Evaluation of maize F_1 hybrids' tolerance to low soil nitrogen using various selection indices

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ABSTRACT

Background and Objective: Traditional breeding methods often prioritize yield-centric indices for assessing genotypic stress tolerance, overlooking the nuanced contributions of other traits. This study introduced the Selection Index based on Trait Points (SIP), a comprehensive approach incorporating all measured traits under stressed and optimum conditions. The study aimed to identify low-nitrogen (N) tolerant maize hybrids and evaluate SIP's efficacy in stress tolerance assessment.

Methodology: A total of 237 maize hybrids resulting from line × tester crosses and three hybrid checks were evaluated under low- and optimum-N conditions in Zaria, Nigeria, during the 2019 and 2020 growing seasons. The trial employed a 15 × 16 alpha lattice design with two replications. Thirteen selection indices were used to assess various aspects of hybrid performance, including yield potential, yield stability, and low-N tolerance level.

Main Results: Genotypic and environmental factors significantly influenced grain yield and other traits under both N conditions. Top yielders in low-N were SMLW-74 × SAM50M (5,742 kg/ha) and SMLW-146 × IITA1878 (5,129 kg/ha). In optimum-N, hybrid SMLW-147 × IITA1878 recorded the highest yield (8,155 kg/ha), demonstrating a 28.7% yield advantage over the best check. Tolerance Index, SIP, and Mean Productivity exhibited significant ($P < 0.01$) strong positive correlations with grain yield under optimum-N conditions. At the same time, most selection indices displayed positive correlations with grain yield under low-N conditions. Hybrids SMLW-146 × IITA1878, SMLW-147 × SAM50M, and SMLW-74 × SAM50M showed promising performance across multiple screening indices, indicating their potential tolerance to low soil-N.

Conclusion: SIP proves to be both representative and discriminating, making it the ideal selection index for selecting maize hybrids with consistent and superior yield performance under contrasting environments. Hybrids SMLW-147 × SAM50M and SMLW-146 × IITA1878 are recommended for further evaluation in multi-locational and on-farm trials for potential commercialization in Nigeria.

Keywords: Yield stability, stress tolerance index, low-N tolerant hybrid, discriminating power, GGE biplot

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INTRODUCTION

Maize (*Zea mays* L.) is a crucial cereal crop globally, essential for ensuring food security worldwide (Erenstein *et al*., 2022). As a C4 plant with high photosynthetic efficiency, maize heavily relies on soil nitrogen (N) availability to support its robust biomass production (Guo *et al*., 2023). However, nitrogen deficiency poses a significant challenge to maize productivity, leading to yield reductions of up to 80% (Obeng-Bio *et al*., 2019; Ertiro *et al*., 2020), particularly in tropical regions characterized by high leaching rates, run-off, and microbial biomass immobilization (Amegbor *et al*., 2017). Despite the conventional solution of fertilizer application to address nitrogen deficiency, its high cost and environmental concerns hinder its effective utilization, especially among resource-constrained farmers (Sheahan and Barrett, 2017). Hence, there's a pressing need for maize hybrids with improved tolerance to low soil-N.

Historically, traditional breeding methods have predominantly relied on selection indices centered on yield and a few secondary traits under stress conditions to screen genotypes for stress tolerance (Bänziger *et al*., 2000; Badu-Apraku *et al*., 2013; Cerón-Rojas *et al*., 2016). However, such reliance on a limited set of traits may inadvertently overlook the potential contributions of other traits that, while individually exerting a subtle impact, collectively influence overall stress tolerance. Existing selection indices, such as the Stress Susceptibility Index (Fischer and Maurer, 1978), Relative Stress Index (Fischer and Wood, 1979), Tolerance Index (Rosielle and Hamblin, 1981), Yield Stability Index (Bouslama and Schapaugh, 1984), Stress Tolerance Index (Fernandez, 1992), and Yield Index (Gavuzzi *et al*., 1997), share common disadvantage in their potential oversimplification of genotype performance under stress conditions. These indices often focus primarily on yield-related metrics or stability without adequately considering the multifaceted nature of stress responses or the contributions of other individual traits. Others, like Mean Productivity (Rosielle and Hamblin, 1981), Geometric Mean Productivity (Fernandez, 1992), and Harmonic Mean (Bidinger *et al*., 1987), can oversimplify evaluations by emphasizing mean productivity or stress susceptibility without a comprehensive consideration of diverse traits.

Furthermore, selection indices such as Low N Tolerance Index (Oyekunle and Badu-Apraku, 2014), Selection Index (Bänziger *et al*., 2000), and IITA Base Index (Badu-Apraku *et al*., 2013) assign arbitrary weights to traits that may not accurately reflect their actual impact on stress tolerance. The assumption of constant trait importance across environments does not align with the dynamic nature of stress responses, where the relevance of traits may vary under different conditions. Moreover, these indices focus exclusively on yield and other agronomic trait performance under stress conditions, with consideration given to only the yield under non-stress conditions, thereby neglecting other important genotype traits (Badu-Apraku *et al*., 2011; Oyekunle and Badru-Apraku, 2014). Studies by Messina *et al*. (2011) and Khan *et al*. (2023) demonstrated how certain maize genotypes exhibited differential responses to stress conditions, with traits such as root architecture, water use efficiency, and leaf morphology playing significant roles in determining overall stress tolerance. Their findings underscore the necessity for selection indices to consider a broader range of traits beyond just yield to accurately assess genotype performance under stress.

In response to the limitations of the existing selection indices, this study posited a hypothesis that a more inclusive and accurate selection index could be devised by incorporating the values of all measured or estimated traits under both stressed and optimum conditions. The proposed approach, designated the Selection Index based on Trait Points (SIP), was tested for its efficacy in identifying tolerant genotypes under low N conditions and systematically compared with other existing selection indices.

