THAI JOURNAL OF
AGRICULTURAL SCIENCE
Vol.58 No.2 April-June 2025
https://li01.tci-thaijo.org/index.php/TJAS

Agronomic performance of okra (*Abelmoschus esculentus* (L.) Moench) accessions and trait association partitioning using path analysis

Folusho Anuoluwapo Bankole[1]
Olawale Serifdeen Aboderin[1,*]
Faozyath Aminou[1]
Hajarat Olufade[1]
Adesike Kolawole[2]
Dorcas Ibitoye[3]

[1] *Department of Agronomy, University of Ilorin, Ilorin 240003, Nigeria*
[2] *Department of Crop Production and Soil Science, Ladoke Akintola University of Technology, Ogbomosho 210214, Nigeria*
[3] *Nigerian Horticultural Research Institute, Oyo State 200272, Nigeria*

Corresponding author:* **olawaleaboderin@yahoo.com

Article History

Submission: 4 December 2024
Revised: 13 March 2025
Accepted: 21 March 2025

Keywords

Correlation
Path analysis
Okra
Structural equation modelling
Component traits

Abstract

Background and Objective: Yield improvement in okra (*Abelmoschus esculentus* (L.) Moench) is challenging due to the complexity of its genetic inheritance. Understanding the relationships between yield and its component traits is essential for effective selection in breeding programs. This study aimed to assess the genetic variability among okra accessions, identify high-yielding and early-maturing varieties, and develop appropriate selection indices for yield improvement.

Methodology: Thirty okra accessions were evaluated across two locations in Nigeria over two growing seasons. Quantitative data were collected on ten agronomic and yield-related traits from five representative plants per plot. The data were analyzed using analysis of variance (ANOVA), correlation analysis, and path coefficient analysis to identify traits influencing yield performance.

Main Results: Significant genotypic variation was observed among the accessions, with NHOKO179, NHOKO158, and NHOKO593 demonstrating the highest yield potential. Correlation analysis showed strong positive relationships between yield and the number of pods per plant ($r = 0.90$; $P < 0.01$) and pod weight per plant ($r = 0.90$; $P < 0.01$). In contrast, negative correlations were found between yield and days to first flowering, days to first picking, and days to first pod appearance ($r = -0.50$; $P < 0.01$ for all).

Path coefficient analysis revealed that days to first picking (7.68) had the highest positive direct effect on yield, followed by days to first flowering (4.55) and pod weight per plant (1.23). Conversely, days to first pod appearance (-12.25) exhibited the most significant negative direct effect on yield.

Conclusions: The study identified pod weight per plant, early flowering, and early picking times as effective selection indices for enhancing okra yield. NHOKO179, NHOKO158, and NHOKO593 emerged as promising candidates for breeding programs aimed at developing high-yielding okra cultivars with improved adaptability and productivity across diverse environments.

How to cite : Bankole, F.A., O.S. Aboderin, F. Aminou, H. Olufade, A. Kolawole and D. Ibitoye. 2025. Agronomic performance of okra (*Abelmoschus esculentus* (L.) Moench) accessions and trait association partitioning using path analysis. Thai J. Agric. Sci. 58(2): 146−159.

INTRODUCTION

Okra (*Abelmoschus esculentus* (L.) Moench), commonly known as lady's finger, is a valuable crop both economically and nutritionally (Nkongho *et al*., 2022). It belongs to the Malvaceae family, an annual dicotyledonous, herbaceous plant with small erect stems that may be either bristly or hairless with heart-shaped leaves. The crop is widely cultivated in tropical and subtropical regions, primarily for its edible, fibrous pods, which are rich in carbohydrates, protein, vitamins, minerals, and dietary fiber (Chowdhury and Kumar, 2019). In addition to the pods, okra seeds contain significant amounts of crude protein, positioning them as a valuable protein source, as well as a promising source of edible oil, particularly rich in linoleic acid, which has significant health benefits. Okra seeds can also be processed into various by-products, such as seed flour, protein concentrate, and hydrolysate (Nnamezie *et al*., 2021).

Okra production occurs on almost every continent, with Africa, particularly Nigeria, leading global production, followed by Sudan, Ghana, and Egypt (Davis, 2022). Despite its widespread cultivation, the average yield of okra in West and Central Africa has been declining, underscoring the need for genetic improvement (Sugri *et al*., 2015). Factors such as low soil organic matter, weed infestation (Kugbe *et al*., 2019), and land degradation (Kumar *et al*., 2010) contribute to this decline. Moreover, the predominance of low-yielding okra varieties limits the crop's potential to meet the nutritional demands of the growing population in developing regions (Chowdhury and Kumar, 2019). Consequently, implementing breeding programs aimed at improving yield, alongside adopting appropriate cultural practices, is crucial to enhancing okra productivity in these regions. Optimizing pod yield remains the primary objective for most okra growers and is the central focus of many okra breeding programs.

In addition, the efficiency of selection in any breeding program largely depends on understanding the associations between key agronomic traits. A comprehensive knowledge of these associations can significantly enhance crop improvement efforts by guiding the development of effective selection indices, thereby improving the accuracy and efficiency of selection (Adekoya *et al*., 2014). Yield in okra, as in most crops, is a complex, polygenic trait influenced by environmental factors and a combination of various yield components. Therefore, understanding the relationships between pod yield and its associated traits, and accurately dissecting these relationships, is essential for the successful selection of superior varieties in breeding programs (Adekoya *et al*., 2014; Bankole *et al*., 2019). Previous studies on different okra genotypes, such as those by Akinyele and Osekita (2006), Abd-allah (2015), and Ibitoye and Kolawole (2022), have found that certain component traits such as the number of pods, pod length and pod weight are associated with pod yield.

