

Article

Matching Cultivar to Nitrogen and Soil: A Diagnostic Framework for Closing Wheat Yield Gaps in the Huang-Huai Region

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Abstract

Closing yield gaps in wheat production requires optimized cultivar selection and nitrogen (N) management; however, the cultivar-specific responses to N fertilizer and soil fertility remain largely unquantified. Twenty-eight wheat cultivars were evaluated under three fertilization treatments (T) (CK, no-fertilizer; N1, 210 kg N ha⁻¹ as single basal application; and N2, split-N at 105 + 105 kg N ha⁻¹, applied only in 2022–2023 and 2023–2024) over three growing seasons in the Huang-Huai region. Two-way interactions (cultivar × T, cultivar × year, and T × year) and the three-way cultivar × T × year interaction were significant ($p < 0.001$), whereas the year main effect was not significant ($p = 0.329$). Fertilization accounted for the largest proportion of yield variance ($\eta^2 = 0.589$), followed by cultivar × year ($\eta^2 = 0.244$) and cultivar ($\eta^2 = 0.141$). Yield ranged from 3435 to 5231 kg ha⁻¹ (a 1.52-fold difference). Hierarchical clustering of basic soil productivity contribution rate (BSPCR) classified cultivars into high, moderate, and low soil fertility dependence classes, enabling fertility-based cultivar matching. Within-cultivar correlation analysis identified spike number as the predominant yield-limiting factor (71.4%). Based on composite scores integrating yield, stability, split-N response index (SNRI), and BSPCR, Tier I cultivars (C20, C1, C21, C14) are recommended for high-fertility fields with split-N application, combining high yield (5004–5231 kg ha⁻¹), strong N responsiveness (SNRI ≥ 1.10), and high BSPCR; Tier II cultivars (C7, C3, C18, C12, C22) offer a balanced performance in yield and stability. The proposed tiered system—prioritizing Tier I and Tier II cultivars according to field fertility and production goals—provides an exploratory, site-specific framework for closing wheat yield gaps in the Huang-Huai region.

Keywords: winter wheat; yield; nitrogen response; yield components; cultivar screening; basic soil productivity



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1. Introduction

Food security is inextricably linked to social stability, economic development, and national security [1]. To meet the food demands of a growing global population [2], future

food production must increase substantially while reducing the environmental footprint of agriculture [3,4]. A key strategy for achieving this goal is to close the existing gap between potential and actual crop yields [5,6].

The yield gap—defined as the difference between attainable and actual yield—has been extensively documented across major cereal cropping systems worldwide [6–8]. Increasing food production by closing the yield gap has fewer environmental consequences than expanding cropland area [9,10]. Significant yield gaps persist among regions and even among adjacent fields, largely due to variations in crop cultivars, soil fertility and farm management practices [8,11,12]. Yield gap analysis has gained recognition as an effective diagnostic tool. Recent methodological advances have been employed to conduct this analysis, enabling researchers to identify and quantify production constraints, thereby providing a basis for management recommendations [6,13–15].

In contrast to conventional yield gap analyses that benchmark against potential yield, this study focuses on the cultivar-related yield gap—defined as the yield variation among cultivars grown under identical conditions. This component of the yield gap can be narrowed through optimized cultivar selection, without requiring land-use change or major infrastructure investment. By quantifying this variation and identifying the agronomic factors that modulate it, we aim to provide a diagnostic framework for matching cultivars to specific N management and soil fertility conditions.

Genetic variation among cultivars is a major determinant of yield gaps, though its relative importance varies substantially across environments and management systems [16]. Even under identical environmental and management conditions, wheat cultivars can differ substantially in yield potential, nitrogen use efficiency, and stress tolerance. Ceccarelli et al. [16] demonstrated that cultivar $\times$ environment interactions often exceed the main effects of either factor alone, underscoring the need for site-specific cultivar recommendations.

Extensive research has documented significant genotype $\times$ nitrogen (G $\times$ N) interactions in wheat, with modern semi-dwarf cultivars generally exhibiting greater N responsiveness than older germplasm [17,18]. However, the physiological basis of these interactions remains debated. Some studies attribute differential N responsiveness to variation in sink capacity [19,20], while others emphasize differences in root architecture and N uptake efficiency [21,22]. Moreover, most G $\times$ N interaction studies have been conducted under controlled conditions or with limited cultivar sets (typically < 10 genotypes). Consequently, how cultivar differences in N responsiveness interact with soil fertility levels—a key source of environmental variation in farmers' fields—remains largely unexplored [23].

In the North China Plain, cultivar substitution has contributed significantly to yield increases over the past three decades [24], yet few studies have systematically evaluated the differential responses of modern cultivars to optimized N management. Understanding how cultivars respond to soil fertility and N fertilizer regimes is therefore essential for developing targeted agronomic recommendations.

Winter wheat is one of China's three major staple crops, and the Huang-Huai region is the primary production area accounting for 55% of the national winter wheat acreage and over 65% of total output [25,26]. However, smallholder farming systems in this region exhibit substantial spatial heterogeneity in soil fertility—organic matter content can vary more than twofold across adjacent fields [23]—and N management practices are highly variable [27]. Previous on-farm surveys have shown that yield gaps among fields are strongly associated with soil organic matter content and N application timing [23], suggesting that both soil fertility and N management interact with cultivar choice to determine yield outcomes.

Yield gaps in this region largely reflect differences in key yield components—spike number, kernels per spike, and 1000-grain weight—which are strongly influenced by

cultivar, environment, and management [28,29]. Studies have reported that nitrogen deficiency is the predominant limitation in certain cropping systems [30], whereas spike number variability explains most of the yield variation in the North China Plain [23]. Recent studies have also demonstrated that winter wheat yield depends on cultivation technology, including crop predecessor, sowing time, seeding rate, and soil water availability [31]. Despite the widespread adoption of improved cultivars and growing awareness of precision N management [32,33], current recommendations in the Huang-Huai region remain largely generic—typically prescribing uniform N rates and application schedules across all cultivars and soil fertility levels [23,34]. This one-size-fits-all approach likely misses opportunities to close yield gaps through better matching cultivar characteristics to specific N management strategies and field conditions.

A critical knowledge gap exists: we lack a systematic understanding of how cultivar choice, N management timing, and soil fertility interact to determine wheat yield and N responsiveness. Three interrelated questions remain unanswered: (1) Do cultivars differ in yield potential and stability under the same management, and are these differences consistent across seasons? (2) Do cultivars vary in their responsiveness to split-N application, and is this responsiveness associated with yield potential? (3) Can cultivars be classified by their dependence on inherent soil fertility to guide site-specific selection? Addressing these questions is essential for moving beyond generic recommendations toward a cultivar-specific, field-adaptive N management framework.

