

Modelling Growth and Yield Components of Okra (*Abelmoschus esculentus* (L.) Moench) and Ayoyo (*Corchorus olitorius* (L.)) Using Multiple Regression

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Abstract

Multiple regression was employed to model the relationship between growth and yield components of okra (*Abelmoschus esculentus* (L.) Moench) and ayoyo (*Corchorus olitorius* (L.)), with the aim of generating a predictive model. Data on growth parameters and yields of okra and ayoyo crops were collected and analysed using IBM SPSS Statistics 21. Ten (10) plants were tagged in each stream, and a metre rule was used to measure their heights at two-week intervals (2, 4, 6, 8, and 10 weeks). The mean was calculated to obtain the average height per plot/experiment/stream. Data were also collected on the number of leaves per plot, leaf area index per experiment, leaf spread per experiment, and fresh and dry weight per plot. Total nitrogen content was determined using the Kjeldahl method, while phosphorus (P) levels were analyzed using the Bray-P solution method. Additionally, potassium (K) concentrations were measured using the flame photometer method. Results showed an average infiltration rate of 160.25 mm/h, suggesting that the site's soils belong to hydrologic soil group A/B. Group A consists of sand, loamy sand, or sandy loam soil types. Group B comprises silt loam or loam with moderate infiltration rates, low runoff potential, and high infiltration rates

when thoroughly wetted. Due to their moderate to high water transmission rates, these soils are suitable for drip and sprinkler irrigation systems. Notably, there is a strong positive correlation between plant height and leaf area (0.889), and between leaf area and leaf area index (0.981). This suggests that as plant height increases, so does the leaf area, and a similar positive relationship exists between leaf area and the leaf area index. Furthermore, the correlation between the number of leaves and other growth parameters such as leaf area (0.966) and leaf area index (0.988) is also strongly positive. This indicates that an increase in the number of leaves is associated with increases in both leaf area and leaf area index. These correlations, ranging from 0.582 to 0.807, indicate a high degree of association. The high R^2 value suggests a strong correlation between predicted and observed yields of okra, indicating reliable predictive capability when the growth parameters of okra are provided. Similarly, for *ayoyo*, a model equation was developed through regression analysis, yielding an R^2 value of 0.941. The yield of *ayoyo* can thus be predicted during cultivation, provided its growth parameters are known. Hence, this study is focused on establishing a multiple regression model for the growth and yield of okra and *ayoyo* under different irrigation stream systems.

Keywords: Multiple regression, Infiltration, Growth, Yield, Okra, *Ayoyo*

Introduction

Predicting crop yields has broad implications for economics, ecology, and human welfare. The large number of factors that determine crop productivity makes modeling crop production at large spatial scales substantially challenging. Forecasting crop production is an even greater challenge, as it requires making inferences about future performance based on past conditions. Manjula and Djodiltachoumy (2017) reiterated that data mining is the process of analyzing data from different perspectives and summarizing it into useful information. Crop yield prediction is an important agricultural problem. Farmers often try to focus on yield as soon as cropping activities commence. In the past, yield prediction was based on the farmer's previous experience with a particular crop. Sangeeta (2020) proposed a system aimed at predicting or forecasting crop yield by learning from past data on farming land, considering factors such as soil conditions, rainfall, temperature, yield, and other variables. He concluded that the proposed model was more efficient than existing models for predicting crop yield. Odey (2018) developed a regression model for predicting the growth of maize on soil influenced by tractor traffic. The model showed that, in any particular cropping season, the yield of maize (Y_m) could be estimated, provided the number of machinery passes on the land was known. Nkakini and Davies (2020) developed a mathematical model equation for the tolerance of okra

plant yield to soil densification. Their findings revealed a close agreement between the experimental and modelled values of okra yield under varying levels of soil compaction caused by tractor passes in different subplots. The model established that okra growth rate and yield increased significantly in response to degenerate traffic passes. Hence, this study is aimed at establishing modeling of growth and yield of okra and *ayoyo* using different tillage systems.

Okra production activities in Ghana have increased in recent years due to its nutritional values. It contains proteins, carbohydrates, minerals salts, sugars, vitamins, aromatic colouring agents, iron, and essential oils that enhance human resistance to diseases. Among other vegetables, okra contains vitamins A and B, is rich in minerals, and has high iodine content (Hossain et al., 2023).

Okra fruits can be boiled, fried, or cooked (Ishafaq et al., 2022). Due to their medicinal properties, okra and *ayoyo* have been found beneficial to people suffering from leucorrhoea, goitre, ulcers, haemorrhoids, and general weakness (Kumar et al., 2022). Okra contains most of the essential substances needed by humans for survival (Elkhalifa et al., 2021). *Ayoyo* is a leafy green vegetable used in various cuisines, particularly in African and Middle Eastern dishes (Sefah et al., 2024). It is packed with vitamins such as A and B (Sefah et al., 2024) and is rich in minerals such as calcium, iron, and magnesium (Sefah et al., 2024). Rich in antioxidants, it helps neutralize free radicals, potentially reducing oxidative stress and inflammation (Akbari et al., 2022). Its high fiber content promotes healthy digestion and may help to prevent constipation. The presence of essential nutrients and antioxidants may also contribute to heart health by reducing cholesterol levels and improving circulation (Cristina et al., 2021).