One of the fundamental tools for evaluating the association between traits is the Pearson correlation coefficient, which measures the degree and direction (positive or negative) of the linear relationship between two or more variables (Aboderin *et al*., 2023). While correlation analysis provides valuable insights into the strength of these relationships, it does not distinguish between direct and indirect effects, which is essential for understanding the underlying causal mechanisms. To address this limitation, path coefficient analysis, originally proposed by Wright (1921), is employed. Path analysis partitions correlation coefficients into direct and indirect effects, providing a more detailed understanding of the cause-and-effect relationships among traits (Mamud, 2021). This method helps breeders identify traits with the most significant direct influence on yield, allowing for more targeted selection strategies. This study was therefore carried out to assess the genetic variability among the okra accessions, identify high-yielding and early-maturing varieties, and develop appropriate selection indices for yield improvement. The objective of the study was to evaluate the agronomic performance of various okra accessions across different ecological zones in Nigeria and explore the relationships among key yield components using correlation and path analysis.

MATERIALS AND METHODS

Source of Germplasm

Thirty okra accessions were obtained from the National Institute of Horticultural Research and Training (NIHORT) and the National Center for Genetic Resources and Biotechnology (NACGRAB), both located in Ibadan, Oyo State, Nigeria (Table 1). These accessions were selected for their diverse agro-ecological origins, distinct morphological and agronomic traits, and potential for high yield and adaptability, ensuring a broad genetic base for the study.

Field Evaluation

The field experiments were conducted over two growing seasons (2019 and 2020) at two distinct locations: the University of Ilorin Teaching and Research Farm, Ilorin, and the NACGRAB research field, Ibadan, Oyo State, Nigeria. The NACGRAB site, situated at approximately 7°23’N latitude and 3°15’E longitude, lies within the tropical rainforest zone. This region experiences a tropical climate with annual rainfall ranging from 1,200 to 1,400 mm, primarily concentrated between March and November, and an average annual temperature of 25 to 32°C, with a distinct dry season from November to February. In contrast, Ilorin, located in the southern Guinea savanna at 8°30’N latitude and 4°32’E longitude, at an altitude of 290 m above sea level, has a tropical savanna climate. It receives an annual rainfall of 1,200 to 1,500 mm, predominantly between April and October, with temperatures ranging from 22 to 34°C.

Experimental Design

The experiments were arranged in a randomized complete block design (RCBD) with three replicates per location. Each trial plot measured 1.5 m in length and comprised two rows per plot, with an inter-row spacing of 60 cm and intra-row spacing of 30 cm. Two seeds were sown per hole to ensure germination, and thinning was performed later to maintain one healthy plant per stand. Compound fertilizer (NPK 15:15:15) was applied at a rate of 60 kg/ha three weeks after planting (WAP). Standard agronomic practices, including weeding, pest control, and irrigation where necessary, were implemented to ensure optimal growth conditions throughout the experimental period.

Table 1 List of okra accessions used for the study

S/N	Seed accessions	Source
1	NHOKO174	NIHORT, Ibadan
2	NHOKO593	NIHORT, Ibadan
3	NHOKO170	NIHORT, Ibadan
4	NHOKO563	NIHORT, Ibadan
5	NGBOO342	NACGRAB, Ibadan
6	NHOKO592	NIHORT, Ibadan
7	NHOKO181	NIHORT, Ibadan
8	NHOKO179	NIHORT, Ibadan
9	NGBOO400	NACGRAB, Ibadan
10	NHOKO418	NIHORT, Ibadan
11	NGBOO469	NACGRAB, Ibadan
12	NHOKO463	NIHORT, Ibadan
13	NHOKO188	NIHORT, Ibadan
14	NHOKO151	NIHORT, Ibadan
15	NHOKO554	NIHORT, Ibadan
16	NHOKO185	NIHORT, Ibadan
17	NHOKO175	NIHORT, Ibadan
18	NGBOO345	NACGRAB, Ibadan
19	NHOKO167	NIHORT, Ibadan
20	NHOKO182	NIHORT, Ibadan
21	NHOKO169	NIHORT, Ibadan
22	NHOKO161	NIHORT, Ibadan
23	NHOKO555	NIHORT, Ibadan
24	NHOKO154	NIHORT, Ibadan
25	NHOKO155	NIHORT, Ibadan
26	NHOKO594	NIHORT, Ibadan
27	NHOKO158	NIHORT, Ibadan
28	NHOKO421	NIHORT, Ibadan
29	NHOKO544	NIHORT, Ibadan
30	NHOKO429	NIHORT, Ibadan

Data Collection and Analysis

Quantitative data were collected on ten agronomic and yield-related traits from five randomly selected plants per plot, which were tagged and used as representative samples to evaluate the performance of each accession. The measured traits included days to first flowering (DTF), representing the interval from planting to the appearance of the first flower, and days to first pod appearance (DFPA), indicating the time from planting to the emergence of the first pod.

Days to first picking (DFP) recorded the time from planting to the initial harvest. Plant height was measured at key growth stages, including height at the first flowering node (HTFN) and height at flowering (HTF). Pod characteristics assessed included pod length (PL), measured from the base to the tip, and the picking period (PP), which reflected the duration of harvest. Yield-related parameters included the number of pods per plant (NPP), pod weight per plant (PWP), and total yield (YLD), expressed in tons per hectare (t/ha).