MATERIALS AND METHODS

Germplasm

The genetic materials used in this study comprised 237 test crosses and three hybrid checks (SAMMAZ50, Oba Super 2, and SC619). Detailed information regarding the inbred lines, testers, and the development of the test crosses has been provided in an earlier report (Aboderin *et al*., in press). In summary, the 237 test crosses were generated by crossing 79 inbred lines (comprising 35 low-N tolerant and 44 susceptible to low N) with three inbred testers in a line × tester mating design at the Institute for Agricultural Research (IAR) experimental field in Zaria.

Phenotypic Evaluation of the Genotypes

The 240 hybrids were evaluated under low- and optimum-N conditions at the IAR experimental fields in Zaria during the 2019 and 2020 growing seasons (July to September). Zaria is located in the Northern Guinea Savanna ecology of Nigeria with an elevation of 640 m, a longitude of 8°22' E, a latitude of 12°N, and an annual rainfall of 1,200 mm. The IAR low N sites at Zaria established by soil depletion of available N through continuous planting of maize for several years without any fertilizer application were used as the low N field for the research. Soil nitrogen content in the low N experimental fields measured 0.11%, falling below the minimum threshold of 0.2%, as per the interpretation by Landon (1991). The combination of years, location, and soil nitrogen level was treated as an environmental factor in the study. The hybrids were evaluated across four environments, namely environments 1, 2, 3, and 4, denoting Zaria low-N 2019, Zaria low-N 2020, Zaria optimum-N 2019, and Zaria optimum-N 2020, respectively. The trial was laid out in each environment using a 15 × 16 alpha (α) lattice design in single-row plots with two replications. Each row was 4 m long, with inter and intra-row spacings of 0.75 m and 0.4 m, respectively. Planting density was set at 66,667 plants/ha, with two seeds planted per hole.

Nitrogen fertilizer was applied at two rates: 30 kg N/ha for low-N and 90 kg N/ha for optimum-N trials (Ribeiro *et al*., 2020; Badu-Apraku *et al*., 2023). For the low N treatment, N-fertilizer (urea) was evenly applied in two split doses at two and five weeks after sowing (WAS) to achieve an available N level of 30 kg N/ha in the plots. The first dose of the N-fertilizer was applied together with muriate of potash at a rate of 60 kg K/ha and single superphosphate at a rate of 60 kg P/ha at 2WAS. Under optimum-N conditions, nitrogen was applied at a rate of 90 kg N/ha from two sources: NPK 15-15-15 and urea. The NPK 15-15-15 fertilizer was applied at a rate of 60 kg N/ha, 60 kg P/ha, and 60 kg K/ha at 2 WAS, followed by an additional top-dressing of urea at a rate of 30 kg N/ha at 4 WAS.

Data Collection

Phenotypic data were recorded for each genotype, either on a plot or sampled plant basis, encompassing flowering traits, growth traits, aspect ratings, and leaf senescence. Flowering traits encompassed days to anthesis, days to silking, and anthesis-silking interval (ASI). The days to anthesis represented the duration in days from planting to when 50% of the plant population in a plot had released their pollen, while days to silking denoted the duration from planting to when 50% of the plant population had emerged silks. The ASI was calculated as the difference between days to anthesis and days to silking. Growth traits, namely plant height and ear height, were determined based on the average measurements of five randomly selected plants within each plot. Plant and ear aspect ratings were visually assessed on a phenotypic scale ranging from 1 to 10, with higher values indicating less desirable characteristics. Leaf senescence, characterized by the stay-green trait, was assessed by visually evaluating the condition of the leaves, including color, overall appearance, and visible signs of aging for each plot in the low-N field. Leaf senescence data were collected 70 days after planting to capture the progression of this trait over time. To standardize this assessment, a visual scale was designed to quantify leaf senescence. This involved assigning numerical values from 1 to 10 to represent different stages of senescence, with 1 indicating a healthy, green leaf and higher numbers representing increasing degrees of senescence. Under low-N conditions, ears harvested from each plot were shelled and used to determine the percentage of grain moisture and grain weight. The grain weight of the shelled ears harvested per plot was recorded in grams (g) and converted to kg/ha at 15% moisture content. Under optimum-N condition, harvested ears from each plot were weighed in kilograms (kg), and representative samples of ears were shelled to determine percentage grain moisture. Harvested ear weight (kg) was subsequently converted to kg/ha, assuming an 80% shelling percentage at 15% moisture content.

Data Analysis

The analysis of variance using SAS software was conducted on the agronomic data collected (SAS, 2008). Means of traits for which the maize hybrids differed significantly were separated using the least significant difference (Steel and Torrie, 1980). The level of tolerance to low soil N of each hybrid was assessed using 13 selection indices, calculated as follows:

Stress Susceptibility Index (SSI) $= \dfrac{1-\left(\dfrac{Y_s}{Y_p}\right)}{1-\left(\dfrac{Y_{ms}}{Y_{mp}}\right)}$

(Fischer and Maurer, 1978)

Yield Stability Index (YSI) $= \dfrac{Y_s}{Y_p}$

(Bouslama and Schapaugh, 1984)

Mean Productivity (MP) $= \dfrac{1}{2}(Y_s + Y_p)$

(Rosielle and Hamblin, 1981)

Geometric Mean Productivity (GMP) $= (Y_s \times Y_p)$

(Fernandez, 1992)

Harmonic Mean (HM) $= \dfrac{2(Y_s \times Y_p)}{(Y_s + Y_p)}$

(Bidinger *et al*., 1987)

Stress Tolerance Index (STI) $= \dfrac{(Y_s \times Y_p)}{(Y_{mp})^2}$

(Fernandez, 1992)

Yield Index (YI) $= \dfrac{Y_s}{Y_{ms}}$

(Gavuzzi *et al*., 1997)

Relative Stress Index (RSI) $= \dfrac{(Y_s / Y_p)}{(Y_{ms} / Y_{mp})}$

(Fischer and Wood, 1979)

Tolerance Index (TOL) $= Y_p - Y_s$
(Rosielle and Hamblin, 1981)

Selection Index (I_N) $= 5Y_s + 2EPP - 2STGR - ASI$
(Bänziger *et al*., 2000)

Low N Tolerance Index (LNTI) =
$(2 \times Y_s) + Y_p + EPP - ASI - PA - EA - STGR$
(Oyekunle and Badu-Apraku, 2014)

IITA Base Index (BI) =
$(2 \times Y_s) + EPP - ASI - PA - EA - STGR$
(Badu-Apraku *et al*., 2013)

where Y_p and Y_s = grain yield of the genotype under optimum and low N conditions, respectively, Y_{mp} and Y_{ms} = mean yields of all the evaluated genotypes under optimum- and low-N conditions, respectively, EPP = number of ears per plant in low N plots, STGR = stay-green characteristics, PA = plant aspect, EA = ear aspect, and ASI = anthesis-silking interval of the genotype in the low N fields. High values are desirable for YSI, MP, GMP, HM, STI, YI, RSI, I_N, and LNTI, while low values are desirable for TOL and SSI.