The multiple regression method is capable of modeling the relationship between a single dependent variable and several independent variables (Korkmaz et al., 2019). In this study, multiple regression analysis was used to establish a predictive model between growth and yield components of okra and *ayoyo*. Hence, this paper provides valuable information for farmers to help predict the yields of okra and *ayoyo* crops.

Methodology

Study Area

The Sagnarigu Municipality, encompassing 79 communities, presents a diverse landscape comprising 20 urban, 6 peri-urban, and 53 rural areas. It spans a substantial land area of approximately 439.8 square kilometres and shares boundaries with several neighbouring regions: Savelugu and Nanton Municipality to the north, Tamale Metropolis to the south and east, Talon District to the west, and Kumbungu District to the northwest. Geographically,

the municipality lies between latitudes 9°16' and 9°34' North, and longitudes 0°36' and 0°57' West. The specific coordinates of the experimental field are latitude 09°47'388" N and longitude 00°0'84"776" W, at an altitude of 167 meters above mean sea level. Despite the area's agricultural relevance, the Zagyuri locality is relatively deficient in natural water bodies, primarily due to a high underground water table. The few existing water sources consist mainly of seasonal streams that flow during the rainy season and dry up in the dry months. Additionally, the area has limited dams and dugouts, such as those in Kpene and Kanvilli-Kpawumo, which serve as alternative water sources for livestock and domestic use.

Figure 1 provides a visual representation of the Sagnarigu Municipality. According to Obuobie *et al.* (2006), the study area is located approximately 8 kilometres from the city centre and covers an area of about 7-12 hectares.

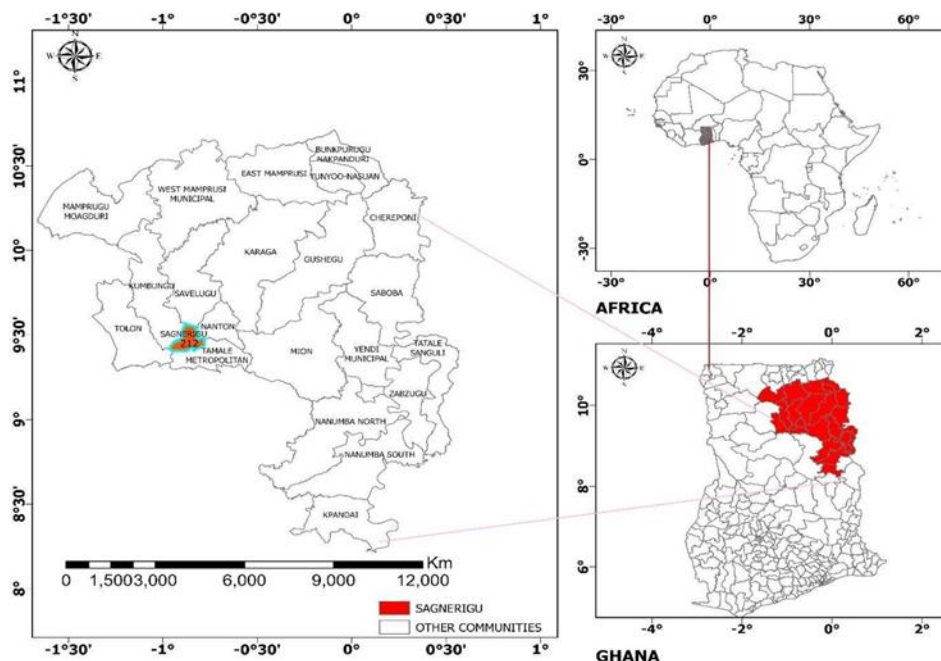


Figure 1. Location map Sagnarigu Municipal

Climate

The municipality experiences a single rainy season that begins in April or May and extends through September or October, with peak rainfall typically occurring in July and August. In contrast, the dry season spans from November to March. The average annual rainfall is approximately 1,100 mm, usually concentrated over 95 days of intense precipitation. Daytime temperatures generally range between 33°C and 39°C, while nighttime temperatures

fluctuate between 20°C and 22°C. Furthermore, the mean annual daily sunshine duration is about 7.5 hours. Within the municipality, various locations are engaged in wastewater-based vegetable farming. Crops such as cabbage (*Brassica oleracea* var. *capitata*), lettuce (*Lactuca sativa*), *Amaranthus spp.*, and *Ayoyo* (*Corchorus olitorius*) are commonly cultivated. This study specifically focused on the Zagyuri community within the Sagnarigu Municipality, where farmers depend on wastewater from a malfunctioning sewer system originating from the Kamina Military Barracks to irrigate their vegetable crops.

Field Preparation

Field preparation was carried out by clearing the land using cutlasses and hoes, followed by ploughing with a tractor. The field was divided into two (2), and an overhead tank (2000 litres) was placed in the middle of the field at a height of 2.5 m to deliver water by gravity. However, the sprinkler for the *Ayoyo* (*Corchorus olitorius*) plot (quadrant) was irrigated under pressure directly from the stream using a pump and sprinkler. *Corchorus olitorius* was cultivated in the first plot under sprinkler irrigation using the broadcasting method. Also, okra (*Abelmoschus esculentus*) was cultivated in the second plot (quadrant) with a spacing of 30 cm x 50 cm under drip irrigation, as shown in Figure 2.