The collected data were analyzed using various statistical methods to evaluate the agronomic performance and relationships among traits in the okra accessions. Analysis of variance (ANOVA) was performed to determine the significance of differences among the accessions for each trait and to partition the observed variability into its components. Pearson correlation coefficients were computed to assess the strength and direction of linear relationships between traits, with correlations categorized as weak (0.00–0.39), moderate (0.40–0.59), or strong (0.60–1.00), following the guidelines of Belsley *et al*. (2005). The correlation analysis and visualization were performed using the ggcorrplot package in R version 4.2.2 (R Core Team, 2022). To further explore the direct and indirect effects of various traits on yield, path analysis was conducted using standardized path coefficients. This analysis was implemented through latent variable modeling with the lavaan package (version 0.6-13) in R. Graphical representations of the path coefficients were generated using the semPlot package, providing a clear visualization of the relationships and their respective strengths (Rosseel, 2012; Epskamp *et al*., 2019).

RESULTS AND DISCUSSION

The combined analysis of variance (ANOVA) revealed that only yield was significantly influenced by the environment ($P < 0.05$; Table 2), indicating that environmental factors such as climatic conditions, soil properties, and management practices played a substantial role in determining the yield performance of okra accessions. This variability in yield across environments underscores the importance of selecting genotypes that are either specifically adapted to particular environments or exhibit broad adaptability to ensure consistent performance under varying conditions (Oyekunle *et al*., 2017; Bankole and Aboderin, 2024). Significant differences among genotypes were observed for pod yield, pod length, and the number of pods per plant ($P < 0.01$). This significant genotypic variation highlights the presence of substantial genetic diversity among the studied accessions for these traits, which can be exploited for genetic improvement (Ibitoye and Kolawole, 2022). In contrast, most other traits did not exhibit significant differences among genotypes, possibly due to limited genetic variability for these traits or the overriding influence of environmental factors that masked the genetic effects (Aboderin *et al*., 2023). The genotype by environment (G × E) interaction was significant ($P < 0.01$) for most traits, except for height at first flowering, height at flowering, pod length, and number of pods per plant. This indicates that the performance of genotypes for traits with significant G × E interactions was inconsistent across environments, complicating the selection process. Breeding programs should therefore focus on identifying genotypes with stable performance across diverse environments or develop region-specific

Agronomic Performance and Yield Potential of Okra Accessions

The evaluation of 30 okra accessions for various agronomic traits revealed significant variation in their performance (Table 3). Days to first flowering ranged from 46.17 days in NHOKO555 to 62.00 days in NHOKO592, with an average of 52.47 days. Similarly, days to first pod appearance and first picking showed wide variation, with NHOKO555 and NHOKO593 maturing earlier. These early maturing accessions could be valuable for breeding programs aimed at developing varieties for regions with shorter growing seasons or in environments where rapid crop turnover is necessary.

Table 2 Mean squares from combined analyses of variance for okra yield and other agronomic traits at Ilorin and Ibadan in 2019 and 2020

Source of variation	df	YLD	DTF	DFPA	DFP	HTFN	HTF	PL	PP	NPP	PWP
Environment (E)	3	8.1*	429.4	420.1	411.0	1795.2	7516	13.9	1723.6	7880	163022
Rep (E)	8	3.7	2.6	2.6	2.6	80.9	294.2	0.2	13.4	206.2	10771
Genotypes (G)	29	4.3*	96.1	98.1	100.2	468.3	1301	1.7**	33.5	198**	5280
G × E	29	2.6*	24.1**	23.1**	22.2**	145.9	462	1.3	17.4*	147	3627*
Error	120	1.6	10.7	11.1	12.3	54.6	177	0.9	10.8	101	2886

Note: *, ** significant at 5% and 1% level of probability, respectively. YLD = yield, DTF = days to first flowering, DFPA = days to first pod appearance, DFP = days to first picking, HTFN = height at first flowering node, HTF = height at flowering, PL = pod length, PP = picking periods, NPP = number of pods per plant, PWP = pod weight per plant.

Significant differences in plant height were also observed, with heights at first flowering node ranging from 14.77 cm (NHOKO555) to 52.90 cm (NHOKO429). Taller accessions such as NHOKO429, and those with greater flowering height at maturity, such as NHOKO169, could be desirable in regions where plant height correlates with higher yields or ease of manual harvesting. Conversely, shorter accessions like NHOKO555 might be better suited for mechanical harvesting, thus offering options for different production systems. Pod length followed a similar pattern, with lengths ranging from 3.32 cm (NHOKO167) to 5.40 cm (NHOKO555), indicating genetic diversity that can be harnessed to select varieties based on market preferences for pod size. Accessions with longer pods could be prioritized for markets where larger pod size is preferred.

There was also considerable variation in the picking period, ranging from 2.67 weeks (NHOKO167) to 12.17 weeks (NHOKO158), and in the number of pods per plant, which ranged from 3.33 (NHOKO167) to 26.00 (NGB00345). Accessions like NHOKO158, NHOKO593, and NGB00345, which had longer picking periods and produced more pods, are promising candidates for breeding programs targeting prolonged pod production and extended harvesting seasons.

In terms of pod weight and yield, substantial differences were noted among the accessions. Pod weight per plant ranged from 12.33 g (NHOKO167) to 122.00 g (NHOKO593), with an average of 77.02 g. The yield per hectare, the primary metric of interest, ranged from 0.35 t/ha (NHOKO167) to 4.27 t/ha (NHOKO179), with an overall mean of 2.29 t/ha. High-yielding accessions, such as NHOKO179, NHOKO158, and NHOKO593, demonstrated clear potential for commercial production, particularly in environments similar to those in which this study was conducted. These accessions could serve as promising candidates for developing high-yielding okra cultivars in breeding programs.