Selection Index based on Trait Points (SIP)
$= nX + mY - \sum_{i=1}^{n}$ Traits values under stress $-$
$\sum_{i=1}^{m}$ Traits values under optimum

where n = number of traits measured under stress condition, m = number of traits measured under optimum condition, X = genotype grain yield point under stress condition, Y = genotype grain yield point under optimum condition, $\sum_{i=1}^{n}$ = Trait 1 point + Trait 2 point +…+ Trait n point under stress condition, $\sum^{m}{}_{i=1}$ = Trait 1 point + Trait 2 point +…+ Trait m point under optimum condition. The point for each trait was determined by comparing the genotype's trait value relative to the most desirable value recorded among all evaluated genotypes.

For grain yield, plant height, and ear height:

$$\text{Trait point} = \frac{\text{Genotype value} \times 100}{\text{Highest value recorded among the genotypes}}$$

For days to anthesis, days to silking, and ASI, where shorter durations are desirable:

$$\text{Days to anthesis point} = \frac{\text{Lowest days to anthesis recorded among all genotypes}}{\text{Genotype days to anthesis}} \times 100$$

$$\text{Days to silking point} = \frac{\text{Lowest days to silking recorded among all genotypes}}{\text{Genotype days to silking}} \times 100$$

$$\text{ASI point} = \frac{\text{Lowest ASI recorded among all genotypes}}{\text{Genotype ASI}} \times 100$$

For traits rated on scales (e.g., plant aspect, ear aspect, and stay-green characteristics), where lower values are desirable:

$$\text{Trait point} = 100 - \left[\frac{\text{Trait value}}{\text{Maximum rating scale}}\right] \times 100$$

Genotypes with positive values for SIP are considered tolerant to low soil nitrogen. The genotype mean values for selection indices with significant differences among genotypes were subjected to genotype-by-trait biplot analysis using GEA-R software (Pacheco *et al*., 2016). This analysis was carried out to assess the performance and stability of the hybrids across the screening indices and to investigate the representativeness and discriminating ability of each selection index. Before this analysis, the data for the selected 30 hybrids (top 20 and bottom 10), identified using the SIP, were standardized based on standard deviation (mean = 0, standard deviation = 1). This was done to minimize the potential confounding effects resulting from variations in how each selection index assessed the tolerance levels of the genotypes. Additionally, simple linear correlation coefficients were calculated between the mean grain yield of the genotypes (under both low- and optimum-N conditions) and the values of the screening indices using SAS software (SAS, 2008).

RESULTS AND DISCUSSION

The combined analysis of variance (ANOVA) across low- and optimum-N environments revealed significant ($P < 0.01$ or $P < 0.05$) mean squares for genotype and environment for grain yield and other measured traits except for ear height (Table 1). Genotype × environment interaction (G × E) effect was significant ($P < 0.05$) for days to anthesis, days to silking, and ear aspect, and highly significant ($P < 0.01$) for anthesis silking interval and plant height. These findings underscore the critical roles of environmental conditions and genetic factors in determining hybrid performance. Specifically, the significant effects of the environment suggest distinct differences between nitrogen stress and optimum nitrogen conditions, highlighting the impact of nitrogen availability on hybrid performance.

In the separate ANOVA (Table 1), genotype mean squares were significant ($P < 0.01$ or $P < 0.05$) for all measured traits except ear per plant and ear aspect under low-N. In contrast, under optimum-N conditions, genotype mean squares were significant ($P < 0.01$ or $P < 0.05$) only for grain yield, days to anthesis, days to silking, and anthesis silking interval. These results indicate substantial genetic diversity among the studied genotypes, offering promise for identifying and improving desirable ones (Ribeiro *et al*., 2020; Adu *et al*., 2021). Similarly, the environment mean squares were significant ($P < 0.01$ or $P < 0.05$) for grain yield and all other traits in both low- and optimum-N conditions, highlighting the sensitivity of yield and other traits to nutrient stress and variations in soil quality. G × E interaction was significant ($P < 0.05$) for grain yield under low-N conditions, leading to varied hybrid yield rankings across different low-N environments. This highlights the importance of extensive testing to identify high-yielding and stable hybrids (Badu-Apraku *et al*., 2013; Ribeiro *et al*., 2020). In contrast, under optimum-N conditions, where the G × E effect was less pronounced, hybrid performance was primarily determined by genetic potential. This suggests that under optimal nitrogen levels, the primary drivers of yield become the ability of the genetic material to harness available nutrients efficiently. These findings align with the observations of Abu *et al*. (2021), who similarly reported significant G × E interaction for maize grain yield under low-N and the opposite pattern under optimum-N conditions.