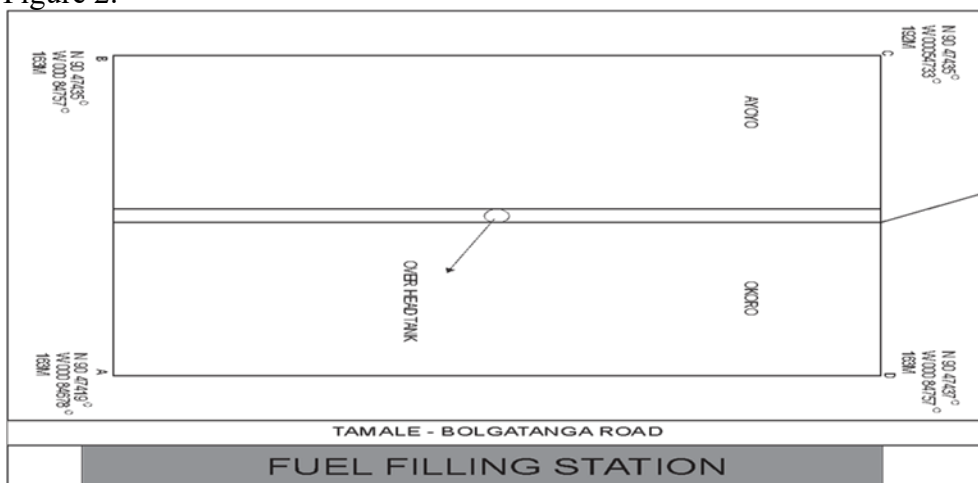


Figure 2. Layout of the Field

Experimental Design

The design used for the experiment was a randomised complete block design (RCBD). Three different stream locations - upstream (U), midstream (M), and downstream (D) - were used as treatments, and each treatment had three replicates of size 25 m x 25 m. The plots were separated from each other by 2m to allow for manoeuvring of the tractor.

Data Collection

Collection of Soil Samples

Composite soil samples were meticulously collected at a depth of 30 cm from distinct locations at the site, considering upstream, midstream, and downstream positions for subsequent analysis of various physical and chemical soil properties.

Modelling of Crop Performance

The model is represented by equation (4) below:

$$Y_i = \beta_1 + \beta_{11}X_{11} + \beta_{12}X_{12} + \dots \dots \dots \beta_{ij}X_{ij} + \varepsilon_i \dots \quad (1)$$

$$Y = \beta + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + e \dots \quad (2)$$

The definition of each variable in model is given below:

Y is the dependent variable (yield), and the other variables - X_1 (plant height), X_2 , (total leaf area), X_3 (leaf area index), and X_4 (total number of leaves) - are the independent variables.

β represents the intercept or the constant term in the model

e is the error term that represents the random variability in the dependent variable that is not explained by the independent variables.

The model assumes a linear relationship between the dependent variable and each of the independent variables.

β_1 , β_2 , β_3 , and β_4 are the coefficients of X_1 , X_2 , X_3 , and X_4 respectively (Korkmaz *et al.*, 2019).

Coefficient of Determination (R^2)

The coefficient of determination represents the proportion of the variance in the dependent variable that is predictable from the independent variables. It ranges from 0 to 1.

Measurement of Growth Parameters of Okra and Ayoyo

Plant Height

Ten (10) plants were tagged in each stream. A metre rule was used to measure the height of the ten (10) plants in each experimental unit at two-week intervals (2, 4, 6, 8, and 10 weeks), and the mean was calculated to obtain the average height per plot/experiment/stream. The same ten tagged plants were used for all the parameters.

Number of Leaves

Ten (10) plants were tagged, and their leaves were counted in each experimental unit/stream. The mean was calculated to represent the number of leaves in each experimental unit or stream at two-week intervals.

Leaf Area Index (LAI)

Ten (10) plants were selected in each experimental unit/stream, and the length and width of the top matured ten (10) leaves were measured using a meter rule. The mean leaf area (L_{MN}) of the ten (10) plants was calculated. The average number of leaves (N) of the ten (10) plants was also calculated, and the area (A) occupied by one plant in the cropped area was determined. These values were substituted into Equation 3 below.

$$LAI = \frac{L_{MN}N}{A} \quad (3)$$

Leaf Spread

Ten (10) plants were tagged, and their leaf spread was determined. Starting from the base of the plant, the distance from one outer edge of a leaf to the opposite was measured. Multiple measurements were taken from different leaves to account for variations in leaf size and orientation. The average leaf spread was calculated by adding all the measurements taken from the ten (10) plants and dividing by the number of leaves measured. The measurement process was repeated for each selected plant, ensuring consistency in technique and accuracy. This was calculated by placing four (4) sticks at the ends (North, South, East, and West) of the ten (10) sampled plants in each experimental unit/stream. Horizontal measurements from leaf tip to leaf tip were taken for the longest and shortest spreads and added together. The sum was then divided by two (2) to get the average leaf spread.

Lay Out of the System

The drip system plot or field was divided into three (3) sections: upstream, midstream, and downstream. Data were collected for all the three (3) streams and analysed using the various equations. Similarly, the sprinkler system plot or field was also divided into upstream, midstream, and downstream sections. Data were collected for all three (3) streams and analysed accordingly. The upstream ranged from 0 to 25 m, the midstream from 25 m to 50 m, and the downstream from 50 m to 75 m.