Correlation and Path Coefficient Analysis of Agronomic Traits

An efficient selection program depends on understanding the relationships between yield and its component traits, as well as among those traits

Table 3 Mean performance of 30 okra genotypes for yield and agronomic traits

S/N	Accessions	DTF (day)	DFPA (day)	DFP (day)	HTFN (cm)	HTF (cm)	PL (cm)	PP (week)	NPP	PWP (g)	YLD (t/ha)
1	NHOKO174	60.00	61.00	64.00	24.62	36.80	3.37	3.33	4.83	24.83	0.80
2	NHOKO593	46.50	47.50	50.50	17.18	30.03	4.68	10.67	25.67	122.00	3.46
3	NHOKO170	49.67	50.67	53.67	18.95	31.97	4.45	11.50	21.00	112.33	2.70
4	NHOKO563	56.50	57.50	60.50	23.60	31.73	4.08	7.00	18.83	87.50	2.31
5	NGB00342	54.50	55.50	58.50	37.08	65.05	4.33	9.17	22.33	113.17	3.08
6	NHOKO592	62.00	63.50	67.00	15.20	28.13	3.80	6.17	12.00	49.33	1.64
7	NHOKO181	52.50	53.50	56.50	22.48	38.43	3.82	8.50	15.17	83.00	2.33
8	NHOKO179	49.67	50.67	53.67	30.13	64.97	5.40	10.67	19.00	117.33	4.27
9	NGB00400	52.33	53.33	56.33	20.03	29.75	4.35	7.67	15.17	73.00	2.17
10	NHOKO418	50.83	51.83	54.83	16.05	26.30	4.23	8.50	16.83	94.67	3.16
11	NGB00469	54.83	55.83	58.83	28.65	47.27	3.75	9.00	15.50	79.00	2.12
12	NHOKO463	52.67	53.67	56.67	19.90	29.93	4.57	10.33	18.00	89.00	2.42
13	NHOKO188	51.00	52.00	55.00	20.05	34.30	4.62	8.33	14.33	67.17	2.24
14	NHOKO151	55.50	56.50	59.50	20.97	30.10	3.95	8.67	14.83	80.17	2.18
15	NHOKO554	51.67	52.67	55.67	22.46	34.37	5.18	5.50	7.33	36.67	1.08
16	NHOKO185	57.00	58.00	61.00	25.52	37.37	4.58	6.83	12.00	57.33	2.02
17	NHOKO175	50.83	51.83	54.83	22.65	27.23	3.92	9.33	13.67	73.50	1.83
18	NGB00345	58.00	59.00	62.00	37.58	54.27	4.15	9.83	26.00	120.17	2.89
19	NHOKO167	54.83	55.83	58.83	14.85	19.37	3.32	2.67	3.33	12.33	0.35
20	NHOKO182	48.17	49.17	52.17	16.03	25.82	5.28	9.00	16.67	76.50	2.46
21	NHOKO169	54.83	55.83	58.83	44.85	69.43	4.90	3.33	5.17	27.83	1.15
22	NHOKO161	54.33	55.33	58.33	19.98	32.22	4.05	6.50	9.67	46.17	1.68
23	NHOKO555	46.17	47.17	50.17	14.77	24.75	5.40	9.17	13.83	81.17	2.24
24	NHOKO154	48.33	49.33	52.33	21.83	31.72	4.27	8.00	15.50	99.17	3.30
25	NHOKO155	47.50	48.50	51.50	27.90	49.12	4.38	7.00	11.00	56.67	1.85
26	NHOKO594	49.83	50.83	53.83	22.35	33.88	4.50	9.83	15.83	85.67	2.82
27	NHOKO158	47.17	48.17	51.17	19.68	34.38	4.05	12.17	24.17	112.83	3.47
28	NHOKO429	55.00	56.00	59.00	52.90	77.80	3.88	6.83	10.67	56.50	1.82
29	NHOKO421	48.67	49.67	52.67	27.13	55.87	4.03	11.17	19.17	106.83	2.93
30	NHOKO544	53.17	54.17	57.17	26.05	41.98	4.40	7.50	13.33	69.00	1.98
	Mean	52.47	53.48	56.50	24.39	39.14	4.32	8.13	15.02	77.02	2.29
	LSD $\alpha = 0.05$	7.23	7.10	6.98	16.71	31.12	1.55	10.16	23.71	111.48	1.96
	CV (%)	8.96	8.81	8.37	43.17	46.50	17.53	52.25	66.85	63.34	47.25

Note: DTF = days to first flowering, DFPA = days to first pod appearance, DFP = days to first picking, HTFN = height at first flowering node, HTF = height at flowering, PL = pod length, PP = picking periods, NPP = number of pods per plant, PWP = pod weight per plant, YLD = yield, LSD = least significant difference, CV = coefficient of variation.

themselves (Aboderin *et al*., 2023). Correlation analysis helps estimate the genetic associations between traits and the degree of relationship between them (Aboderin *et al*., 2023), while path coefficient analysis provides insight into the cause-and-effect relationships, offering a more precise interpretation of the associations (Bankole *et al*., 2019). In this study, both correlation and path coefficient analyses were used as tools to investigate the relationships between yield and other agronomic traits in okra.