Table 1 Analysis of variance for grain yield, agronomic traits, and screening index values for 240 hybrids evaluated under low- and optimum-N conditions at Zaria in 2020 and 2021

Source of variation	df	Grain yield (kg/ha)	Days to anthesis	Days to silking	Anthesis-silking interval	Plant height	Ear height	Ear per plant	Plant aspect	Ear aspect	Stay green characteristic
Combined											
Environment (E)	3	1108.97**	16834.42**	27950.71**	1871.58**	343691.67**	112990.06	1.98**	286.79**	421.38**	
Rep (E)	4	2.42	12.84	16.44	5.96	4257.75**	629.80	0.12	4.75**	4.13**	
Block (E × Rep)	112	1.64*	16.06**	22.14**	5.15**	1015.91**	427.44	0.06	0.95**	1.67**	
Genotype (G)	239	1.77**	14.22**	17.80**	3.19**	785.88**	316.20	0.02*	0.33*	0.85**	
G × E	717	1.14	9.53*	12.56*	2.89**	544.75**	210.34	0.58	0.29	0.70*	
Pooled error	844	1.04	7.55	9.64	2.21	496.56	189.37	0.11	0.27	0.58	
CV (%)		52.79	4.48	4.77	39.20	15.12	20.36	36.37	15.09	23.03	
Low-N											
Environment (E)	1	12.06**	459.27**	2877.34*	1037.50**	472150.10**	112495.47**	0.72*	317.98**	20.01*	17.60**
Rep (E)	2	2.82**	11.34	13.96	6.32	2172.24*	594.07*	0.18	4.57**	2.09	31.68**
Block (E × Rep)	56	0.52**	16.86**	24.56**	8.27**	1221.07**	425.66**	0.18	1.25**	2.70**	3.35**
Genotype (G)	239	0.28**	12.80**	18.38**	5.11**	853.91**	278.60**	0.16	0.29	0.99*	1.13*
G × E	239	0.21*	11.94**	17.16**	4.63*	622.63	169.00	0.15	0.30	0.85*	1.11
Pooled error	422	0.17	8.09	11.52	3.53	555.88	163.52	0.14	0.26	0.68	0.94
CV (%)		65.34	4.30	4.75	35.53	18.08	22.43	42.03	14.38	20.09	21.69
Optimum-N											
Environment (E)	1	72.05*	3473.20*	1793.07**	275.20**	5427.83*	11455.40**	2.00**	80.04**	6.50**	
Rep (E)	2	2.01	14.35	18.91	5.60*	6343.25*	665.52*	0.23	1.66	6.16**	
Block (E × Rep)	56	2.76*	15.26**	19.72**	2.03**	810.75	429.21**	0.10	0.24**	0.65*	
Genotype (G)	239	2.79**	10.43**	11.52**	1.14*	467.65	232.24	0.10	0.14	0.54	
G × E	239	1.91	7.65	8.44	1.00	475.95	266.90*	0.07	0.13	0.58	
Pooled error	422	1.90	6.47	7.59	1.03	743.17	256.06	0.06	0.23	0.41	
CV (%)		42.75	4.70	4.75	41.03	12.72	18.77	30.79	14.87	27.63	

Screening indices	df	TOL	MP	GMP	HM	SSI	STI	YI	YSI	RSI	IN	LNTI	BI	SIP
Hybrids	236	2877184**	962280**	1113827**	1383522**	0.22**	0.09**	0.23**	0.06**	0.27**	84.11**	28.11**	25.71**	57155**

Note: *, ** Significant at 0.05 and 0.01 probability levels, respectively. TOL = Tolerance Index, MP = Mean Productivity, GMP = Geometric Mean Productivity, HM = Harmonic Mean, SSI = Stress Susceptibility Index, STI = Stress Tolerance Index, YI = Yield Index, YSI = Yield Stability Index, RSI = Relative Stress Index, I_N = Selection Index, LNTI = Low N Tolerance Index, BI = IITA Base Index, SIP = Selection Index based on Trait Points.

Furthermore, highly significant (P < 0.01) differences were observed among the hybrids for all the screening indices (Table 1). This highlights the relevance and effectiveness of these indices in discriminating among the genotypes, emphasizing their capability to capture the variability in hybrid performance across multiple traits. Additionally, the observed diverse range of performances across the screening indices indicates that each index provides unique insights into the strengths and weaknesses of each hybrid across various traits, facilitating informed decision-making in breeding programs. By employing multiple selection indices, breeders can comprehensively assess hybrid performance and identify genotypes with desirable traits for further development and commercialization (Zhao *et al*., 2019; Aga *et al*., 2022).

Hybrid Performance Under Different Nitrogen Conditions

The range in grain yield among the hybrids in low-N environments was 5,195 kg/ha with a mean of 2,473 kg/ha. In comparison, the range was 5,804 kg/ha with a mean of 5,263 kg/ha in the optimum-N environment (Table 2). Top yielders under low-N conditions included hybrids SMLW-74 × SAM50M, SMLW-146 × IITA1878, and SMLW-147 × SAM50M. Under the optimum-N condition, hybrid SMLW-147 × IITA1878 recorded the highest yield (8,155 kg/ha), demonstrating a 28.7% yield advantage over the best check (SAM50M). Notably, four hybrids (SMLW-147 × IITA1878, SMLW-146 × IITA1878, SMLW-147 × SAM50M, and SMLW-120 × IITA1878) exhibited higher grain yields under both low- and optimum-N conditions, indicating their inherent genetic potential to produce good yields regardless of nitrogen availability.

The average reduction in grain yield among all hybrids was 51.6% under low-N compared to optimum-N conditions (Table 2). Among the 237 test crosses, 110 hybrids (46.4%) demonstrated yield reduction below the average. Notably, SMLW-74 × SAM50M recorded the lowest yield reduction (1.3%), while SMLW-143 × IITA1876 recorded the highest (89.2%). Genotypes with low yield reduction percentages indicate superior performance under low-N conditions, suggesting a higher tolerance to nitrogen stress, whereas genotypes with high yield reduction percentages indicate greater susceptibility to low-N conditions (Oyekunle and Badru-Apraku, 2014; Aga *et al*., 2022).

Correlation between Grain Yield and the Screening Index Values

The correlation coefficients presented in Table 3 offer valuable insights into the relationship between screening indices and maize hybrid grain yield under both low- and optimum-N conditions. Notably, under low-N conditions, LNTI, HM, YI, BI, I_N, YSI, and RSI all exhibited strong significant (P < 0.01) positive correlations with grain yield. The correlation coefficients ranged from 0.75 to 1.00 (Table 3), indicating their reliability as predictors of hybrid performance in low-N environments. High positive values for these indices imply high tolerance to nitrogen stress and good yield performance under low-N conditions (Bänziger *et al*., 2000; Badu-Apraku *et al*., 2013; Zhao *et al*., 2019). Conversely, in optimum-N conditions, these indices showed weaker correlations with grain yield, suggesting their reduced influence in identifying superior genotypes under optimal-N conditions.