We lack a systematic understanding of how cultivar choice, N timing, and soil fertility interact to determine wheat yield. The $G \times E \times M$ framework [35] posits that crop performance arises from genetic, environmental, and management interactions—with cultivar choice and N management as the primary manipulable factors and soil fertility largely fixed in the short term. The specific hypotheses tested were: (H1) cultivar choice significantly affects grain yield under identical management; (H2) cultivars differ in their response to split-N application timing; and (H3) cultivars combining high yield potential with strong N responsiveness can be identified through multi-criteria screening. Confirmatory analyses (ANOVA) were used to test H1 and H2, while exploratory analyses—hierarchical clustering of BSPCR, composite scoring, and tier ranking—were employed to identify cultivars with combined high yield and strong N responsiveness.

To address these hypotheses, we conducted a three-year field experiment with 28 wheat cultivars under three fertilizer regimes (CK, N1, N2) in the Huang-Huai region. The specific objectives were: (1) to quantify yield variation among cultivars and identify top-performing cultivars; (2) to assess cultivar-specific responses to split-N application; (3) to classify cultivars based on their dependence on soil fertility using basic soil productivity contribution rate (BSPCR); (4) to identify the primary yield-limiting component within each cultivar; and (5) to develop a tiered cultivar recommendation system based on multi-criteria evaluation to guide cultivar selection and N management strategies aimed at closing yield gaps.

2. Materials and Methods

2.1. Study Site and Experimental Design

This study was conducted at the experimental station of Nanyang Normal University (32°57' N, 112°43' E; altitude 128 m a.s.l.) in Henan province, China, during the 2021–2022, 2022–2023 and 2023–2024 wheat growing seasons (hereinafter referred to as 2021–2022, 2022–2023 and 2023–2024). The region has a semi-humid continental monsoon climate [29]. Monthly minimum temperatures, maximum temperatures and rainfall for the three growing seasons, together with the 30-year (1995–2024) monthly averages, are shown in Figure 1. The annual mean minimum temperatures for the three seasons and the 30-year average

were 7.2, 6.9, 7.3, and 7.9 °C, respectively; the corresponding annual mean maximum temperatures were 19.7, 19.3, 19.6, and 18.1 °C; and the total rainfall values were 261.1, 465.1, 306.8, and 396.8 mm. The experiment was conducted under rainfed conditions without supplemental irrigation.

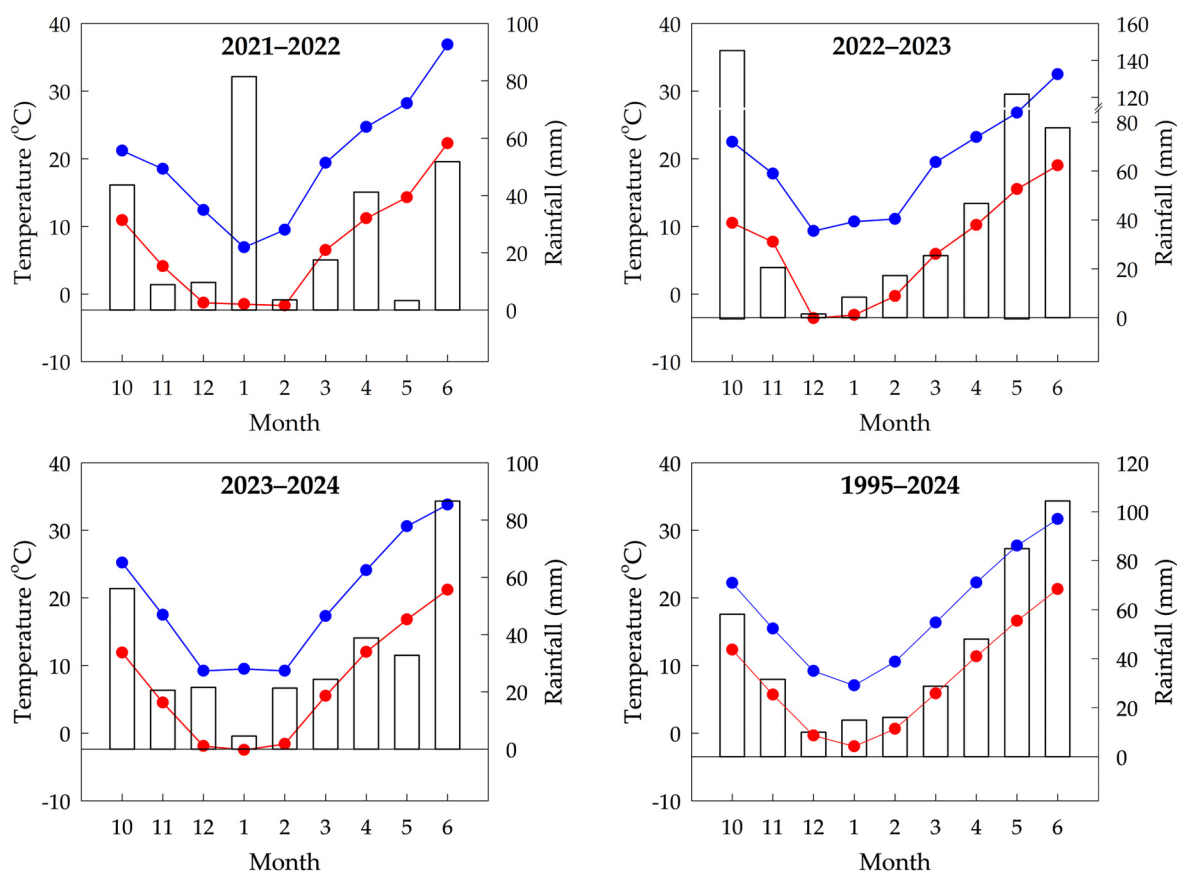


Figure 1. Monthly minimum temperatures (red circles), maximum temperatures (blue circles) and rainfall distribution (bars) for the three wheat growing seasons (2021–2024) and mean value of 30-year (1995–2024).

The soil type was classified as yellow–brown soil according to the Chinese Soil Taxonomy [36], corresponding to Eutric Cambisol in the World Reference Base for Soil Resources (WRB), with a pH of 7.1. Soil samples were collected from the 0–20 cm and 20–40 cm layers prior to sowing in each growing season, with three composite samples per layer per plot (each composite consisting of 5 subsamples collected in an ‘S’ pattern). Organic matter was determined by the $K_2Cr_2O_7$ oxidation method; alkali-hydrolyzable N by the alkaline diffusion method; available P by the $NaHCO_3$ extraction–molybdenum blue colorimetric method; and available K by the NH_4OAc extraction–flame photometry method. The cultivated layer (0–20 cm and 20–40 cm) had organic matter contents of 18.4 and 12.5 g kg⁻¹, alkali-hydrolyzable N of 96.5 and 74.1 mg kg⁻¹, available P of 28.4 and 2.3 mg kg⁻¹, and available K of 108.8 and 79.0 mg kg⁻¹, respectively (Supplementary Table S1).