The correlation analysis presented in Figure 1 revealed that yield had a highly significant and strong positive correlation with the number of pods per plant ($r = 0.90$; $P < 0.01$) and pod weight per plant ($r = 0.90$; $P < 0.01$). This strong association highlights the importance of these traits in selecting high-yielding okra accessions. Improving either the number of pods or pod weight per plant will likely lead to increased yield. Similar positive associations between yield and these traits were reported by Rambabu *et al*. (2019), Vrunda *et al*. (2019), and Ashraf *et al*. (2020).

The picking period showed a highly significant and positive correlation with yield ($r = 0.80$; $P < 0.01$), number of pods per plant ($r = 0.90$; $P < 0.01$), and pod weight per plant ($r = 0.90$; $P < 0.01$). This suggests that accessions with longer picking periods tend to produce more pods and heavier pod weights, ultimately achieving higher yields. The extended picking period allows for prolonged harvesting, which, when combined with increased pod production, results in higher cumulative yields. These findings highlight the importance of selecting accessions with extended harvesting periods, particularly in environments where harvesting flexibility or maximizing yield over a longer period is desired.

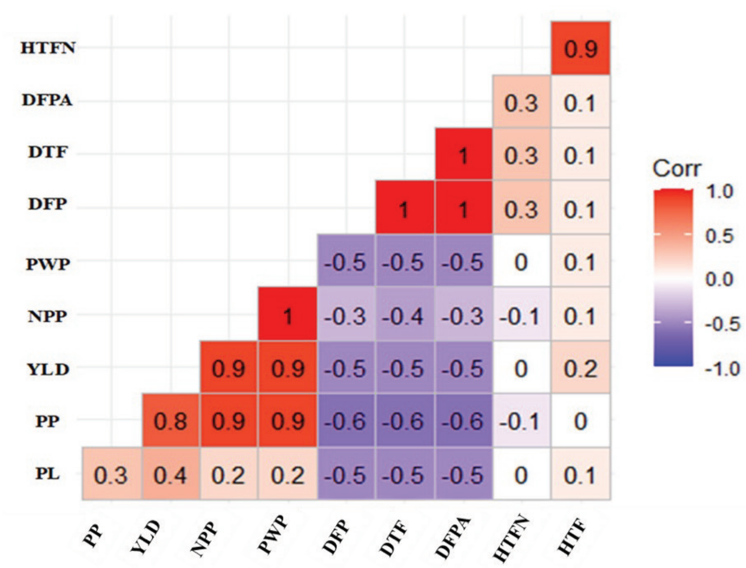

Figure 1 Pearson's correlation matrix showing the relationships between measured traits. Positive correlations are displayed in red, and negative correlations in blue, with color intensity reflecting the strength of the association. YLD = yield, DTF = days to first flowering, DFPA = days to first pod appearance, DFP = days to first picking, HTFN = height at first flowering node, HTF = height at flowering, PL = pod length, PP = picking periods, NPP = number of pods per plant, PWP = pod weight per plant.

Interestingly, the number of pods per plant showed a perfect correlation (r = 1.00; P < 0.01) with pod weight per plant, which is expected. As the number of pods increases, the total weight of pods per plant also rises. This relationship highlights the direct impact of pod number on pod weight, reinforcing that increasing the number of pods is a reliable strategy for improving overall yield. A significant positive correlation was observed between days to first picking and days to first flowering (r = 1.00; P < 0.01), as well as days to first pod appearance. This indicates that early-flowering accessions tend to exhibit early pod development and picking, establishing a clear link between flowering time and subsequent pod development stages. Early-flowering accessions may be particularly valuable in environments with shorter growing seasons or for farmers seeking earlier harvests.

However, yield (r = -0.50; P < 0.01), pod weight per plant (r = -0.50; P < 0.01), pod length (r = -0.50; P < 0.01), and the picking period (r = -0.60; P < 0.01) all showed significant negative correlations with days to first flowering, days to first picking, and days to first pod appearance. This implies that accessions that take longer to flower, develop pods, or reach picking maturity tend to have lower yields, shorter pod lengths, and shorter picking periods. This inverse relationship suggests that earlier-maturing accessions are more likely to produce higher yields, making them desirable in environments where early harvest and high yield are prioritized. It also suggests that delaying flowering and pod development could limit overall productivity. These findings are consistent with those of Shuirkar *et al*. (2018) and Rynjah *et al*. (2020) but contrast with Yang *et al*. (2019), who opined that extended days to maturity avails crop sufficient time for photosynthesis resulting in the production of more biomass thus increasing the yield of crops.

The insignificant association of height at flowering with the number of pods per plant points to the fact that the performance of the okra accessions was not dependent on the plant height at flowering. Traits with non-significant correlations will not be prioritized in selection for varietal improvement, as changes in one trait have no significant impact on the other. These independent traits are not strongly linked to yield and should not be the focus of selection in breeding programs.

Path Analysis

Path analysis was employed to explore the direct and indirect effects of various traits on yield. Using a postulated model optimized over 100 iterations, the Maximum Likelihood (ML) method estimated the parameters, and the chi-square (χ^2) test was used to assess the model's fit to the data. Despite the relatively small sample size (n = 30), the chi-square result was not statistically significant, indicating that the model fit well by closely approximating the actual data.

Several fit indices were also considered (Table 4). The Standardized Root Mean Square Residual (SRMR) had a value of 0.021, suggesting that the model fit was excellent. According to Hu and Bentler (1998; 1999), SRMR values below 0.05 suggest an excellent fit, and this study's result falls well within that range. Similarly, the Comparative Fit Index (CFI) was 0.968, another indicator of a strong model fit, as values above 0.95 are highly desirable. However, the Tucker-Lewis Index (TLI) was 0.891, slightly below the ideal target of 0.95, and the Root Mean Square Error of Approximation (RMSEA) was 0.181, exceeding the acceptable threshold of 0.08 (Cudeck and Browne, 1992; Jöreskog and Sörbom, 1993). While the RMSEA indicated some limitations, the non-significant chi-square, high CFI, and low SRMR collectively suggest that the model fits the data well (Shipley, 2000; Pugesek *et al*., 2003).