Interestingly, TOL and SSI exhibited significant (P < 0.01) strong negative correlations with grain yield in low-N conditions, while in optimum-N conditions, they showed significant (P < 0.01) positive correlations (Table 3). This divergence in correlation trends suggests that these indices may have different implications for hybrid performance depending on soil-N condition. In low-N conditions, the negative correlations imply that genotypes with lower values for these indices tend to have higher grain yields, indicating their high tolerance to stress (Pour-Aboughadareh *et al*., 2019; Zhao *et al*., 2019). Conversely, under optimum-N conditions, the positive correlations suggest that genotypes with higher values for TOL and SSI tend to have higher grain yields, reflecting their ability to thrive in non-stress conditions.

Table 2 Grain yield and screening index values of maize hybrids (best 15 and worst 5) evaluated under low- and optimum-N conditions at Zaria in 2020 and 2021

GEN	GY (kg/ha)		Rank	YRD	TOL	MP	GMP	LNTI	BI	SIP	HM	SSI	STI	YI	YSI	RSI	I_N
	Low-N	OPT	(OPT)	(%)													
SMLW-74 × SAM50M	5,742	5,815	60	1.3	73	5,779	5,778	13.0	12.4	182.4	5,778	0.0	1.2	2.3	1.0	2.1	24.1
SMLW-146 × IITA1878	5,129	7,476	5	31.4	2,347	6,303	6,192	6.5	4.2	324.2	6,084	0.6	1.4	2.1	0.7	1.5	13.2
SMLW-147 × SAM50M	5,126	7,337	9	30.1	2,211	6,232	6,133	13.5	11.4	228.6	6,035	0.6	1.4	2.1	0.7	1.5	13.0
SMLW-7 × IITA1878	4,551	6,399	30	28.9	1,848	5,475	5,396	8.5	7.3	54.2	5,319	0.5	1.1	1.8	0.7	1.5	19.1
SMLW-100 × IITA1876	4,486	5,023	139	10.7	537	4,755	4,747	9.3	9.6	-102.3	4,739	0.2	0.8	1.8	0.9	1.9	16.5
SMLW-146 × SAM50M	4,288	5,170	121	17.1	882	4,729	4,708	3.8	3.8	-77.9	4,688	0.3	0.8	1.7	0.8	1.8	13.6
SMLW-120 × IITA1878	4,236	7,174	10	40.9	2,938	5,705	5,513	6.2	4.2	147.4	5,327	0.8	1.1	1.7	0.6	1.2	12.5
SMLW-145 × IITA1878	4,131	4,810	161	14.1	679	4,471	4,458	0.8	1.2	-143.6	4,445	0.3	0.7	1.7	0.9	1.8	7.5
SMLW-57 × IITA1878	4,125	7,144	11	42.3	3,019	5,635	5,429	8.5	6.6	4.0	5,230	0.8	1.1	1.7	0.6	1.2	15.6
SMLW-144 × IITA1878	4,078	4,218	212	3.3	140	4,148	4,147	3.7	4.7	-207.3	4,147	0.1	0.6	1.6	1.0	2.0	8.7
SMLW-146 × IITA1876	4,044	5,782	65	30.1	1,738	4,913	4,836	6.3	5.7	-48.6	4,759	0.6	0.8	1.6	0.7	1.5	8.1
SMLW-120 × SAM50M	4,028	5,822	59	30.8	1,794	4,925	4,843	7.8	7.2	-94.6	4,762	0.6	0.9	1.6	0.7	1.5	12.2
SMLW-147 × IITA1878	4,019	8,155	1	50.7	4,136	6,087	5,725	6.2	3.3	195.9	5,384	1.0	1.2	1.6	0.5	1.0	6.9
SMLW-70 × SAM50M	3,963	4,569	184	13.3	606	4,266	4,255	8.5	9.2	-225.7	4,244	0.3	0.7	1.6	0.9	1.8	10.5
SMLW-70 × IITA1878	3,918	6,629	23	40.9	2,711	5,274	5,096	3.4	1.9	19.7	4,925	0.8	0.9	1.6	0.6	1.2	7.1
SMLW-135 × SAM50M	1,055	4,459	195	76.3	3,404	2,757	2,169	-5.2	-4.4	-634.2	1,706	1.4	0.2	0.4	0.2	0.5	-8.9
SMLW-140 × SAM50M	1,054	5,248	111	79.9	4,194	3,151	2,352	-4.6	-4.6	-580.1	1,755	1.5	0.2	0.4	0.2	0.4	-9.2
SMLW-143 × SAM50M	1,010	6,605	25	84.7	5,595	3,808	2,583	-2.1	-3.5	-445.6	1,752	1.6	0.2	0.4	0.2	0.3	-10.8
SMLW-64 × IITA1876	950	6,341	33	85.0	5,391	3,646	2,454	-1.4	-2.5	-494.1	1,652	1.6	0.2	0.4	0.1	0.3	-8.5
SMLW-143 × IITA1876	547	5,060	136	89.2	4,513	2,804	1,664	-4.9	-4.7	-620.4	987	1.7	0.1	0.2	0.1	0.2	-14.8
Check 1 SAMMAZ50	1,730	6,335	34	72.7													
Check 2 Oba Super 2	980	6,088	46	83.9													
Check 3 SC619	2,185	6,321	35	65.4													
Mean	2,473	5,263		51.6	2,767	3,867	3,551	0.9	0.9	-354.5	3,278	1.0	0.5	1.0	0.5	1.0	0.1
Minimum	547	2,351		1.3	73	2,022	1,664	-7.8	-7.9	-721.1	987	0.0	0.1	0.2	0.1	0.2	-14.8
Maximum	5,742	8,155		89.2	6,483	6,303	6,192	13.5	12.4	324.2	6,084	1.7	1.4	2.3	1.0	2.1	24.1

Note: The rankings presented in this table are based on the grain yield performance of the hybrids under low-N condition. GY = grain yield, Low-N = low-N condition, OPT = optimum-N condition, YRD = yield reduction, TOL = Tolerance Index, MP = Mean Productivity, GMP = Geometric Mean Productivity, LNTI = Low N Tolerance Index, BI = IITA Base Index, SIP = Selection Index based on Trait Points, HM = Harmonic Mean, SSI = Stress Susceptibility Index, STI = Stress Tolerance Index, YI = Yield Index, YSI = Yield Stability Index, RSI = Relative Stress Index, I_N = Selection Index.

