercept value.

The final estimated multiple linear regression model including these input variables and their important combinations is as presented in equation (15).

$$\begin{aligned} y_i &= 1.5100x_1 - 0.0068x_2 + 0.1931x_3 + 0.0149x_4 \\ &\quad + 0.0029x_5 - 0.0570x_6 + 0.0058x_7, \end{aligned} \tag{15}$$

x_1 = D, x_2 = WC, x_3 = MC, x_4 = WS, x_5 = CI, x_6 = D:MC, x_7 = WC:BD.

Table 8: Forward stepwise selection for best model ploughing operation

Parameters	Estimates	Std. error	*t*-value	*P*-value
Intercept	5.1124795	4.3126616	1.185	0.236931
D	2.5373008	0.6571578	3.861	0.000143*
WC	−0.0582697	0.0198565	−2.935	0.003643*
MC	0.5647208	0.1689288	3.345	0.000952*
BD	−4.9948011	2.6058076	−1.917	0.056373***
WS	0.0203033	0.0075953	2.673	0.007996*
CI	0.0042445	0.0084175	0.504	0.614521
D:MC	−0.0820288	0.0191261	−4.289	2.54×10^{-5}*
D:BD	−0.6350407	0.3281823	−1.935	0.054085**
WC: BD	0.0434395	0.0129545	3.353	0.000919*
MC:CI	−0.0015360	0.0007975	−1.926	0.055215***
D:CI	0.0025497	0.0012952	1.969	0.050082**
D:WC	−0.0012837	0.0008395	−1.529	0.127472

Residual standard error: 0.4552 on 257 DF.
Multiple *R*-square: 0.8945, Adjusted *R*-square: 0.8896.
F-statistic: 181.7 on 12 and 257 DF, *p*-value: $<2.2 \times 10^{-16}$.
*, **, and *** Represent significant at 1, 5, and 10%, respectively.

Table 9: Final ploughing operation TF model

Parameters	OLS estimate	Std. error	*t*-value	*P*-value	VIF	Ridge estimate
D	1.5100	0.077482	19.489	$<2 \times 10^{-16}$*	160.024	1.5126
WC	−0.0068	0.002959	−2.310	0.02165**	451.621	−0.0066
MC	0.1931	0.033520	5.759	2.5×10^{-8}*	106.801	0.1938
WS	0.0149	0.007532	1.975	0.04929**	15.450	0.0148
CI	0.0029	0.001386	2.056	0.04072**	62.988	0.0028
D:MC	0.0058	0.008279	−6.880	4.37×10^{-11}*	143.152	0.0572
WC:BD	0.0058	0.001872	3.105	0.00211*	414.314	0.0057
MSE	0.0073					0.00710

Residual standard error: 0.4684 on 263 DF Multiple *R*-square: 0.8846, Adjusted *R*-square: 0.8754.
F-statistic: 9,648 on 7 and DF: 263, *p*-value: $<2.2 \times 10^{-16}$.
** and ** Represent significance at 1 and 5%, respectively.

It can be observed from equation (15) that holding all other variables constant, a unit change in the D will result in 1.51% change in the response variable. Similarly, a unit change in WC will result in a 0.0068% reduction in the TF. This expression depicts the dynamic contribution of the predictors on TF either in the positive or negative trends during ploughing operation on a tropical Alfisol.

Summarily, the adoption of these contributing indices will help to integrate only variables that significantly influence the response variable so that energy and resources can be maximally applied. The use of only significant variables permit the development of simplified models that not only reduce the cost of collecting irrelevant data but also lessen the risk of overfitting the model, which reduces the prediction accuracy for unseen (new) data [66,67]. Mahore et al. [4] reported a perfect R^2 score of 1.000 on the training set based on Decision Tree algorithm, indicating an excellent fit to the data. However, a higher RMSE score on the testing set was affirmed, potentially suggesting overfitting.

The best model quality of fit as investigated using the coefficient of multiple determination (R^2), achieved an adjusted (R^2), of 87.54%. This established the fact that using the seven terms in the final model, the response variable can be predicted by the model up to 87.54%, which depicts the level of how the variation in the dependent variable can be explained by the regression model. Correlating with the ASABE draft prediction model that integrate soil texture, implement width, tillage depth, and speed of operation with R^2 = 0.62, the model performs more fairly.