Table 4 Summary of the analyzed structural equation model

Parameter	Postulated model
Degrees of freedom (df)	5
P-value (Chi-square: χ^2)	0.078
P-value	<0.000
Comparative Fit Index (CFI)	0.968
Tucker-Lewis Index (TLI)	0.891
Standardized Root Mean Squares Residuals (SRMR)	0.021
Root Mean Square Error of Approximation (RMSEA)	0.181

The results of the path analysis (Figure 2, Table 5) show that five traits had a positive direct effect on yield, with the strongest positive effect coming from days to first picking (7.68), followed by days to first flowering (4.55), and pod weight per plant (1.23). These results suggest that selecting for earlier flowering and picking times, alongside increased pod weight, can significantly improve yield. However, despite their positive direct effects, both days to first picking and days to first flowering exhibited negative correlations with yield, indicating that indirect factors complicate their relationship with yield. Conversely, pod weight per plant stands out because it not only has a strong positive direct effect but also a strong positive correlation with yield. This suggests that increasing pod weight directly boosts yield and makes it a reliable trait for selection in breeding programs. These findings align with those of Aminu *et al*. (2016) and Rambabu *et al*. (2019), who highlighted the importance of pod weight and the number of pods per plant in improving okra yield.

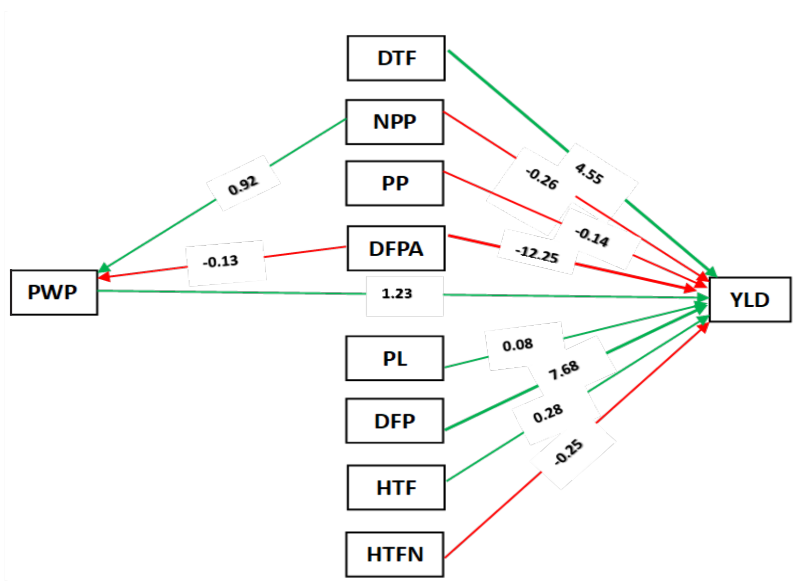

Figure 2 Path diagram showing the direct and indirect effects of other traits on yield. The rectangles represent observable endogenous and exogenous variables, and the width of the arrow represents the strength of the relationship. Green arrows represent positive effects while red arrows represent negative effects. YLD = yield, DTF = days to first flowering, DFPA = days to first pod appearance, DFP = days to first picking, HTFN = height at first flowering node, HTF = height at flowering, PL = pod length, PP = picking periods, NPP = number of pods per plant, PWP = pod weight per plant.

Table 5 Path analysis of okra accessions by structural equation modeling

Variables		Estimate	Standard error	Wald statistic (z-value)	P(>|z|)	Standardized latent variables	Completely standardized solution
	YLD ~						
Exogenous variables (Latent)	DTF	4.55	8.25	0.55	0.58	4.55	4.60
	DFPA	-12.25	16.30	-0.75	0.45	-12.25	-12.40
	DFP	7.68	8.33	0.92	0.36	7.68	7.75
	HTFN	-0.25	0.18	-1.40	0.16	-0.25	-0.26
	HTF	0.28	0.17	1.64	0.10	0.28	0.28
	PL	0.08	0.06	1.32	0.19	0.08	0.08
	PP	-0.14	0.13	-1.02	0.31	-0.14	-0.14
	NPP	-0.26	0.22	-1.15	0.25	-0.26	-0.26
	PWP	1.23	0.21	5.98	0	1.23	1.24
	PWP ~						
	DFPA	-0.13	0.06	-2.33	0.02	-0.13	-0.13
	PL	0	0.05	0.08	0.94	0	0
	NPP	0.92	0.05	19.04	0	0.92	0.92
	Residual variance						
Endogenous variables (Observed)	YLD	0.07	0.02	3.87	0	0.07	0.08
	PWP	0.06	0.02	3.87	0	0.06	0.06

Note: YLD = yield, DTF = days to first flowering, DFPA = days to first pod appearance, DFP = days to first picking, HTFN = height at first flowering node, HTF = height at flowering, PL = pod length, PP = picking periods, NPP = number of pods per plant, PWP = pod weight per plan.

Kumari *et al*. (2019) also reported positive direct effects of pod weight on yield at both the genotypic and phenotypic levels.