Twenty-eight wheat cultivars (Table 1) widely grown in the Huang-Huai region were selected for this study. The experiment employed a randomized complete block design with three replicates. Fertilization treatments varied slightly across years, as summarized in Table 2. Briefly, the N1 treatment (210 kg N ha⁻¹ as single basal application) represents a common but suboptimal practice observed in some local farms, whereas the N2 treatment follows recommended split-application management to improve nitrogen use efficiency.

Table 1. Cultivar codes, names, and growth habits of 28 wheat cultivars.

Code	Cultivar Name	Growth Habit	Code	Cultivar Name	Growth Habit
C1	Bainong 201	Weak spring	C15	Pingan 11	Semi-winter
C2	Bainong 207	Semi-winter	C16	Yumai 49–198	Semi-winter
C3	Bainong 307	Semi-winter	C17	Xuke 316	Semi-winter
C4	Yunong 186	Semi-winter	C18	Luomai 26	Semi-winter
C5	Tianmin 198	Weak spring	C19	Luomai 31	Semi-winter
C6	Xinmai 26	Semi-winter	C20	Zhoumai 30	Semi-winter
C7	Bainong 418	Semi-winter	C21	Zhoumai 27	Semi-winter
C8	Bainong 419	Semi-winter	C22	Zhoumai 32	Semi-winter
C9	Zhengmai 366	Semi-winter	C23	Zhoumai 36	Semi-winter
C10	Zhengmai 379	Semi-winter	C24	Xinhuamai 818	Semi-winter
C11	Zhengmai 119	Semi-winter	C25	Xinong 979	Semi-winter
C12	Zhengmai 369	Semi-winter	C26	Fengdecunmai 5	Semi-winter
C13	Zhengmai 7698	Semi-winter	C27	Yumai 158	Semi-winter
C14	Zhengmai 0943	Semi-winter	C28	Shangmai 156	Semi-winter

Note: Growth habit classification follows the local standard for the Huang-Huai wheat region.

Table 2. Fertilization treatments applied during three wheat growing seasons (2021–2024).

Season	Treatment	Basal N (kg ha ^{−1})	Topdressing N at Jointing (kg ha ^{−1})	P ₂ O ₅ (kg ha ^{−1})	K ₂ O (kg ha ^{−1})
2021–2022	CK	0	0	0	0
	N1	210	0	120	120
2022–2023	CK	0	0	0	0
	N1	210	0	120	120
	N2	105	105	120	120
2023–2024	CK	0	0	0	0
	N1	210	0	120	120
	N2	105	105	120	120

Fertilizers were applied as urea (N), calcium superphosphate (P₂O₅), and potassium sulfate (K₂O). Each plot was 13.5 m² (9 m × 1.5 m) with 6 rows at 25 cm spacing. The previous crop was summer maize, with all straw returned to the soil before tillage each year. Standard chemical treatments were applied to control diseases, pests, and weeds throughout the growing season. A schematic layout of the field experiment is shown in Supplementary Figure S1. The same plots were used across three seasons with a fixed randomization layout. To minimize N carry-over between wheat seasons, the wheat–maize rotation system was employed, as residual N from wheat is largely captured by the subsequent maize crop or mineralized during the maize growing season [37,38]; this design, together with the moderate N rate (210 kg ha^{−1}), effectively resets soil N before each wheat season.

2.2. Grain Yield and Yield Component Determination

The final grain yield was determined by manually harvesting all plants in a 6 m² (1.5 m × 4 m) subarea at the center of each plot at maturity. Wheat was threshed two days after harvest using a threshing machine (QKT-320B, Xinchang Machine Manufactory, Weihui County, China). Grain was air-dried, weighed, and adjusted to a standard 12% moisture content (88% dry matter, kg ha^{−1}). Spike number was determined by counting spikes in the sampled area and converting to spikes per hectare. Kernel number per spike was determined by counting the total grains from 30 randomly selected spikes. The 1000-grain weight was measured by weighing 1000 kernels with three replicates.

2.3. Basic Soil Productivity and Its Contribution Rate

Basic soil productivity was quantified as the grain yield achieved in a no-fertilizer (CK) plot (Y_{CK}) [39]. Y_{CK} reflects the combined effect of indigenous soil nutrient supply and the cultivar's inherent capacity to acquire and utilize these nutrients under no-fertilizer conditions. Basic soil productivity contribution rate (BSPCR) was calculated as [40]:

$$\text{BSPCR (\%)} = [Y_{CK}/Y_{N1}] \times 100 \quad (1)$$

where Y_{CK} is the yield in CK plots (kg ha^{-1}) and Y_{N1} is the yield in N1 plots (kg ha^{-1}). Higher BSPCR indicates greater capacity to exploit soil-derived nutrients under no-fertilizer conditions. Annual BSPCR values were calculated for each cultivar for 2021–2022, 2022–2023, and 2023–2024, followed by calculation of the 3-year mean and standard deviation.

2.4. Split-Nitrogen Response Index (SNRI)

The split-N response index (SNRI) was calculated as the ratio of grain yield under split-N application (N2) to that under single basal N application (N1). The SNRI reflects the responsiveness of each cultivar to optimized nitrogen management and was calculated as:

$$\text{SNRI} = Y_{N2}/Y_{N1} \quad (2)$$

where Y_{N2} is the yield in N2 plots (kg ha^{-1}) and Y_{N1} is the yield in N1 plots (kg ha^{-1}). Since the N2 treatment was only implemented in 2022–2023 and 2023–2024, SNRI values were calculated for each cultivar using the mean yields across these two seasons. An SNRI > 1.00 indicates a positive response to split-N application, while SNRI < 1.00 indicates a negative or negligible response. This index was used as one of the four criteria in the comprehensive evaluation and screening of superior cultivars (Section 3.5).

2.5. Statistical Analysis

Data compilation and descriptive statistics were performed using Microsoft Excel 2019 (Microsoft Corp., Redmond, WA, USA). Figures were plotted in SigmaPlot 10.0 (Systat Software Inc., San Jose, CA, USA), and box plots were generated using Origin 2024 (Learning Edition, OriginLab Corp., Northampton, MA, USA).

All statistical analyses were performed using R 4.3 (R Core Team, 2023). A linear mixed model was fitted using the *lmerTest* package with Satterthwaite approximation for denominator degrees of freedom:

$$\text{Yield} \sim \text{Cultivar} \times \text{T} \times \text{Year} + (1 | \text{Block})$$

Cultivar, T, and Year were treated as fixed factors with treatment coding (*contr.sum*) for sum-to-zero contrasts; Block was treated as a random factor. Type III sums of squares were used. Model diagnostics included visual inspection of residual plots and Q-Q plots to assess normality and homogeneity of variance. Due to the absence of N2 in 2021–2022, the design is unbalanced; the mixed-model approach with Satterthwaite approximation appropriately handles this imbalance by estimating denominator degrees of freedom for each fixed effect.