Inferences from the R^2 may depict the need to establish the presence of multicollinearity as the independent variables may be related [58,59,68,69]. The R^2 is not a sufficient method to diagnose if the model suffers from multicollinearity, hence the model was further diagnosed using the VIF. Those with a VIF greater than 10 show that the model suffers from multicollinearity. One of the consequences of this problem is that ordinary least square (OLS) estimates are no longer reliable because the variance of the regression coefficients becomes very large and sometimes possesses a wrong sign [70,71]. One of the estimators suggested as an alternative to the OLS is the ridge regression [72]. The VIF result in Table 10 shows that there is multicollinearity. Therefore, the model was analysed using the ridge regression estimator, and the results are depicted in Table 9.

Table 10: ANOVA table for final fitted regression model

Parameters	DF	Sum of Sq.	Means Sq.	*F*-value	*P*-value
D	1	14689.5	14689.5	66963.1441	$<2.2 \times 10^{16}$*
WC	1	90.9	90.9	414.1665	$<2.2 \times 10^{16}$*
MC	1	4.4	4.4	19.9519	1.180×10^{-5}*
WS	1	2.1	2.1	9.4044	0.002390*
CI	1	9.3	9.3	42.1925	4.114×10^{-10}*
D:MC	1	16.6	16.6	75.8555	3.454×10^{-16}*
WC:BD	1	2.1	2.1	9.6387	0.002113*
Residuals	263	54.7	0.2		

*Represents significance at 1%.

Table 11: Tests of normality for model residuals

Data	K–S[a]			S–W		
	K–S statistic	DF	*p*-value	W-Statistic	DF	*p*-value
Model residuals	0.044	270	0.200*	0.995	270	0.476

*Lower Bound of the True Significance; [a]Lilliefors Significance Correction.

Though the estimates produced by both estimators are not too far from each other, the result of the ridge regression estimate is more reliable, especially when there is severe multicollinearity. The MSE is the criteria used to compare the two estimators. The estimator with the minimum MSE is generally preferred. The model developed for tractive performance investigations during ploughing operations can be a viable tool for use in the planning of operational characteristics of a tractor-implement matching within the investigated tractor horsepower ranges and input parameters on a tropical *Alfisol*. The ANOVA for the final fitted regression model is as shown in Table 10. All the terms in equation (12) have a significant effect on the tractor TF during ploughing operations.

3.7 Model diagnostics to investigate the validity of regression assumptions

Before checking the prediction performances of the final model on test/unseen data, there is a need to check whether required regression assumptions hold for the model by