Laboratory Analysis

Soil samples collected from the experiment were subjected to laboratory analysis at the Soil Laboratory of the Savannah Agricultural

Research Institute (SARI) in Nyankpala. Notably, the soils in the area displayed limited depth, averaging less than 30 cm due to the presence of hardpan and lateritic outcrops. The soil physico-chemical properties examined included pH, CEC (Cation Exchange Capacity), potassium (K), nitrogen, organic carbon, phosphorus, calcium, magnesium, and soil texture. Total nitrogen content was determined using the Kjeldah method (Bremner & Mulvancy, 2023), while phosphorus (P) levels were analysed using the Bray-P solution method. Potassium (K) concentrations were measured using the flame photometer method recommended by the United States Salinity Laboratory Staff (Chavan et al., 2024). pH and organic carbon (OC) content were determined using the Walkley and Black technique (2017), while calcium (Ca) and magnesium (Mg) were assessed using the Ammonium Acetate method (Tang et al., 2021). These analyses were conducted to ensure soil suitability for drip and sprinkler irrigation. In addition to laboratory assessments, on-site soil water infiltration tests were carried out in both upstream and downstream locations. These tests aimed to determine the maximum infiltration capacity or hydraulic conductivity of the soils in their natural environment. Unbiased plotting positions were employed for the collected data. Knowledge of soil infiltration rates was vital not only for calculating crop water requirements but also for selecting appropriate drip emitter discharge rates to prevent surface water runoff and water wastage at the Zagyuri site within the drip irrigation system. The double-ring infiltrometer method was utilized for the field infiltration rate measurements (Figure 3). This method required specific equipment, including a double-ring infiltrometer, wooden support for driving the rings into the soil, a mallet, bucket, measuring jug, stopwatch, notebook, measuring ruler, and an adequate water supply. The method involves two concentric metal rings, with measurements taken within the inner cylinder to assess soil infiltration properties. The outer cylinder serves to guide water flow downward and prevent lateral spreading during the test.



Figure 3. Infiltration test at the experimental site

Statistical Analysis

Data for the growth and yield of okra and *ayoyo* in this experiment were analysed using IBM Statistical Package for Social Sciences (SPSS) Statistics Version 21. Correlation, regression, and ANOVA analyses were carried out.

Results and Discussion

Soil Survey and Infiltration

The average infiltration rate for the site was 160.25 mm/h. The results of the infiltration test suggest that the soils at the site belong to Hydrologic Soil Group A/B. Group A includes sand, loamy sand, or sandy loam soils, while Group B comprises silt loam or loam soils (Nielsen *et al.*, 2017). These groups are characterized by moderate infiltration rates when thoroughly wetted, low runoff potential, and high water transmission rates. A measured infiltration rate of 160.25 mm/h indicates a relatively high capacity for water absorption. This is advantageous for irrigation practices, as it suggests that the soil can efficiently adapt and distribute water to plant roots. High infiltration rates can reduce the risk of surface runoff and water wastage, thereby enhancing irrigation efficiency. This observation aligns with the findings of Badr *et al.* (2022), who concluded that soils with high infiltration rates are well-suited for efficient irrigation methods such as surface or subsurface drip irrigation. These methods enable better control over water application and minimise losses due to runoff. Accordingly, the soils at the study site are suitable for both drip and sprinkler irrigation systems. The detailed results are presented in Figure 4 (a), Figure 4(b), and Table 1.

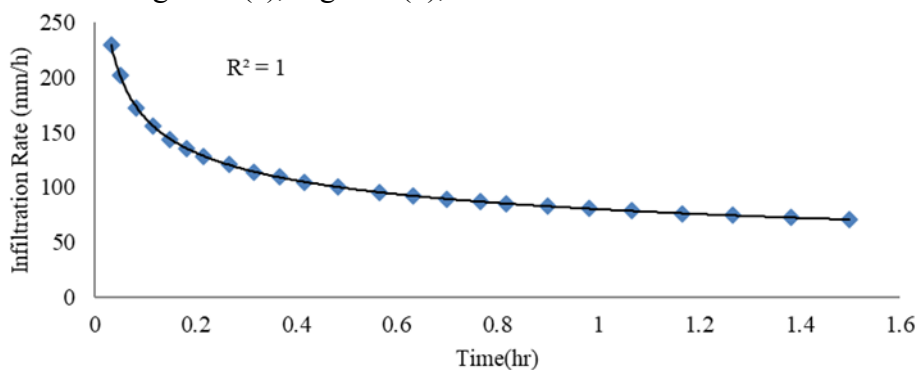


Figure 4 (a). Down-stream Infiltration Curve (F=70.5 mm/H)

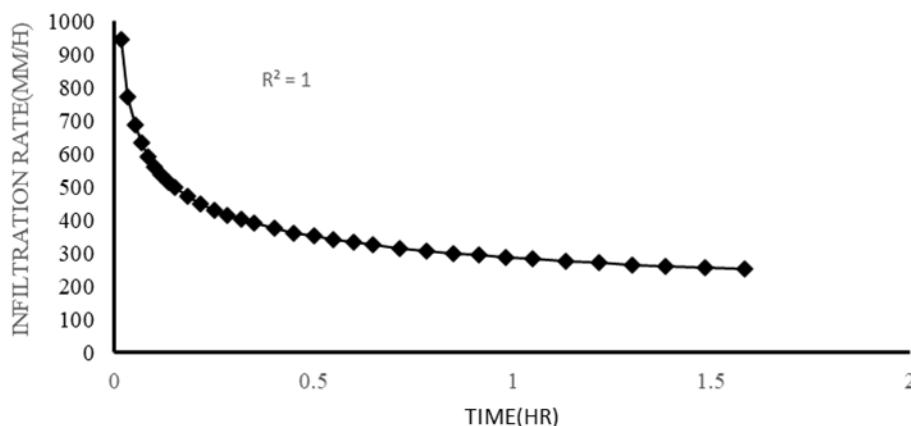


Figure 4 (b). Up-stream Infiltration Curve (F = 250 Mm/H)