The model included Block as a random intercept to account for variation among the three replicate blocks in the randomized complete block design. Blocks were treated as random because they represent a sample of environmental conditions rather than fixed treatments of interest. The same blocks were used across all three seasons but were not treated as a repeated factor because plots were destructively sampled for yield determination each year, and the primary focus of this study is on the fixed effects of cultivar,

fertilization, and year. Post hoc comparisons were performed using Tukey's HSD test (*emmeans* package).

For each cultivar, Pearson correlation coefficients between yield and the yield components (spike number, kernels per spike, and 1000-grain weight) were calculated. The primary yield-limiting factor for each cultivar was identified as the yield component with the highest absolute correlation coefficient that was statistically significant ($p < 0.05$). Hierarchical clustering (Ward's method, Euclidean distance) was used to classify cultivars based on BSPCR values.

The coefficient of variation (CV) for each cultivar was calculated as the ratio of the standard deviation to the mean of its yields across all treatment-year combinations, providing a measure of overall performance variability.

A composite score was calculated for each cultivar using min–max normalized values with the following weights: yield potential 40%, stability (inverse coefficient of variation, CV) 20%, split-N response index ($SNRI = Y_{N2}/Y_{N1}$) 30%, and BSPCR 10%. Weights were assigned based on the relative importance of each trait in cultivar selection: yield as the primary productivity trait (40%), SNRI reflecting the study's focus on N responsiveness (30%), stability for yield consistency (20%), and BSPCR as a secondary soil adaptation indicator (10%). Min–max normalization was performed using the global range across all 28 cultivars: yield (3435–5231 kg ha^{−1}), CV (9.9–39.5%), SNRI (1.02–1.24), and BSPCR (47.8–86.0%). The weights were assigned to reflect the relative importance of each criterion in cultivar selection. Cultivars were then ranked and assigned to management tiers based on their composite scores.

3. Results

3.1. Analysis of Variance for Grain Yield

The three-way mixed-model ANOVA (Table 3) revealed highly significant main effects of cultivar ($F_{27, 446} = 357.86$, $p < 0.001$) and fertilization treatment (T) ($F_{2, 446} = 20,223.41$, $p < 0.001$). However, the year main effect was not significant ($F_{2, 446} = 1.12$, $p = 0.329$). Fertilization application accounted for the largest proportion of variance ($SS = 6.795 \times 10^8$, $\eta^2 = 0.589$), exceeding that of cultivar ($SS = 1.623 \times 10^8$, $\eta^2 = 0.141$), indicating that fertilizer management was the predominant factor influencing yield.

Table 3. Tests of fixed effects for grain yield as affected by cultivar, fertilization treatment, and year (mixed-model ANOVA with Satterthwaite approximation).

Source of Variation	Sum of Squares (SS)	df	F-Value	p-Value	Significance	η^2
Cultivar (C)	162,321,420	27	357.83	<0.001	***	0.141
Treatment (T)	679,544,836	2	20,223.41	<0.001	***	0.589
Year (Y)	37,494	2	1.12	0.329	ns	<0.001
C × T	51,788,630	54	57.08	<0.001	***	0.045
C × Y	281,510,866	54	310.29	<0.001	***	0.244
T × Y	78,623,659	3	1559.91	<0.001	***	0.068
C × T × Y	59,649,210	81	43.83	<0.001	***	0.052

Note: *** $p < 0.001$; ns = not significant ($p > 0.05$). N2 treatment was only implemented in 2022–2023 and 2023–2024. The mixed model was fitted using the *lmerTest* package with Satterthwaite approximation for denominator degrees of freedom. $SS_{total} = 1,313,378,116$ (sum of all effect SS). η^2 values (effect sizes) are reported in the text as SS_{effect}/SS_{total} using Type III sums of squares.

The cultivar × T interaction was significant ($F_{54, 446} = 57.08$, $p < 0.001$), the cultivar × year interaction was significant ($F_{54, 446} = 310.29$, $p < 0.001$), and the T × year interaction was also significant ($F_{3, 446} = 1559.91$, $p < 0.001$). These results show that cultivars differed fundamentally in their N response, that cultivar performance varied substantially

across seasons, and that fertilizer effects were modulated by seasonal water availability. Moreover, the three-way interaction ($C \times T \times Y$) was highly significant ($F_{81, 446} = 43.83$, $p < 0.001$), revealing that cultivar-specific N responses were not stable across years and that the optimal cultivar $\times$ T combination may be year-dependent.

3.2. Cultivar Yield Potential and Stability

Yield increased progressively from CK through N1 to N2 (median: 3181, 5175, and 5483 kg ha⁻¹; Figure 2). Tukey's HSD test confirmed significant differences between all treatment pairs ($p < 0.0001$ for CK vs. N1 and CK vs. N2; $p = 0.024$ for N1 vs. N2). The interquartile range (IQR) narrowed from CK (798 kg ha⁻¹) to N1 (664 kg ha⁻¹) but expanded under N2 (868 kg ha⁻¹), suggesting that split-N application amplified cultivar-specific responses. This pattern is consistent with the significant cultivar $\times$ T interaction reported in Table 3.

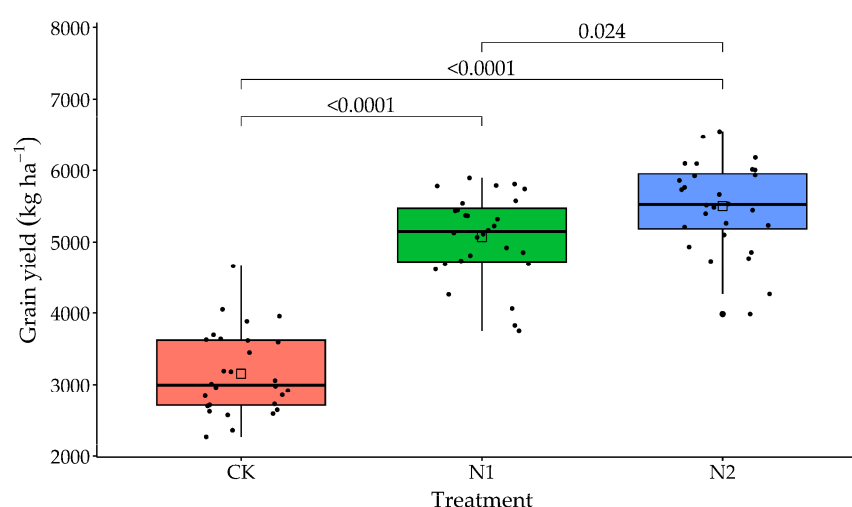


Figure 2. Boxplots of grain yield for 28 wheat cultivars under three treatments (CK, N1, and N2). The box represents the interquartile range (IQR), the horizontal line within the box indicates the median, and the square ($\square$) indicates the mean. Whiskers extend to $1.5 \times$ IQR. The p -values above the boxes indicate pairwise comparisons based on Tukey's HSD test. $n = 28$ per treatment. N2 was applied only in 2022–2023 and 2023–2024.