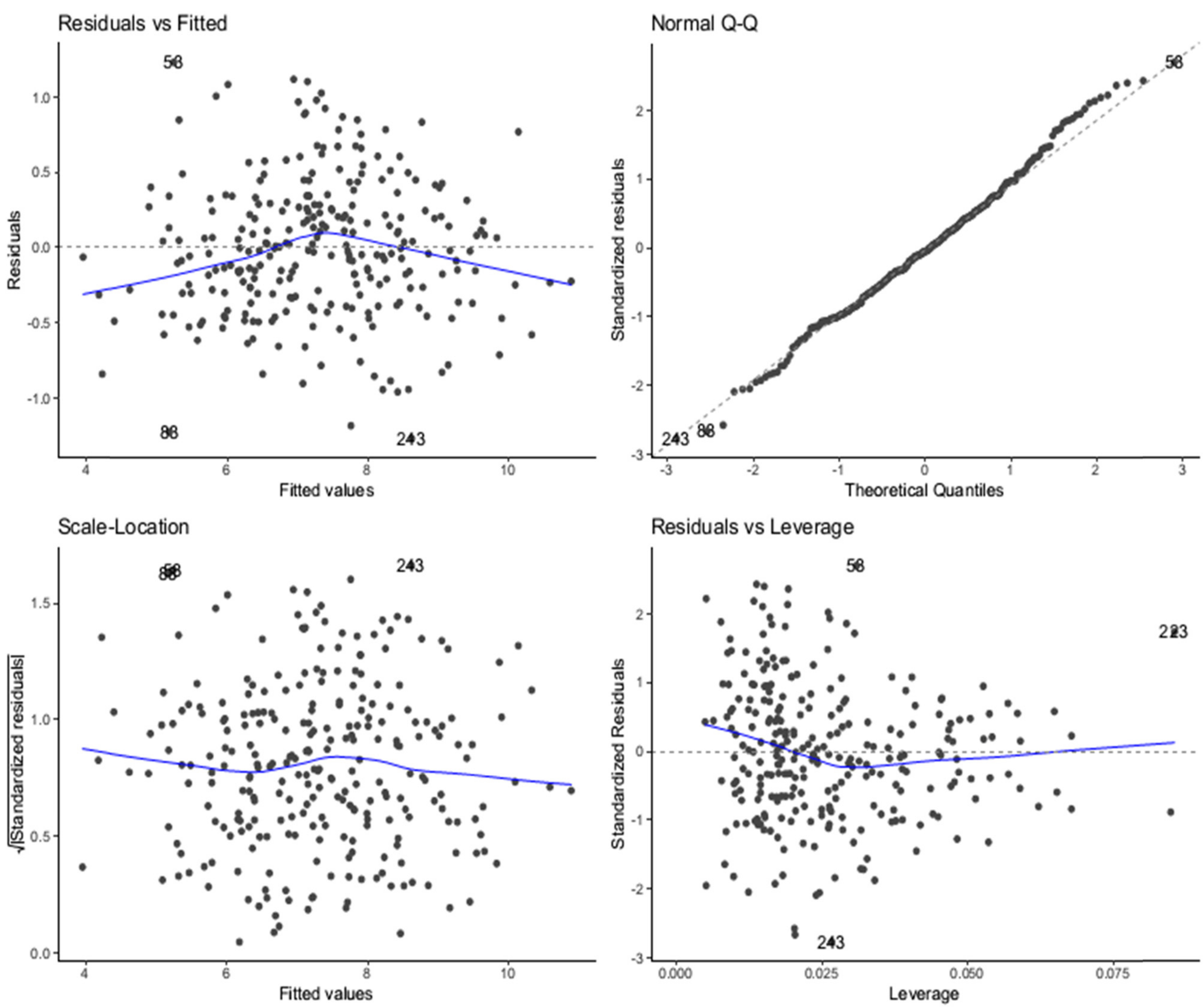

Figure 2: Regression diagnostic plots for ploughing operation showing residuals vs fitted values plot (top left), Spread-location plot for homogeneity of variance (bottom left), the normal quantile plot (top right), and the residuals vs leverage plot (bottom right).

testing the null hypothesis of normally distributed residuals using Kolmogorov–Smirnov (K–S) and Shapiro–Wilk (S–W) test of normality [72,73] as presented in Table 11. The data evidence reveals that residuals of the final model are normally distributed since the p-value 0.4756 of S–W test is larger than the critical value (α = 0.05). The same also applies to the value obtained with the K–S test with a p-value of 0.200.

Regression diagnostic plots for ploughing operation for the developed model is as shown in Figure 2. It is evident from residuals against fitted values plot that there is no pattern in the residual plot. This suggests that a linear relationship between the response variables and the predictors can be assumed. Because the horizontal line in bottom left plot has approximately evenly distributed points, the residuals are equally spread along the ranges of the independent variables. Hence, assumptions of homogeneity of error variances hold on the fitted model. Again, the inference from test of normality assumption for fitted model residuals is further supported by the top right normal quantile plot, the normal probability plot of residuals approximately follows a straight line. Supportively, the bottom right plot highlights the top three most extreme points (No. 2, No. 53, and No. 223), with a standardized residuals below −2 or above 2. However, there is no outliers that exceed 3 standard deviations, which is good and acceptable.

Table 12: Results of cross validation iterations for MSEs and RMSEs

CV. MSE	CV. RMSE
0.2256038	0.4749777
0.2238347	0.4731117
0.2228289	0.4720475
0.2232126	0.4724539
0.2251526	0.4745025
0.2246143	0.4739949
0.2240182	0.4733056
0.2250816	0.4744276
0.2226552	0.4718635
0.2245915	0.47399108

Furthermore, no high leverage point can be found in the data. This implies that all data points have a leverage statistic below $2(p + 1)/n = 16/270 = 0.0593$ (since there are p = 7 predictors in the final model).