Table 3 Correlation coefficients between grain yield of the hybrids and their screening index values

Index values	Grain yield (kg/ha)	
	Low-N	Optimum-N
Low N Tolerance Index	0.75**	0.28**
IITA Base Index	0.75**	0.03
Tolerance Index	-0.60**	0.72**
Mean Productivity	0.71**	0.80**
Geometric Mean Productivity	0.90**	0.56**
Harmonic Mean	0.96**	0.36**
Stress Susceptibility Index	-0.82**	0.41**
Stress Tolerance Index	0.89**	0.56**
Yield Index	1.00**	0.15*
Yield Stability Index	0.82**	-0.46**
Relative Stress Index	0.82**	-0.46**
Selection Index	0.90**	0.06
Selection Index based on Trait Points	0.80**	0.67**

Note: *, **, Significant at 0.05 and 0.01 probability levels, respectively.

The MP, GMP, STI, and SIP consistently showed strong positive correlations with grain yield in both low-N and optimum-N conditions, underscoring their utility as predictors of overall maize hybrid performance under normal and stressed conditions. In line with our findings, Khan and Mohammad (2016) and Aga *et al*. (2022) also identified MP, GMP, and STI as preferred choices for identifying low-N tolerant genotypes. Importantly, the SIP demonstrated a significant ($P < 0.01$) strong positive correlation with grain yield in both low- and optimum-N conditions, suggesting that hybrids selected using this index are likely to exhibit balanced performance across both low and optimum-N conditions.

Polygon View of Genotype-by-Trait Biplot of Screening Indices of Maize Hybrids Under Low- and Optimum-N Conditions

In the polygon view of the genotype-by-trait biplot (Figure 1), the genotype positioned at the vertex (endpoint) of the polygon, closest to the point representing a selection index, signifies superior performance based on the traits prioritized in that selection index. Vertex hybrids SMLW-146 × IITA1878 (1) and SMLW-147 × SAM50M (2) were the closest to the points corresponding to selection indices MP, HM, GMP, and STI, suggesting their resilience to stress and sustained high productivity across both low- and optimum-N conditions (Zhao *et al*., 2019; Aga *et al*., 2022). Conversely, Hybrid SMLW-74 × SAM50M (4) closely associates with vertices of selection indices SIP, LNTI, I_N, and BI, indicating a high level of tolerance to low-N conditions and the ability to yield satisfactorily under nitrogen limitations (Bänziger *et al*., 2000; Badu-Apraku *et al*., 2013). Moreover, its proximity to the vertices of YI, YSI, and RSI underscores its inherent genetic potential for stable yield performance across both low- and optimum-N conditions. Additionally, SMLW25 × SAM50M (20) and SMLW143 × IITA1876 (56) were the vertex hybrids for selection indices TOL and SSI, respectively, indicating that they have the highest values for the indices. However, higher values for these indices imply a higher sensitivity to nitrogen stress rather than tolerance (Zhao *et al*., 2019). Despite performing well under optimum-N conditions, their elevated values in TOL and SSI imply that they struggle to maintain their performance in stress-prone environments.