Overall mean yields ranged from 3435 to 5231 kg ha⁻¹, representing a 1.52-fold difference (Figure 3). Most cultivars showed a consistent yield increase with fertilizer supply ($CK < N1 < N2$). Overall performance variability, measured as CV, varied considerably among cultivars, with no consistent association between yield level and stability at the population level. These results demonstrate that cultivar selection is the primary genetic strategy for closing yield gaps.

Among the top-yielding group (mean > 4800 kg ha⁻¹), stability varied markedly: C20 combined the highest yield with the lowest CV (9.88%), whereas C14 and C15 exhibited high CVs ($> 27\%$), suggesting a yield-stability trade-off. At the lower end, C17 and C27 (< 3600 kg ha⁻¹) displayed moderate CVs (~ 22 – 24%), reflecting stable but intrinsically limited productive potential.

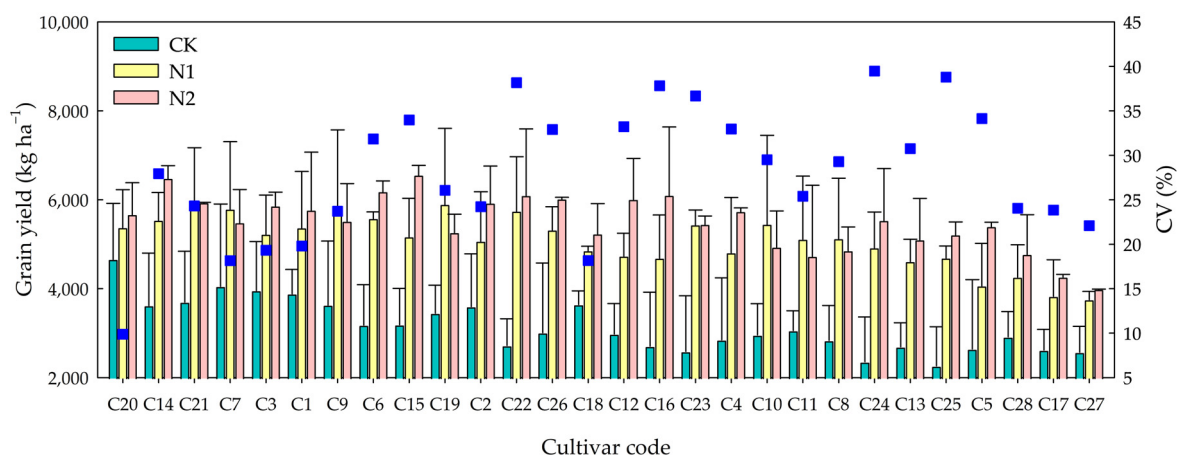


Figure 3. Grain yield (bars) and coefficient of variation (CV%, blue squares) for 28 cultivars, arranged in descending order of overall mean yield under three treatments (CK, N1 and N2). Bars represent standard deviations. Mean yields for CK and N1 were calculated from three growing seasons (2021–2022, 2022–2023, 2023–2024); N2 data were from 2022–2023 and 2023–2024 only (N2 not applied in 2021–2022). CV values indicate overall performance variability across fertilization treatments and years (see Section 2.5).

3.3. Cultivar-Specific Responses to Split-Nitrogen Application

The yield increment (derived by subtracting N1 yield from N2 yield) ranged from 132.45 (C3) to 1156.55 kg ha⁻¹ (C12), with a mean of 587.37 kg ha⁻¹; the split-N response index (SNRI) ranged from 1.02 to 1.24 (mean 1.12) (Figure 4), indicating an average yield increase of 12.2% under split-N application (N2) relative to single basal N application (N1).

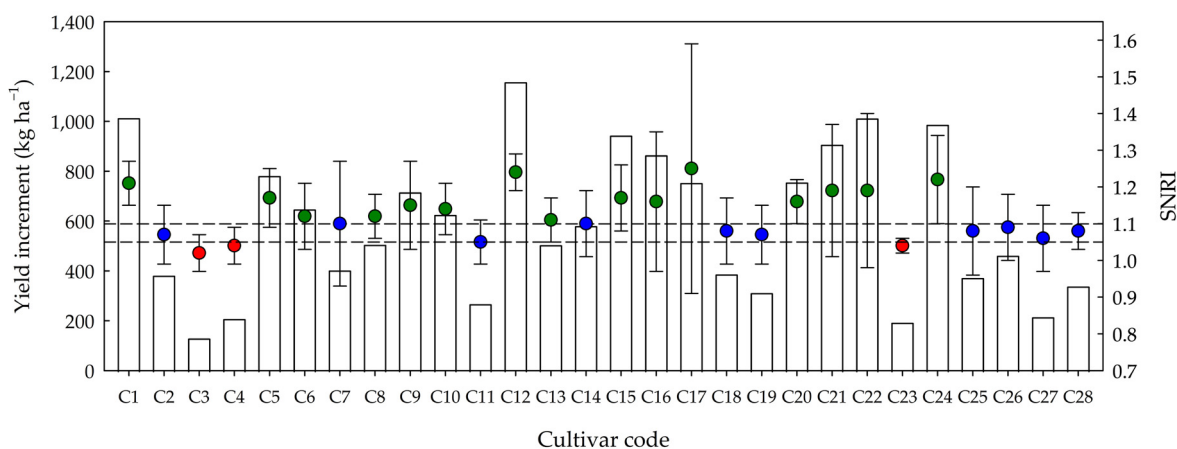


Figure 4. Yield increment (bars), split-N response index (SNRI) values and 95% confidence intervals (error bars) for 28 cultivars, based on 2022–2023 and 2023–2024 data. Cultivars are color-coded by response category: green (SNRI > 1.10), blue (SNRI 1.05–1.10), and red (SNRI < 1.05). Dashed horizontal lines indicate classification thresholds at SNRI = 1.05 (moderate response) and 1.10 (high response). Yield increment is from $Y_{N2} - Y_{N1}$; SNRI: split-N response index (Y_{N2} / Y_{N1}).