Table 1. Soil Physico-Chemical Properties

Treatment	pH (1:2.5 water)	%O.C	% Total N	P (mg/kg)	K (mg/kg)	Ca (mg/kg)	Mg (mg/kg)	CEC (cmol/kg)	% Sand	% Silt	% Clay	Texture
Up- stream	5.20	0.45	0.044	65.37	111.31	141.60	127.50	11.47	54.00	25.60	20.40	Sandy Loam
Down- stream	5.50	0.67	0.044	70.49	115.49	172.52	139.89	13.66	43.43	29.71	27.29	Loam

The data present the soil physicochemical properties, including pH, organic carbon content (%O.C), total nitrogen (%N), phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), cation exchange capacity (CEC), and texture, under two different treatment conditions: upstream and downstream.

pH

The pH values for both upstream and downstream treatments are slightly acidic, with upstream having a pH of 5.2 and downstream 5.5. These values fall within the acceptable range for most crops.

Organic Carbon Content (%O.C)

Organic carbon content is a key indicator of soil fertility and nutrient availability. The upstream treatment recorded an organic carbon content of 0.45 %, while the downstream treatment had a slightly higher value of 0.67 %. These results suggest that the downstream site may possess greater organic matter content, implying potentially higher fertility. Adequate organic matter enhances nutrient retention, water-holding capacity, and overall soil health. According to Tequam (2017), soils with organic carbon levels between 0.5

and 1.5% are considered low in organic carbon. Therefore, the soil at the study site, with values below 3%, indicates poor soil health (Tequam & WSP, 2017).

Total Nitrogen (%N)

Total nitrogen is essential for plant growth and an important component of soil fertility. Both upstream and downstream treatments recorded identical nitrogen levels at 0.044%N. Based on the classification by Teresa (2024), total nitrogen content < 0.05 % is considered very low, 0.05 - 0.12 % as low, 0.12 - 0.25 % as moderate, and >0.25 % as high. The recorded values fall into the “very low” category, indicating nitrogen as a limiting factor for optimal crop growth. This aligns with the findings of Kebede (2019), who reported nitrogen as the most limiting soil nutrient due to its volatility and the leaching potential.

Phosphorus (P), Potassium (K), Calcium (Ca), and Magnesium (Mg)

The concentrations of phosphorus, potassium, calcium, and magnesium - key macronutrients essential for plant growth and development - were assessed under both treatment conditions. In the upstream treatment, the values were 63.37 mg/kg for phosphorus, 111.31 mg/kg for potassium, 141.60 mg/kg for calcium, and 127.50 mg/kg for magnesium. The downstream treatment recorded slightly higher concentrations: 70.49 mg/kg (P), 115.49 mg/kg (K), 172.52 mg/kg (Ca), and 139.89 mg/kg (Mg). The relatively elevated nutrient levels in the downstream soil suggest improved nutrient availability, which may enhance plant metabolic functions, growth performance, and overall yield potential.

Cation Exchange Capacity (CEC)

CEC is a measure of the soil's ability to retain and exchange essential nutrients. The upstream treatment recorded a CEC of 11.47 cmol/kg, while the downstream treatment showed a higher CEC of 13.66 cmol/kg. Higher CEC values reflect a greater capacity for nutrient retention and availability, which is beneficial for crop productivity.

Soil Texture

Soil texture affects water-holding capacity and drainage. The upstream soil was classified as sandy loam, comprising 54 % sand, 25.6 % silt, and 20.4 % clay. The downstream soil was classified as loam, with 43.43% sand, 29.71% silt, and 27.29 % clay. These textures differ in their water and nutrient retention capacities and influence crop management practices. The results are consistent with those of Buru et al. (2012) and Shaibu et al. (2023), who reported that soils in the northern zones of Ghana range from sand to sandy loam and silt, with relatively low clay content.

Modelling the Growth and Yield of Okra and *Ayoyo* Correlation of Plant Growth Parameters and Yield in Okra

The results in Table 2 illustrate the correlation coefficients between various plant growth parameters and the yield of okra.