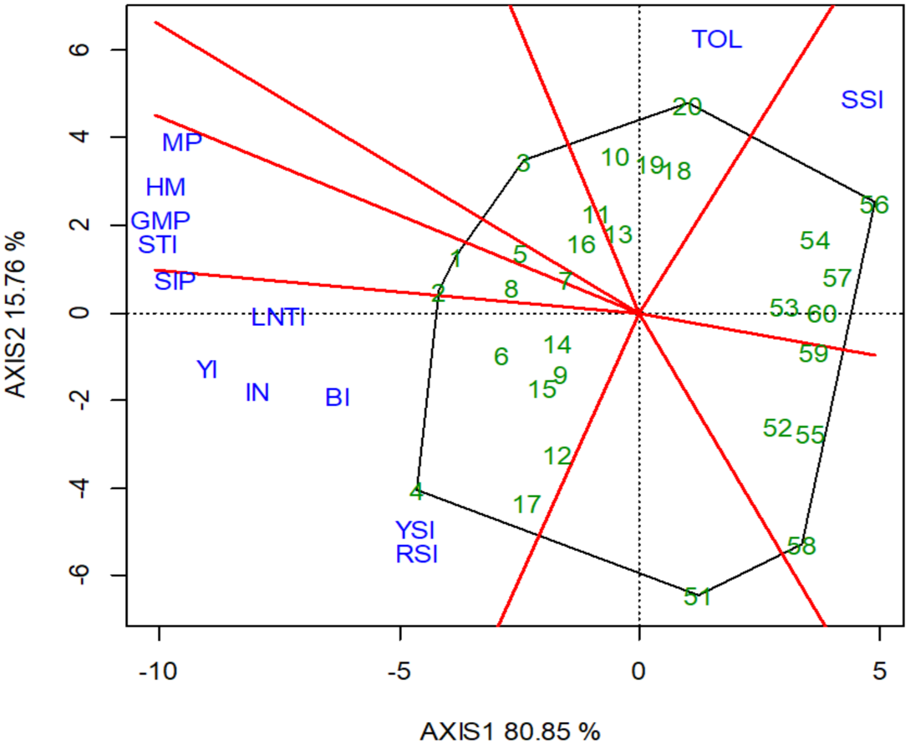

Figure 1 Which won where polygon view of genotype-by-trait biplot showing screening indices values of maize hybrids (top 20 and bottom 10) evaluated across low- and optimum -N environments in 2019 and 2020. Selection indices: TOL = Tolerance Index, MP = Mean Productivity, GMP = Geometric Mean Productivity, LNTI = Low N Tolerance Index, BI = IITA Base Index, SIP = Selection Index based on Trait Points, HM = Harmonic Mean, SSI = Stress Susceptibility Index, STI = Stress Tolerance Index, YI = Yield Index, YSI = Yield Stability Index, RSI = Relative Stress Index, I_N = Selection Index. Hybrid: 1 = SMLW-146 × IITA1878, 2 = SMLW-147 × SAM50M, 3 = SMLW-147 × IITA1878, 4 = SMLW-74 × SAM50M, 5 = SMLW-120 × IITA1878, 6 = SMLW-7 × IITA1878, 7 = SMLW-70 × IITA1878, 8 = SMLW-57 × IITA1878, 9 = SMLW-146 × IITA1876, 10 = SMLW-121 × IITA1878, 11 = SMLW-165 × IITA1876, 12 = SMLW-146 × SAM50M, 13 = SMLW-162 × SAM50M, 14 = SMLW-106 × SAM50M, 15 = SMLW-120 × SAM50M, 16 = SMLW-37 × IITA1876, 17 = SMLW-100 × IITA1876, 18 = SMLW-163 × IITA1878, 19 = SMLW-52 × IITA1876, 20 = SMLW-25 × SAM50M, 51 = SMLW-77 × IITA1878, 52 = SMLW-17 × IITA1876, 53 = SMLW-140 × IITA1876, 54 = SMLW-122 × SAM50M, 55 = SMLW-5 × IITA1876, 56 = SMLW-143 × IITA1876, 57 = SMLW-135 × SAM50M, 58 = SMLW-140 × IITA1878, 59 = SMLW-135 × IITA1876, 60 = SMLW-21 × SAM50M.

Figure 2 illustrates the "mean vs stability" view to identify a low-N tolerant hybrid with superior performance and ranking consistency across 13 screening indices. The absolute length of each hybrid's projection on the average tester axis reflects its average performance across all the selection indices. In contrast, its projection on the ATC y-axis assesses its ranking consistency across the screening indices. Hybrids SMLW-147 × SAM50M (2), SMLW-74 × SAM50M (4), and SMLW-146 × IITA1878 (1) demonstrated the highest overall performance across the screening indices. However, considering the length of their projections on the y-axis, SMLW-147 × SAM50M (2) and SMLW-146 × IITA1878 (1) showed relatively consistent rankings across the different screening indices, suggesting greater stability in their performance. In contrast, SMLW-74 × SAM50M (4) exhibited inconsistent rankings across 13 screening indices, indicating that its observed high performance varied significantly depending on the specific trait or condition being assessed.

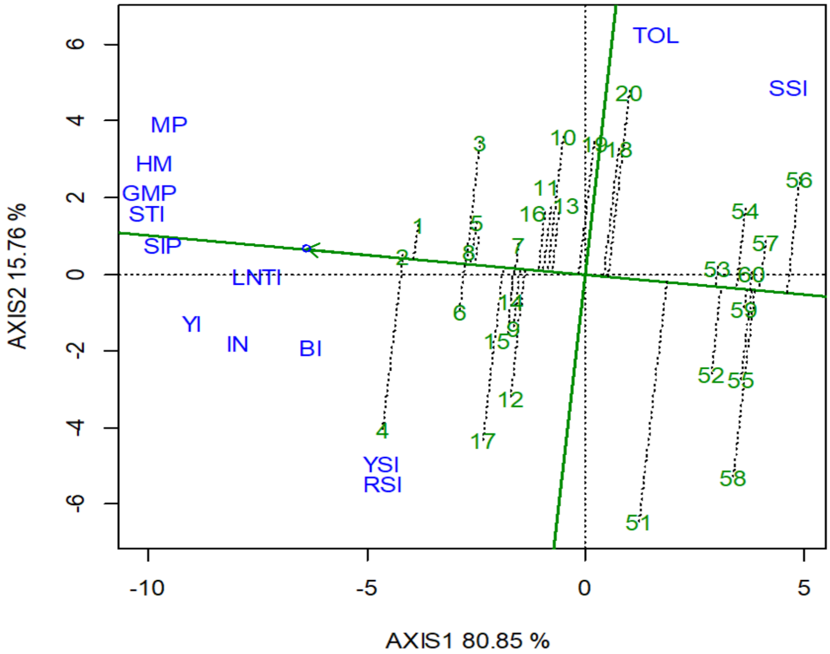

Figure 2 Performance and stability of maize hybrids (top 20 and bottom 10) across the screening indices values. Selection indices: TOL = Tolerance Index, MP = Mean Productivity, GMP = Geometric Mean Productivity, LNTI = Low N Tolerance Index, BI = IITA Base Index, SIP = Selection Index based on Trait Points, HM = Harmonic Mean, SSI = Stress Susceptibility Index, STI = Stress Tolerance Index, YI = Yield Index, YSI = Yield Stability Index, RSI = Relative Stress Index, I_N = Selection Index. Hybrid: 1 = SMLW-146 × IITA1878, 2 = SMLW-147 × SAM50M, 3 = SMLW-147 × IITA1878, 4 = SMLW-74 × SAM50M, 5 = SMLW-120 × IITA1878, 6 = SMLW-7 × IITA1878, 7 = SMLW-70 × IITA1878, 8 = SMLW-57 × IITA1878, 9 = SMLW-146 × IITA1876, 10 = SMLW-121 × IITA1878, 11 = SMLW-165 × IITA1876, 12 = SMLW-146 × SAM50M, 13 = SMLW-162 × SAM50M, 14 = SMLW-106 × SAM50M, 15 = SMLW-120 × SAM50M, 16 = SMLW-37 × IITA1876, 17 = SMLW-100 × IITA1876, 18 = SMLW-163 × IITA1878, 19 = SMLW-52 × IITA1876, 20 = SMLW-25 × SAM50M, 51 = SMLW-77 × IITA1878, 52 = SMLW-17 × IITA1876, 53 = SMLW-140 × IITA1876, 54 = SMLW-122 × SAM50M, 55 = SMLW-5 × IITA1876, 56 = SMLW-143 × IITA1876, 57 = SMLW-135 × SAM50M, 58 = SMLW-140 × IITA1878, 59 = SMLW-135 × IITA1876, 60 = SMLW-21 × SAM50M.