Cultivar-specific responses varied substantially. Based on SNRI thresholds, 15 cultivars (53.6%) were classified as high responses (SNRI > 1.10), including C1, C5, C6, C8, C9, C10, C12, C13, C15, C16, C17, C20, C21, C22 and C24, with C17, C12, C24 and C1 exhibiting the largest increases (SNRI ≥ 1.21). Ten cultivars (35.7%) showed moderate responses (SNRI 1.05–1.10), including C2, C7, C11, C14, C18, C19, C25, C26, C27 and C28. Only three cultivars (10.7%)—C3, C4 and C23—showed weak responses (SNRI < 1.05). Thresholds of 1.05 and 1.10 were chosen to represent approximately 5% and 10% yield gains, respectively, which are agronomically meaningful benchmarks for cultivar selection. These thresholds

were applied after confirming that the 95% confidence intervals of SNRI values did not overlap with the threshold boundaries.

3.4. Basic Soil Productivity Contribution Rate (BSPCR) and Cultivar Classification

A significant positive correlation was detected between Y_{CK} (yield under CK) and Y_{N1} (yield under N1) ($r = 0.465$, $p < 0.001$; Figure 5), but Y_{CK} explained only 21.7% of the variation in Y_{N1} ($R^2 = 0.2166$). The regression equation ($Y_{N1} = 0.478Y_{CK} + 3563.0$, $p < 0.001$) indicates that the slope (0.478) is significantly less than 1, meaning that the advantage of high- Y_{CK} cultivars diminishes under fertilization. This low explanatory power underscores that cultivar-specific response to fertilizer application—rather than baseline yield potential—is the dominant factor determining performance under fertilization.

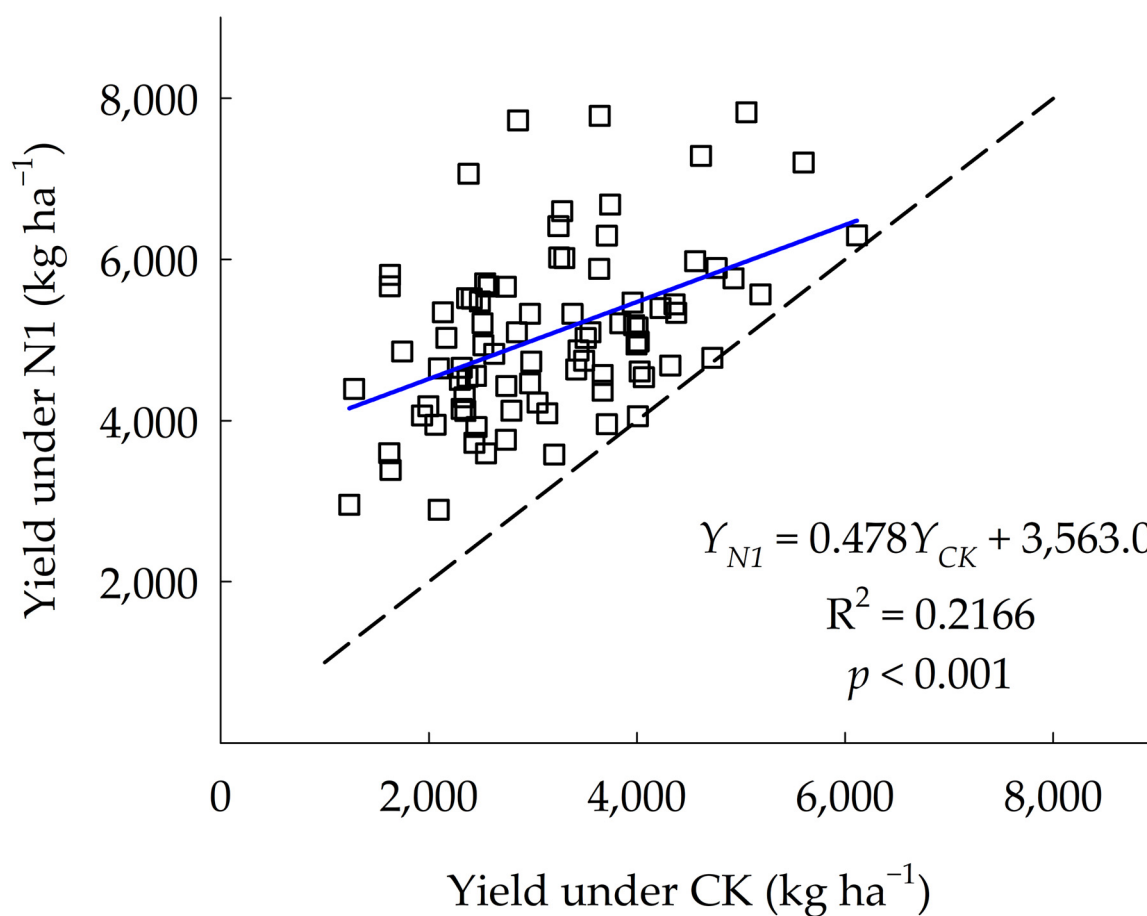


Figure 5. Relationship between Y_{CK} (yield under CK) and Y_{N1} (yield under N1) across 28 wheat cultivars ($n = 84$, 28 cultivars $\times$ 3 years). The dashed diagonal line represents $y = x$ (equal performance under both conditions). Regression line (blue solid): $Y_{N1} = 0.478Y_{CK} + 3563.0$ ($R^2 = 0.2166$, $p < 0.001$).

Hierarchical cluster analysis (Ward's method, Euclidean distance) was applied to multi-year BSPCR data to classify 28 cultivars based on mean contribution rate and temporal stability. The dendrogram and silhouette coefficient jointly supported a three-cluster solution with clear inter-group separation (Table 4). Class I ($n = 7$) exhibited the highest mean BSPCR ($76.2 \pm 9.4\%$), with multiple entries exceeding 90% in 2022–2023, indicating strong responsiveness to soil fertility conditions. Class II ($n = 18$) exhibited intermediate values ($61.5 \pm 5.1\%$) with minimal inter-annual fluctuation, reflecting superior stability. Class III ($n = 3$) showed the lowest mean ($48.3 \pm 1.3\%$) and remarkably low temporal variability ($CV < 5\%$), suggesting a limited but highly stable nutrient contribution.

Table 4. Classification of 28 cultivars based on hierarchical clustering of BSPCR values during three growing seasons (2021–2024).

BSPCR Class	Cultivars	<i>n</i>	Range (%)	Mean $\pm$ SD (%)	Inter-Annual CV (%)
I (High)	C1, C2, C3, C7, C18, C20, C22	7	67.2–86.0	76.2 $\pm$ 9.4	12.3
II (Moderate)	C4, C5, C6, C8, C9, C10, C11, C12, C13, C14, C15, C16, C17, C19, C21, C26, C27, C28	18	55.0–69.1	61.5 $\pm$ 5.1	8.3
III (Low)	C23, C24, C25	3	47.8–48.7	48.3 $\pm$ 1.3	2.7

3.5. Within-Cultivar Correlation of Yield with Yield Components

Correlation analysis across all cultivars revealed that grain yield was most strongly associated with spike number ($r = 0.691$, $p < 0.001$), followed by kernels per spike ($r = 0.258$, $p < 0.001$), whereas the correlation with 1000-grain weight was not statistically significant ($r = 0.075$, $p > 0.05$) (Table 5).