As evident in Figure 3, observations number 53, 223, and 243 cannot be removed from the model because they have high Cook's distance scores and they are to the upper right of the leverage plot. They have leverage, signifying

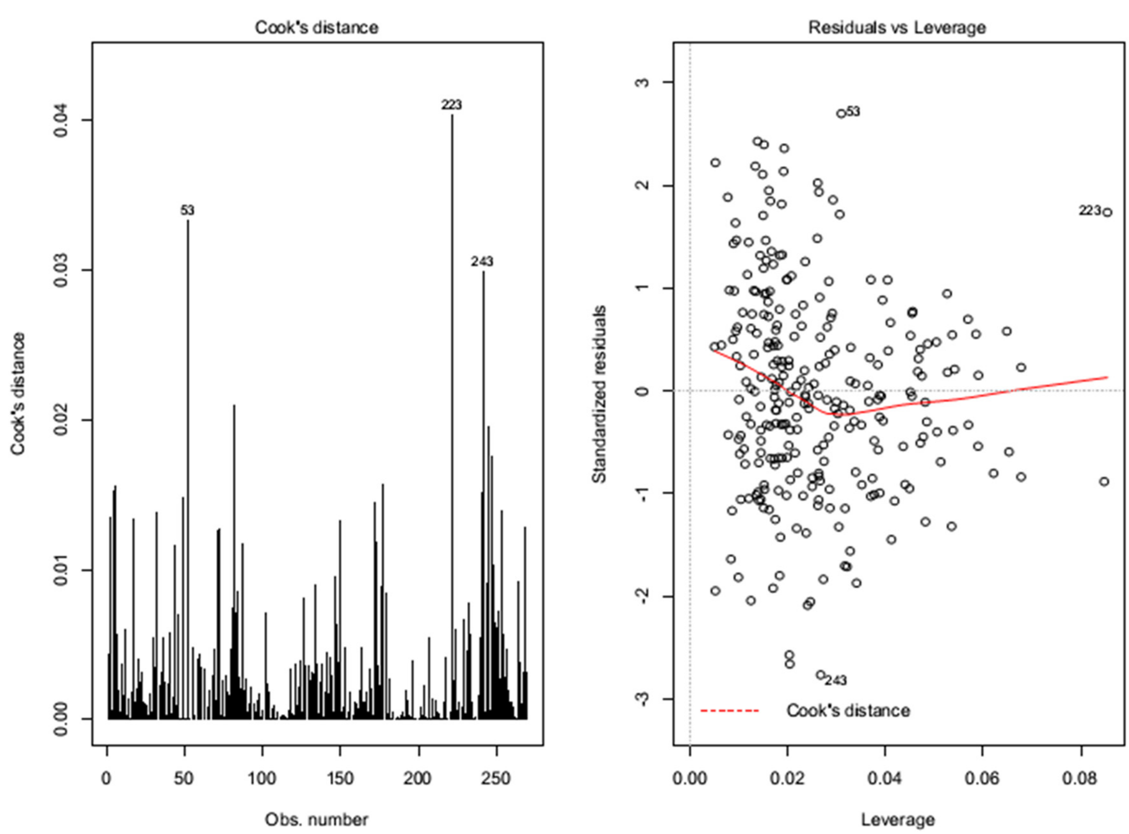

Figure 3: Cook's distance plot (left) and leverage plot (right).

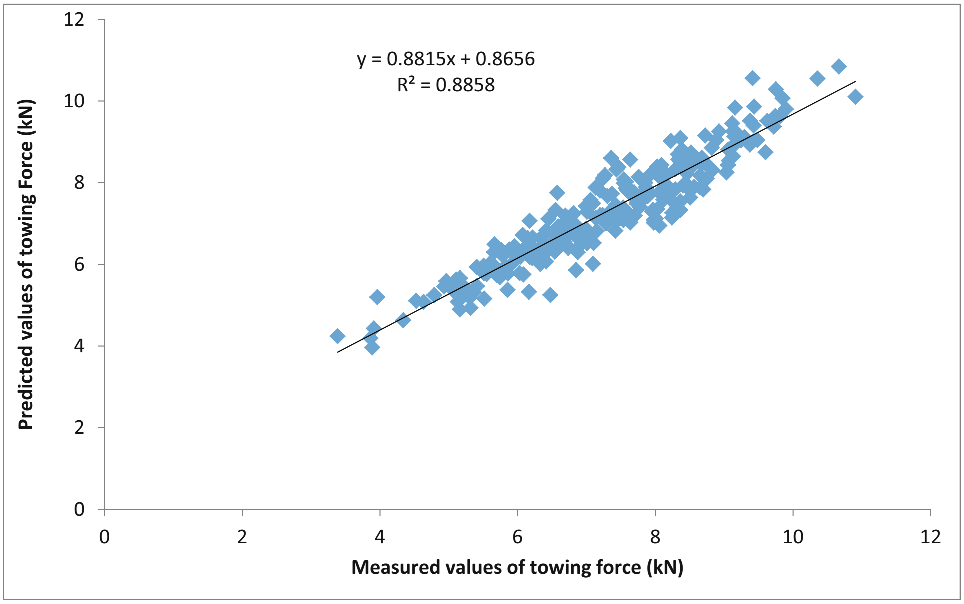

Figure 4: The accuracy of the predicted model and measured values for the TF during ploughing operation.