Table 2. Correlation of Plant Growth Parameters and Yield in Okra

	Plant height	Leaf Area	Leaf Area Index	Number of Leaves	Yield (kg)
Plant height	1				
Leaf Area	0.889	1			
Leaf Area Index	0.896	0.981	1		
Number of Leaves	0.886	0.966	0.988	1	
Yield (kg)	0.807	0.582	0.605	0.647	1

Notably, a strong positive correlation was observed between plant height and leaf area (0.889), as well as between leaf area and leaf area index (0.981). These findings suggest that increases in plant height are associated with corresponding increases in leaf area, and similarly, leaf area expansion is closely tied to a rise in leaf area index. Additionally, the number of leaves exhibited strong positive correlations with both leaf area (0.966) and leaf area index (0.988), indicating that a greater number of leaves contributes significantly to broader leaf coverage and a higher leaf area index. While the correlations between yield (kg) and individual growth parameters - such as plant height, leaf area, leaf area index, and number of leaves - were also positive, they were relatively weaker ranging from 0.582 to 0.807. This suggests that although these growth parameters positively influence yield, their predictive strength is comparatively lower, likely due to additional biophysical or environmental factors not captured in this analysis. These results are consistent with those of Canisius et al. (2018), who also reported robust relationships among vegetative growth traits in crop species. Such alignment across studies supports the reliability of these correlations in characterizing okra growth dynamics.

Regression of Growth Parameters on Okra Yield

Multiple regression analysis was conducted to evaluate the collective influence of selected growth parameters on okra yield per hectare and to develop a predictive model. The summary of results is presented in Tables 3 and 4.

Table 3. Regression of Growth Parameters on Okra Yield

Source	Coefficient	Standard error	T	sig.	Lower Mund (95%)	Upper Mund (95%)
Intercept	1610.726	514.596	3.130	0.035	181.978	3039.474
plant height	25.393	8.623	2.945	0.042	1.451	49.335
Leaf Area	-5.044	9.956	-0.507	0.639	-32.687	22.599
Leaf Area Index	-131.714	117.987	-1.116	0.327	-459.297	195.869

Table 4. Model Summary

R ²	Adjusted R ²	MSE	RMSE	p value
0.832	0.664	400994.143	633.241	0.075

The regression equation for predicting okra yield is as follows:

$$Yield \left(\frac{kg}{ha} \right) = 1610.726 + 25.394 X_1 - 5.044 X_2 - 131.714 X_3 + 31.627 X_4 + 0.1682 \quad (4)$$

R²=0.832

An R² value of 0.832 signifies that the model accounts for about 83% of the variability in okra yield. The p-values associated with the coefficients indicate that plant height and the number of leaves have statistically significant impacts on okra yield. However, leaf area, leaf area index, and the intercept are not statistically significant predictors in this context. The intercept in the model is 1610.726, indicating the estimated yield of okra when all predictor variables are zero. It was found to be statistically significant with a p-value of 0.035. Moreover, plant height had a coefficient of 25.393 with a standard error of 8.623. This suggests that for every unit increase in plant height (in an appropriate unit of measurement), the okra yield is expected to increase by 25.393 kg/ha. Plant height was also statistically significant (p = 0.042). In addition, leaf area had a coefficient of -5.044 with a standard error of 9.956. This coefficient indicates that for every unit increase in leaf area, the okra yield is expected to decrease by 5.044 kg/ha. However, this relationship was not statistically significant (p = 0.639). Leaf area index had a coefficient of -131.714 with a standard error of 117.987. While this coefficient suggests a negative relationship between leaf area index and okra yield, it was not statistically significant (p = 0.327). Also, the coefficient for the number of leaves was 31.627 with a standard error of 21.568. This implies that for every additional leaf on an okra plant, the yield is expected to increase by 31.627 kg/ha. However, the relationship was not statistically significant at the 0.05 level (p = 0.216).

The results align with previous research that has emphasized the significance of certain growth parameters in predicting crop yield. For instance, Smith *et al.* (2020) found that plant height was a critical determinant of yield in various crop species, including okra. Additionally, Johnson *et al.* (2020) highlighted the importance of leaf characteristics, such as the number of leaves, in predicting crop yield.

The regression analysis has generated a predictive model for okra yield, with plant height and the number of leaves emerging as statistically significant predictors. While other factors may also influence yield, this model provides valuable insights for optimizing okra cultivation. The modelled equation, with a coefficient of determination (R^2) of 0.832, reveals predicted output closely matching the observed yield of okra. The yield of okra can be predicted during cultivation, provided the growth parameters of okra are known.

Correlation of Ayoyo Yield and Growth Parameters

The correlation coefficients in Table 5 indicate the strength and direction of associations among plant height, leaf area, leaf area index, the number of leaves, and the yield of *Ayoyo*. There was a strong positive correlation between plant height and leaf area (0.856), as well as between plant height and the number of leaves (0.856). This suggests that as the height of *Ayoyo* plants increases, both leaf area and the number of leaves tend to increase as well. This positive correlation indicates that these growth parameters are positively related and tend to co-occur during the growth of *Ayoyo*. There was also a positive correlation between the yield of *Ayoyo* and the other growth parameters, including leaf area (0.171), leaf area index (0.820), and the number of leaves (0.171). This indicates that as these growth parameters increase, the yield of *Ayoyo* also tends to increase. In other words, *Ayoyo* plants with larger leaf areas, higher leaf area index, or more leaves may produce higher yields. Additionally, there was a weaker positive correlation between leaf area and leaf area index (0.495), suggesting a moderate positive relationship between these two growth parameters.

Table 5. Correlation of Ayoyo Yield and Growth Parameters

	plant height	Leaf Area Index	Number of Leaves	Yield (kg)
plant height	1.00			
Leaf Area Index	0.771	1.00		
Number of Leaves	0.856	0.495	1.00	
Yield (kg)	0.341	0.820	0.171	1.00

Regression of *Ayoyo* Yield and Growth Parameters

Multiple regression analysis was employed to examine the relationship between growth parameters and the yield of *Ayoyo* per hectare, with the aim of generating a predictive model. The regression equation for predicting *Ayoyo* yield is presented below. Tables 6 and 7 show the summary of the results.