In contrast to the traits with positive effects, four traits demonstrated negative direct effects on okra yield (Figure 2, Table 5). The most pronounced negative effect was observed in days to first pod appearance (-12.25), indicating that a delayed appearance of the first pod significantly reduces yield. This result is further supported by the strong negative correlation (r = -0.50) between days to first pod appearance and yield, highlighting that early pod formation is critical for maximizing yield potential. A possible explanation is that a delay in pod formation shortens the period for pod growth and maturation, limiting the overall number of pods produced, which ultimately reduces yield. Similarly, height at first flowering node had a negative direct effect (-0.25), but its small effect size and lack of a strong correlation with yield imply limited influence.

The picking period and the number of pods per plant showed negative direct effects but strong positive correlations with yield, indicating that while these traits directly reduce yield, they contribute significantly to yield through indirect pathways. For instance, an extended picking period may initially divert resources, reducing yield directly, but allows for more pods to develop and be harvested over time, ultimately enhancing total yield. Similarly, while a higher number of pods per plant may reduce resource allocation to individual pods, the overall increase in pod numbers compensates for this, contributing positively to yield. Therefore, breeders should consider the indirect effects of these traits when selecting for higher yield, as focusing solely on direct effects may overlook their potential contribution to improving okra yield.

Lastly, the residual variance for yield (0.07) and pod weight (0.06) was low, suggesting that the exogenous variables (such as days to first flowering, pod appearance, etc.) explain a significant portion of the variance in yield and pod weight. This indicates that the model provides a good overall fit and that the traits analyzed are reliable predictors of okra yield.

CONCLUSIONS

This study concludes that sufficient genetic variability exists among the okra accessions to allow for the successful improvement of most of the measured traits. Accessions NHOKO179, NHOKO158, and NHOKO593 demonstrated high yield potential, making them promising candidates for developing improved okra cultivars in breeding programs. Traits such as pod weight per plant, as well as earlier flowering and earlier picking times, should receive priority in okra improvement efforts, as they have shown to significantly influence yield performance.

REFERENCES

Abd-allah, S.A.M. 2015. Path coefficient analysis for some characters on fruit and seed yield of okra. J. Horticulture. 2(2): 140. http://doi.org/10.4172/2376-0354.1000140.

Aboderin, O.S., F.A. Bankole, M. Oyekunle, G. Olaoye and Z. Saminu. 2023. Performance of maize inbred lines of different maturity groups under different soil nitrogen levels. Abuja Journal of Agriculture and Environment. 3(2): 225–245.

Adekoya, M.A., O.J. Ariyo, O.B. Kehinde and A.E. Adegbite. 2014. Correlation and path analyses of seed yield in okra (*Abelmoschus esculentus* (L.) Moench) grown under different cropping seasons. Pertanika J. Trop. Agric. Sci. 37(1): 39–49.

Akinyele, B.O. and O.S. Osekita. 2006. Correlation and path coefficient analyses of seed yield attributes in okra (*Abelmoschus esculentus* (L.) Moench). Afr. J. Biotechnol. 5(14): 1330–1336.

Aminu, D., O.B. Bello, B.A. Gambo, A.H. Azeez, J.O. Agbolade, U.A. Abdulhamid and A. Iliyasu. 2016. Varietal performance and correlation of okra pod yield and yield components. Bangladesh J. Pl. Breed. Genet. 29(1): 11–20. http://doi.org/10.3329/bjpbg.v29i1.33703.

Ashraf, A.T.M.H., M.M. Rahman, M.M. Hossain and U. Sarker. 2020. Study of correlation and path analysis in the selected okra genotypes. Asian Res. J. Agric. 12(4): 1–11. http://doi.org/10.9734/ARJA/2020/v12i430087.

Bankole, F.A., A. Menkir, G. Olaoye, O. Olakojo and G. Melaku. 2019. Association studies between grain yield and agronomic traits of a MARS maize (*Zea mays* L.) population under drought and non-stress conditions. Acta Agric. Slov. 114(1): 75–84. http://doi.org/10.14720/aas.2019.114.1.9.

Bankole, F.A. and O.S. Aboderin. 2024. Yield performance and adaptability of maize hybrids of different maturity groups in multiple environments in Nigeria. Thai J. Agric. Sci. 57(3): 164–180.

Belsley, D.A., E. Kuh and R.E. Welsch. 2005. Regression Diagnostics: Identifying Influential Data and Sources of Collinearity. John Wiley & Sons, Inc., New Jersey, USA.

Chowdhury, S. and S. Kumar. 2019. Exploitation of heterosis for yield and yield attributes in okra [*Abelmoschus esculentus* (L.) Moench]. Int. J. Chem. Stud. 7(4): 853–857.

Cudeck, R. and M.W. Browne. 1992. Constructing a covariance matrix that yields a specified minimizer and a specified minimum discrepancy function value. Psychometrika. 57(3): 357–369. http://doi.org/10.1007/BF02295424.

Davis, T.W. 2022. Grower's guide: A review for sustainable production of okra (*Abelmoschus esculentus*) in West Africa and other regions. Int. J. Res. Appl. Sci. Eng. Technol. 10: 128–138. http://doi.org/10.22214/ijraset.2022.46950.

Epskamp, S., S. Stuber, J. Nak, M. Veenman and T.D. Jorgensen. 2019. Path diagrams and visual analysis of various SEM packages' output, vol. 34. Available Source: https://github.com/SachaEpskamp/semPlot. February 3, 2023.

Hu, L.T. and P.M. Bentler. 1998. Fit indices in covariance structure modeling: Sensitivity to under-parameterized model misspecification. Psychol. Methods. 3(4): 424–453. http://doi.org/10.1037/1082-989X.3.4.424.