they are important to the regression results. The regression results will be altered if these cases are excluded.

3.8 Evaluating model predictive performance

The quality of the fitted model in terms of predicting tractor tractive performance of future ploughing operation runs with the identified significant input variables as investigated in terms of MSEs and RMSEs over 10-fold cross-validation iterations as presented in Table 12. The results obtained are within the range of values obtained in a previous study [74] that investigated the development of empirical regression equations for predicting the performances of disc plough and harrow in clay-loam soil.

Based on the cross-validated standard error of prediction (CV. RMSE), the final model has a good prediction performance over all the ten folds. This inference is further supported by the graph of predicted vs observed ploughing operational runs presented in Figure 4. The predicted TF by the model traced out the observed/measured TF as closely as possible. Hence, an estimation of the predicting model obtained in the study reveals a good agreement with the measured or experimental data obtained from the field performance. Multiple regression analysis was employed to predict a describing model for TF as influenced by the predictors with a reliable coefficient of determination (R^2 = 0.8858). This implies that the comparison of the predicted model with the experimental data for TF achieved 88.58% accuracy of prediction during ploughing operations. The result is similar to what was established by Mahore et al. [4] in a study that used machine learning to predict the draft of a mouldboard ploughing in a sandy clay loam soil. The study affirmed that the algorithms linear regression, ridge, and support vector machine exhibit R^2 scores ranging from 0.801 to 0.808, indicating moderate to good predictive performance.

3.9 Confidence interval for the model coefficients

The fact that none of the confidence intervals for the parameters contains zero further confirms that all estimated parameters are significantly different from zero. Hence, all input variables remaining in the model are significant predictors of TF at 95% confidence level (Table 13).

Table 13: 95% confidence interval for the model coefficients

Terms	Lower bound	Upper bound
D	1.3575	1.6626
WC	−0.0127	−0.0010
MC	0.1271	0.2591
WS	0.0001	0.0297
Ave. CI	0.0001	0.0056
D:MC	−0.0733	−0.0407
WC:BD	0.0021	0.0095

4 Conclusion

The study investigated tractor tractive performance during ploughing operations on a tropical *Alfisol* using the R software statistical computing approach. This helps to predict TF with moderate higher accuracy based on multiple linear regression. The empirical model was trained and tested from dataset obtained from field experimentation during ploughing operation. The influence of the individual variable and their interactions with the outcome was established.

The following findings were established from the investigation:

1. Evaluated variables revealed a range of 1.56–7.79 kN, 5.15–27.20%, 9.10–32.00 cm, 4.50–13.94%, 1.31–1.67 g/cm^3, and 95.89–207.78 kPa for D, WS, DC, MC, BD, and CI, respectively.
2. D, WS, and WC exhibit a strong significant relationship with tractor TF.
3. The developed final multiple linear regression model with all the terms having significant effect on TF is expressed as $Y = 1.5100X_1 - 0.0068X_2 + 0.1931X_3 + 0.0149X_4 + 0.0029X_5 - 0.0570X_6 + 0.0058X_7$.
4. The ANOVA for the final fitted regression model shows D, WC, MC, WS, CI, D:MC, and WC:BD have a significant effect on tractor TF during ploughing operation.
5. The accuracy of the predicted model and measured for the response variable during ploughing operations traced out each other as closely as possible confirming good agreement.

The developed regression model for tractive performance investigations during ploughing operations can be a viable tool for use in the planning of operational characteristics of a tractor-implement matching within the investigated tractor horsepower ranges and input parameters on a tropical *Alfisol*. It can be used to predict TF during ploughing operation on a tropical Alfisol using the input parameters to enhance work quality and energy efficiency.

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Conflict of interest: Authors state no conflict of interest.

Data availability statement: The data that has been used is available from the corresponding author and will be made available on request.

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