Table 6. Regression of *Ayoyo* Yield and Growth Parameters

Source	Coefficient	Standard error	T	Sig.	Lower Mund (95%)	Upper Mund (95%)
Intercept	185.805	28.881	6.433	0.001	111.563	260.047
plant height	9.016	2.225	4.052	0.010	3.297	14.735
Leaf Area	15.668	7.128	2.198	0.079	33.990	2.654
Leaf Area Index	43.370	5.378	8.065	0.000	57.194	29.546
sNumber of Leaves	20.5	2.115				

Table 7. Model Summary

R ²	Adjusted R ²	MSE	RMSE	p value
0.941	0.905	302.258	17.386	0.002

The regression equation for predicting *Ayoyo* is as follows:

$$Yield \left(\frac{kg}{ha} \right) = 185.805 + 9.016X_1 + 15.668X_2 + 43.370X_3 + 0.05 \quad (5)$$

R² = 0.941

The R² value of 0.941 (Table 6) indicates that the model explains a substantial portion of the variability in *Ayoyo* yield, with 94.1% of the variance being accounted for. The adjusted R² value of 0.905 suggests that the model's predictive power remains strong even after adjusting for the number of predictors.

The intercept in the model was found to be 185.805 with a standard error of 28.881. This intercept represents the estimated yield of *Ayoyo* when all other predictors are zero, although this scenario may not hold practical significance in the context of agricultural yield predictions. The intercept was highly significant (p = 0.001), indicating a substantial baseline yield of *Ayoyo* even in the absence of significant growth parameters.

Plant height had a positive coefficient of 9.016 with a standard error of 2.225. This suggests that an increase of one unit in plant height is associated with an increase of 9.016 kg/ha in *Ayoyo* yield. The t-statistic of 4.052 and a p-value of 0.010 confirm the statistical significance of this relationship. In addition, leaf area had a positive coefficient of 15.668 with a standard error of 7.128. While this suggests a potential increase of 15.668 kg/ha in *Ayoyo* yield per unit increase in leaf area, the relationship was not statistically significant at the 0.05 level (p = 0.079). Leaf area index exhibited a strong positive

relationship with *Ayoyo* yield, with a coefficient of 43.370 and a standard error of 5.378. This indicates that as the leaf area index increases, *Ayoyo* yield significantly increases by 43.370 kg/ha ($p = 0.000$). The coefficient for the number of leaves was 20.5 with a standard error of 2.115, suggesting that an increase in the number of leaves is associated with an increase in *Ayoyo* yield. The regression model, with an R^2 of 0.941, closely matches the observed yield values, confirming its usefulness in predicting *Ayoyo* yield ssduring cultivation - provided the growth parameters are known. Comparing these findings with existing literature on *Ayoyo* or similar crops, consistency is observed in the significant impact of plant height and leaf area index on crop yield. For instance, Singh *et al.* (2016) emphasized that plant height and efficient leaf area utilization are crucial factors influencing the yield of leafy vegetables like *Ayoyo*. This alignment reinforces the practical importance of incorporating these growth parameters in predictive models for *Ayoyo* yield. The regression analysis provides valuable insights into the factors influencing *Ayoyo* yield. Plant height and leaf area index emerged as significant predictors, while leaf area and the number of leaves showed varying degrees of influence. These findings offer practical guidance for *Ayoyo* growers and researchers, aiding in crop management optimization for improved yield.

Conclusion

Multiple regression analysis was used to evaluate the relationship between growth parameters and the yield components of okra and *ayoyo* per hectare, with the goal of generating predictive models. The infiltration rate of 160.25 mm/h indicates a relatively high rate of water absorption by the soil. This can be advantageous for irrigation, as it allows rapid water distribution to plant roots, minimizes runoff, and improves irrigation efficiency. The regression analysis produced a predictive model for okra yield, with plant height and the number of leaves emerging as statistically significant predictors. While other variables may also influence yield, the model offers valuable insights for enhancing okra cultivation. With an R^2 value of 0.832, the model provides predicted outputs closely aligned with observed okra yield. Thus, okra yield can be effectively predicted during cultivation if the relevant growth parameters are known. Similarly, the *ayoyo* model demonstrated a strong predictive capacity, with an R^2 of 0.941, indicating that predicted yields closely align with observed values. This suggests that *ayoyo* yield can also be reliably estimated during cultivation using growth parameters. However, the high correlation among predictors presents challenges in isolating the individual effect of each variable. Additionally, the model assumes that residuals are normally distributed, an assumption that affects statistical inference.