The discriminating power versus representativeness of the selection indices is depicted in Figure 3. Discriminating power refers to the selection index's capability to differentiate among genotypes based on their performance, quantified by the vector length of the indices in the biplot. Longer vectors signify higher discriminating power (Yan and Tinker, 2006). In this study, most screening indices exhibit long vectors, indicating high discriminating power. On the other hand, the representativeness of screening indices assesses their ability to represent other indices and is determined by the angle measured between the screening indices and the Average Environment Axis (AEA). Screening indices with smaller angles to the AEA are deemed more representative of others. In our study, SIP stands out as the closest to the AEA, indicating its high representativeness among other indices.

Additionally, screening indices exhibiting high discriminating power and representativeness are particularly valuable for effectively differentiating hybrids based on their performance under stress conditions while accurately representing the overall performance across various traits measured by other indices. In this regard, SIP stands out as both representative and discriminating, making it the ideal index for selecting genotypes with superior performance under both low-N and optimum-N conditions. Conversely, selection indices TOL, SSI, YSI, and RSI, while non-representative, are highly discriminating and can be useful for identifying genotypes that are specifically tolerant to low-N conditions (Pour-Aboughadareh *et al*., 2019).

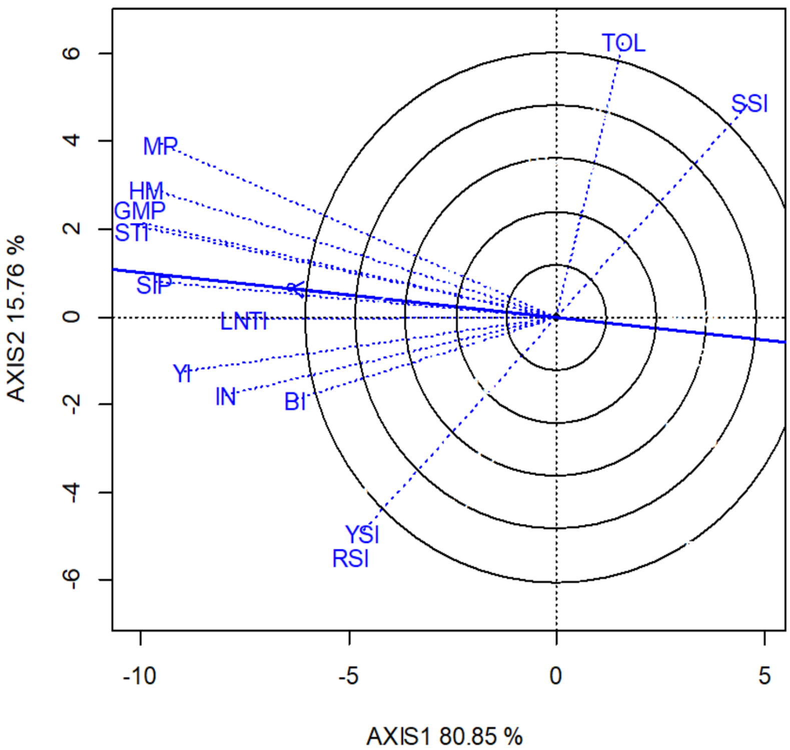

Figure 3 The discriminating power and representativeness view of the screening indices on the genotype-by-trait biplot. Selection indices: TOL = Tolerance Index, MP = Mean Productivity, GMP = Geometric Mean Productivity, LNTI = Low N Tolerance Index, BI = IITA Base Index, SIP = Selection Index based on Trait Points, HM = Harmonic Mean, SSI = Stress Susceptibility Index, STI = Stress Tolerance Index, YI = Yield Index, YSI = Yield Stability Index, RSI = Relative Stress Index, I_N = Selection Index.

The screening indices were grouped based on the angles formed between them (Figure 3). The angle indicates similarities or dissimilarities in their patterns of discrimination among genotypes. When selection indices form small angles between them, it suggests they have similar discrimination patterns, meaning they prioritize similar traits or exhibit comparable discriminative abilities among genotypes. The 13 selection indices were grouped into five categories based on these angles: MP, HM, STI, and GMP formed group 1; YI, BI, and I_N comprised group 2; TOL and SSI were in group 3; RSI and YSI formed group 4; and LNTI and SIP constituted the last group. The indices in each group can be interchangeably used to select tolerant genotypes (Pour-Aboughadareh *et al*., 2019; Aga *et al*., 2022). Notably, the grouping of SIP with LNTI, a widely recognized index in various studies (Badu-Apraku *et al*., 2013; Obeng-Bio *et al*., 2019; Ribeiro *et al*., 2020; Abu *et al*., 2021), further validates SIP's efficacy as a dependable selection index for identifying genotypes tolerant to low-N conditions.

CONCLUSIONS

In conclusion, our study findings underscore the importance of prioritizing hybrids with high SIP values in maize breeding programs. The observation that hybrids SMLW-147 × SAM50M and SMLW-146 × IITA1878, which exhibited the highest SIP values, also demonstrated high yields under both nitrogen conditions, indicates that SIP is a reliable predictor of hybrid performance across varying nitrogen levels. Moreover, consistently identifying these hybrids as tolerant by all other screening indices used in the study further reinforces the reliability of SIP as a selection index. Therefore, for the identification of maize genotypes with consistent and superior yield performance under contrasting environments, the adoption of SIP as a selection index is strongly recommended. Additionally, the outstanding hybrids in the study should be further evaluated in multi-locational and on-farm trials for potential commercialization in Nigeria.

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