Table 5. Correlation coefficients between grain yield and its components ($n = 224$).

Item	Grain Yield	Spike No.	Kernels No.
Spike N.	0.691 ***		
Kernels No.	0.258 ***	−0.316 ***	
1000-GW	0.075	−0.251 **	0.417 ***

Note: **, and *** represent significance at $p < 0.01$, and $p < 0.001$, respectively. Spike No., spike number; Kernel No., kernels per spike; 1000-GW, 1000-grain weight. $n = 224$ represents the total number of observations (28 cultivars $\times$ 8 observations per cultivar).

At the individual cultivar level, however, within-cultivar correlation analyses (Table 6) revealed marked heterogeneity in the predominant yield-limiting components. Among the 28 cultivars, 20 cultivars (71.4%) were spike-number-limited, with C14 exhibiting the highest correlation ($r = 0.977$, $p < 0.001$); three cultivars (10.7%, C8, C19, and C22) were kernel-number-limited, with C19 showing the strongest association ($r = 0.734$, $p < 0.01$); two cultivars (7.1%, C17 and C20) were grain-weight-limited ($r = 0.806$ and 0.839 , $p < 0.01$, respectively); and three cultivars (10.7%, C7, C11, and C28) showed no significant correlation with any of the three yield components.

Table 6. Within-cultivar correlation coefficients between grain yield and its components across 28 wheat cultivars ($n = 8$ per cultivar).

Cultivar	<i>r</i> (Yield–Spike No.)	<i>r</i> (Yield–Kernel No.)	<i>r</i> (Yield–1000-GW)
C1	0.660 *	0.224	0.332
C2	0.908 ***	0.039	0.070
C3	0.843 **	−0.447	−0.520
C4	0.927 ***	−0.143	−0.223
C5	0.948 ***	−0.129	0.201
C6	0.861 **	−0.209	−0.089
C7	0.479	0.483	0.398
C8	0.252	0.652 *	0.461
C9	0.746 *	0.536	0.559
C10	0.802 **	0.468	0.114
C11	0.235	0.535	0.297
C12	0.950 ***	−0.301	−0.390
C13	0.731 *	−0.037	−0.019
C14	0.977 ***	−0.201	−0.361
C15	0.925 ***	−0.072	−0.208
C16	0.905 ***	−0.338	0.209
C17	0.441	0.253	0.806 **

Table 6. Cont.

Cultivar	r (Yield–Spike No.)	r (Yield–Kernel No.)	r (Yield–1000-GW)
C18	0.862 **	−0.223	0.003
C19	0.438	0.734 *	0.542
C20	0.726 *	0.798 **	0.839 ***
C21	0.660 *	0.436	0.060
C22	0.663 *	0.683 *	0.281
C23	0.752 *	0.674 *	−0.022
C24	0.795 **	0.550	−0.182
C25	0.768 **	0.188	0.443
C26	0.884 ***	0.616	−0.162
C27	0.639 *	0.299	−0.049
C28	0.515	0.256	0.170

Note: *, **, and *** represent significance at $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively. Spike No., spike number; Kernel No., kernels per spike; 1000-GW, 1000-grain weight.

3.6. Comprehensive Evaluation and Screening of Superior Cultivars

Based on composite scores integrating yield potential (40%), stability (inverse CV, 20%), SNRI (30%), and BSPCR (10%), the 28 cultivars were ranked and classified into four management tiers (Table 7). Tier I (score > 68) included C20, C1, C21, and C14, which combined high yield (5004–5231 kg ha^{−1}) with strong N responsiveness (SNRI ≥ 1.10), and is recommended for high-fertility fields with split-N application. Among these, C20 ranked first due to its superior yield, exceptional stability (CV = 9.9%) and the highest BSPCR (86.0%).

Table 7. Composite scores and management tiers for 28 cultivars.

Rank	Cultivar Code	Mean Yield (kg ha ^{−1})	CV (%)	SNRI	BSPCR (%)	Composite Score	Tier
1	C20	5231.1	9.9	1.15	86.0	85.6	I
2	C1	5003.5	19.8	1.21	76.2	72.8	I
3	C21	5136.5	24.3	1.18	65.6	72.0	I
4	C14	5209.8	27.9	1.10	64.9	68.7	I
5	C7	5107.0	18.2	1.08	67.2	67.4	II
6	C3	5012.1	19.3	1.02	75.7	62.8	II
7	C18	4576.0	18.2	1.08	75.0	60.8	II
8	C12	4572.6	33.2	1.24	63.6	60.5	II
9	C22	4851.1	38.2	1.20	50.1	60.2	II
10	C15	4967.3	34.0	1.17	61.8	59.9	III
11	C17	3570.2	23.8	1.22	68.9	59.8	III
12	C9	4983.5	23.7	1.15	62.7	59.3	III
13	C6	4977.9	31.9	1.12	57.4	58.0	III
14	C26	4780.0	32.9	1.08	55.0	56.8	III
15	C2	4860.3	24.2	1.07	71.6	56.7	III
16	C19	4867.1	26.1	1.06	60.4	55.8	III
17	C24	4268.4	39.5	1.22	48.7	55.3	III
18	C27	3435.0	22.1	1.06	69.1	54.0	III
19	C28	3982.1	24.0	1.08	68.4	53.9	III
20	C11	4298.4	25.4	1.06	61.7	53.2	III
21	C16	4495.6	37.8	1.17	57.0	52.5	III
22	C13	4134.6	30.8	1.11	59.2	52.4	III
23	C8	4272.7	29.3	1.12	55.2	52.3	III
24	C10	4446.2	29.5	1.15	60.2	51.8	III
25	C4	4463.0	33.0	1.04	58.2	50.3	III
26	C23	4489.1	36.7	1.04	48.5	50.1	III
27	C25	4053.6	38.8	1.08	47.8	48.6	IV
28	C5	4032.6	34.1	1.17	62.1	47.2	IV

Note: SNRI = split-N response index (Y_{N2}/Y_{N1}). Composite score weighting: yield 40%, stability (inverse CV) 20%, SNRI 30%, BSPCR 10%. Tier I: score > 68; Tier II: 60 < score ≤ 68; Tier III: 50 < score ≤ 60; Tier IV: score ≤ 50.