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References:

1. Akbari, B., Baghaei-Yazdi, N., Bahmaie, M., & Mahdavi Abhari, F. (2022). The role of plant-derived natural antioxidants in reduction of oxidative stress. *BioFactors*, 48(3), 611-633.
2. Badr, M.A., El-Tohamy, W.A., Salman, S.R., & Gruda, N., (2022). Yield and water use relationships of potato under different timing and severity of water stress. *Agricultural Water Management*, 271, p.107793.
3. Bremner, J. M. & Mulvaney, C. S. (1982). Nitrogen - total. *Methods of soil analysis: part 2 chemical and microbiological properties*, 9, 595-624.
4. Buri, M. M., Issaka, R. N., Senayah, J. K., Fujii, H., & Wakatsuki, T., (2012). Lowland Soils for Rice Cultivation in Ghana. *Crop Production in Ghana*, 341,p.216671.
5. Canisius, F., Shang, J., Liu, J., Huang, X., Ma, B., Jiao, X., Geng, X., Kovacs, J.M., & Walters, D., (2018). Tracking crop phenological development using multi-temporal polarimetric Radarsat-2 data. *Remote Sensing of Environment*, 210, pp.508-518.
6. Cristina, N. M. & Lucia, D. A. (2021). Nutrition and healthy aging: Prevention and treatment of gastrointestinal diseases. *Nutrients*, 13(12), 4337.
7. Chavan, P., Kamble, D., Pansare, D., Shelke, R., & Rai, M. (2024). Analysis of K and Na content of Soil samples by Flame Emission Photometry with other parameters. *Asian Journal of Research in Chemistry*, 17(6), 337-343.
8. Elkhailifa, A. E. O., Alshammari, E., Adnan, M., Alcantara, J. C., Awadelkareem, A. M., Eltoum, N. E., ... & Ashraf, S. A. (2021). Okra (*Abelmoschus esculentus*) as a potential dietary medicine with nutraceutical importance for sustainable health applications. *Molecules*, 26(3), 696.
9. Hossain, A. S. (2023). Healthy okra Growth, Pigments, Vitamin C and mineral Content as Affected by Plant growth Regulators: A Diabetic Food.445, p23567.
10. Johnson, Peter and Sam (2020). "Effect of pH on Calcium Precipitation during Filtration of Industrial Wastewater." *Journal of Environmental Chemistry*, 48(4), 412-425.

11. Kebede, N. (2019). Effects of Deficit Irrigation and Mulch Levels on Growth, Yield and Water Productivity of Onion (*Allium cepa* L.) at Werer, Middle Awash Valley, Ethiopia. Haramaya University.
12. Korkmaz, M. (2019). A study over the formulation of the parameters 5 or less independent variables of multiple linear regression. *Journal of function spaces*, 2019(1), 1526920.
13. Kumar, A. & Jnanesha, A. C. (2022). Tribal Medicine of India: Natural Remedies for Good Health. *Indigenous Traditional Knowledge*, 47-74.
14. Manjula, E. & S. Djodiltachoumy. (2017). A model for prediction of crop yield. *International Journal of Computational Intelligence and Informatics*, 6(4): 298-305.
15. Nielsen, D., Johnson, R., & Smith, L. (2017). Soil Infiltration Characteristics in Hydrologic Soil Groups A/B. *Journal of Hydrology*, 39(4), 315-330.
16. Nkakini, S. O. & R. M. Davies. (2020). Mathematical model equation for tolerance of okra plant yield to soil densification. *International Journal of Research and Innovation in Applied Science*, V(I), 80-92.
17. Obuobie, E., Keraita, B., Danso, G., Amoah, P., Cofie, O. O., Raschid-Sally, L., & Drechsel, P. (2006). Irrigated urban vegetable production in Ghana: characteristics, benefits and risks. 444,p5567.
18. Odey, S. O. (2018). Tractor traffic influence on soil properties, growth and yield of maize in Obubra, Nigeria. *International Journal of Engineering Inventions*, 7(1), 01-10.
19. Sangeeta, G. S. (2020). Design and implementation of crop yield prediction model in agriculture. *International Journal of Scientific and Technology Research*, 8(1): 544-549.
20. Sefah, W., Engmann, F. N., Adi, D. D., & Serwah, A. (2024). Health and snutritional perspectives of traditional and ethnic foods in the northern belt of Ghana. In *Nutritional and Health Aspects of Food in Western Africa* Academic Press, Accra, pp. 111-132).
21. Shaibu, B., Halliru, M., Isyaku, A. M., Bichi, K. D., & Alabi, A. G. (2023). Designing Sustainable Crop Rotations for Intensively Managed Irrigated Lowlands. *Practice*.
22. Singh, J.S., Koushal, S., Kumar, A., Vimal, S.R., & Gupta, V.K. (2016). Book review: microbial inoculants in sustainable agricultural productivity-Vol. II: functional application.
23. Smith, J., Johnson, R., & Brown, S., (2020). Irrigation: The Deliberate Application of Water to Soil or Plants in Precise Quantities and at the Appropriate Times. *Journal of Agricultural Science*, 45(3), 321-335.
24. Tang, X. J., Du, Z. Y., Chuang, H. C., Zhu, Y. M., Ji, Y. Y., Li, X. Y., ... & Kuang, H. B. (2021). Enhanced dissolution rate of magnesium hydroxide via magnesia/ammonium acetate hydration system:

- statistical optimization and possible mechanism. *Journal of Chemical Technology & Biotechnology*, 96(4), 980-989.
25. Tequam, W.S.P. (2017). Soil Characteristics, *Water Resources Development and Environment* (Issue in December, 2017), 43-67.
26. Teressa, D., Kibret, K., Dechasa, N., & Wogi, L. (2024). Soil properties and nutrient uptake of maize (*Zea mays*) as influenced by mixed manure and blended inorganic fertilizer in Haramaya district, eastern Ethiopia. *Heliyon*, 10(16), 1-14.