Hu, L.T. and P.M. Bentler. 1999. Cutoff criteria for fit indices in covariance structure analysis: Conventional criteria versus new alternatives. Struct. Equ. Modeling. 6(1): 1–55. http://doi.org/10.1080/10705519909540118.

Ibitoye, D.O. and A.O. Kolawole. 2022. Farmers' appraisal on okra [*Abelmoschus esculentus* (L.)] production and phenotypic characterization: A synergistic approach for improvement. Front. Plant Sci. 13: 787577. http://doi.org/10.3389/fpls.2022.787577.

Jöreskog, K.G. and D. Sörbom. 1993. LISREL 8: Structural Equation Modeling with the SIMPLIS Command Language. Scientific Software International, Lawrence Erlbaum Associates, Inc., Mahwah, New Jersey, USA.

Kugbe, J.X., W. Mawiya, A.M. Hafiz and C. Maganoba. 2019. Increase in the use of organic fertilizers in the maintenance of soil fertility and environmental sustainability. World J. Agri. & Soil Sci. 4(1). http://doi.org/10.33552/WJASS.2019.04.000577.

Kumar, S., S. Dagnoko, A. Haougui, A. Ratnadass, D. Pasternak and C. Kouame. 2010. Okra (*Abelmoschus* spp.) in West and Central Africa: Potential and progress on its improvement. Afr. J. Agric. Res. 5(25): 3590–3598. https://doi.org/10.5897/AJAR10.839.

Kumari, M., A.K. Dubey, K. Kumar, D.P. Singh and S. Tomar. 2019. Assessment of direct and indirect relationships among fruit yield and yield components in okra (*Abelmoschus esculentus* L. Moench). J. Plant Dev. Sci. 11(7): 427–430.

Mamud, A. 2021. Genetic variability, heritability, and association of quantitative traits in maize (*Zea mays* L.) genotypes: Review paper. EAS J. Biotechnol. Genet. 3(2): 38–46. http://dx.doi.org/10.36349/easjbg.2021.v03i02.002.

Nkongho, R.N., J.T. Efouba-Mbong, L.M. Ndam, G.A. Ketchem, E.G. Etchu-Takang and D.T. Agbor. 2022. Seed production system and adaptability of okra (*Abelmoschus esculentus* L.) cultivars in Buea, Cameroon. PLoS ONE. 17(12): e0278771. http://doi.org/10.1371/journal.pone.0278771.

Nnamezie, A.A., A.A. Famuwagun and S.O. Gbadamosi. 2021. Characterization of okra seed flour, protein concentrate, protein isolate, and enzymatic hydrolysates. Food Prod. Process. Nutr. 3(1): 14. http://doi.org/10.1186/s43014-021-00059-9.

Oyekunle, M., A. Haruna, B. Badu-Apraku, I.S. Usman, H. Mani, S.G. Ado, G. Olaoye, K. Obeng-Antwi, R.O. Abdulmalik and H.O. Ahmed. 2017. Assessment of early-maturing maize hybrids and testing sites using GGE biplot analysis. Crop Sci. 57(6): 2942–2950. https://doi.org/10.2135/cropsci2016.12.1014.

Pugesek, B.H., A. Tomer and A. Von Eye. 2003. Structural Equation Modeling: Applications in Ecological and Evolutionary Biology. Cambridge University Press, Cambridge, UK.

R Core Team. 2022. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.

Rambabu, B., D.P. Waskar and V.S. Khandare. 2019. Correlation and path coefficient analysis of fruits yield and yield attributes in okra [*Abelmoschus esculentus* (L.) Moench]. Int. J. Curr. Microbiol. App. Sci. 8(4): 764–774. http://doi.org/10.20546/ijcmas.2019.804.084.

Rosseel, Y. 2012. Lavaan: An R package for structural equation modelling. J. Stat. Softw. 48(2): 1–36. http://doi.org/10.18637/jss.v048.i02.

Rynjah, S., T. Arumugam, K.N. Ganesan and P.R. Kamalkumaran. 2020. Correlation and path coefficient analysis studies in okra (*Abelmoschus esculentus* (L.) Moench). J. Pharmacogn. Phytochem. 9(3): 1423–1427.

Shipley, B. 2000. Cause and Correlation in Biology: A User's Guide to Path Analysis, Structural Equations, and Causal Inference. Cambridge University Press, Cambridge, UK.

Shuirkar, G., A.K. Naidu, B.R. Pandey, A.K. Mehta and S.K. Dwivedi. 2018. Correlation coefficient analysis in okra. The Pharma Innovation Journal. 7(6): 644–647.

Sugri, I., M.S. Abdulai, A. Larbi, I. Hoeschle-Zeledon, F. Kusi and R.Y. Agyare. 2015. Participatory variety selection of okra (*Abelmoschus esculentus* L.) genotypes for adaptation to the semi-arid agroecology of Northern Ghana. Afr. J. Plant Sci. 9(12): 466–475. http://doi.org/10.5897/ajps2015.1340.

Vrunda, R., A.I. Patel, J.M. Vashi and B.N. Chaudhari. 2019. Correlation and path analysis studies in okra (*Abelmoschus esculentus* (L.) Moench). Acta Sci. Agric. 3(2): 65–70.

Wright, S. 1921. Correlation and causation. J. Agric. Res. 20: 557–587.

Yang, J., Y. Li, H. Cao, H. Yao, W. Han and S. Sun. 2019. Yield-maturity relationships of summer maize from 2003 to 2017 in Huanghuaihai Plain of China. Sci. Rep. 9: 11417. http://doi.org/10.1038/s41598-019-47561-2.