Tier II ($60 < \text{score} \leq 68$) included C7, C3, C18, C12, and C22. C7 offered the best yield–stability balance ($\text{CV} = 18.2\%$), while C12 and C22 were highly N-responsive ($\text{SNRI} \geq 1.20$) but more variable. Tier III ($50 < \text{score} \leq 60$) contained 17 cultivars with diverse traits. Tier IV ($\text{score} \leq 50$) comprised C25 and C5, characterized by low yield potential.

4. Discussion

4.1. Cultivar Differences as a Major Source of Yield Variation

The 1.52-fold yield range ($3435\text{--}5231 \text{ kg ha}^{-1}$, $\approx 1800 \text{ kg ha}^{-1}$ variation) observed among 28 cultivars under identical management confirms cultivar choice as a major entry point for closing yield gaps. This magnitude is consistent with the estimated 30–40% contribution of cultivar substitution to historical yield gains in the North China Plain [23,34,41]. The significant cultivar $\times$ year interaction ($p < 0.001$) indicated that cultivar performance varied substantially across seasons, reflecting the influence of inter-annual rainfall (261.1–465.1 mm) and temperature on crop establishment and yield formation [42]. Collectively, these findings suggest that optimized cultivar deployment—matching the right cultivar to the right field and management system—could close a substantial portion of the regional yield gap without additional genetic improvement.

High-yielding cultivars (C1, C14, C21) were classified as spike-number-limited based on within-cultivar correlation analyses (Table 6), indicating that their high yield potential was primarily achieved through superior tillering capacity and spike formation, which translated into higher spike numbers per unit area. Although modern wheat cultivars in China have undergone substantial genetic improvement in harvest index, nitrogen use efficiency, and disease resistance [23,43], our results demonstrate that substantial yield variation exists among current cultivars under identical management and that this variation interacts significantly with both N management and soil fertility. This suggests that optimized cultivar–N–soil matching—rather than simply selecting the highest-yielding cultivar—could better exploit the genetic potential of current germplasm.

4.2. Coupling of Yield Potential and Split-N Responsiveness

The significant cultivar $\times$ T interaction ($p < 0.001$) confirms that cultivars differ fundamentally in their fertilizer response. The tiered screening identified Tier I cultivars (C20, C1, C21, C14) that concurrently met thresholds for high yield ($>5000 \text{ kg ha}^{-1}$) and strong N responsiveness ($\text{SNRI} \geq 1.10$), with yield gains of 10–21% under N2. This result demonstrates the feasibility of multi-criteria screening for identifying cultivars with both traits.

The identification of cultivars that combine high yield potential with strong N responsiveness (Tier I) has important physiological and practical implications. Such cultivars likely benefit more from split-N application due to their greater sink capacity and N demand during the reproductive period, when N is critical for spike and floret development [19]. This is consistent with the source–sink balance theory [20] and previous findings that high-yielding cultivars exhibit greater post-anthesis N uptake and remobilization efficiency [44]. Low-yielding cultivars, by contrast, appear sink-limited and cannot convert additional N into grain yield. For these cultivars, simplified N management (e.g., single basal application) may be equally effective and more economical, as excess N could lead to environmental losses without yield benefits [27,45].

The significant three-way interaction ($C \times T \times Y$, $p < 0.001$) indicates that cultivar-specific fertilizer responses varied across years, suggesting that genetic N responsiveness is modulated by rainfall and temperature. Thus, while Tier I cultivars performed well across years, their ranking may shift under extreme conditions—warranting year-specific calibration in long-term recommendations.

4.3. BSPCR-Based Cultivar Classification for Soil Fertility-Based Matching

The relationship between yield under CK and N1 (Figure 5) revealed that baseline yield explained only 21.7% of the variation in fertilized performance ($R^2 = 0.2166$), indicating that cultivar-specific responses to fertilizer application are largely independent of baseline yield potential. To capture cultivar-specific dependence on soil fertility, BSPCR was calculated as the ratio of zero-fertilizer yield to full NPK fertilization yield [39,40]. Hierarchical clustering of multi-year BSPCR data classified the 28 cultivars into three classes: Class I (high BSPCR, $n = 7$), Class II (moderate, $n = 18$), and Class III (low, $n = 3$).

High-BSPCR cultivars (Class I) possess greater capacity to acquire indigenous soil nutrients, sustaining relatively high yields under no-fertilizer conditions. Low-BSPCR cultivars (Class III), by contrast, perform relatively poorly without fertilization. The observed BSPCR variation may be associated with differences in root architecture and nutrient uptake efficiency, as suggested by previous studies [21,22], but direct measurements of these traits were not made in this study. Thus, the physiological mechanisms underlying BSPCR differences remain to be elucidated in future research.

In practice, high-fertility fields should adopt Class I cultivars (e.g., C20). Class III cultivars had the lowest BSPCR (48.3%) and smallest inter-annual variation ($CV < 3\%$), indicating that their yields are more dependent on applied fertilizer than on indigenous soil nutrient supply.

4.4. Divergence of Yield-Limiting Factors Among Cultivars

Beyond BSPCR-based classification of soil fertility dependence (Table 4), within-cultivar correlation analyses (Table 6) revealed marked divergence in yield-limiting components among cultivars. Spike number was the primary yield-limiting factor for 71.4% of cultivars (20 of 28), while 10.7% (C8, C19, and C22) were kernel-number-limited, 7.1% (C17 and C20) were grain-weight-limited, and 10.7% (C7, C11, and C28) showed no significant correlation with any yield component.

Spike-number-limited cultivars (e.g., C1, C3, C14, C21) require management promoting tillering and spike formation, including appropriate seeding rates and early-season N application [46]. Kernel-number-limited cultivars (C8, C19, C22) require management promoting floret development and grain set, with N topdressing at booting [47]. Grain-weight-limited cultivars (C17, C20) require management extending the grain-filling period and preventing leaf senescence [48]. Cultivar C20, one of the two grain-weight-limited cultivars, exhibited the highest BSPCR (86.0%) and lowest CV (9.9%), indicating that grain-weight limitation can coexist with high yield potential and stability.

These findings underscore the need for cultivar-specific management strategies. A “one-size-fits-all” approach to yield component management is likely to be suboptimal, as different cultivars have various physiological limitations that require different management interventions.

4.5. Practical Implications and Limitations

The tiered system provides a practical framework for cultivar selection by integrating yield potential, stability, SNRI, and BSPCR into a composite score. Tier I cultivars (C20, C1, C21, C14) are recommended for high-fertility fields (soil organic matter $> 15 \text{ g kg}^{-1}$) with split-N application at jointing, combining high yield ($5004\text{--}5231 \text{ kg ha}^{-1}$) with strong N responsiveness ($SNRI \geq 1.10$). Tier II C7 offers a favorable yield–stability balance (5107 kg ha^{-1} , $CV = 18.2\%$) for moderate-fertility fields. For practical application, farmers should assess field fertility based on soil organic matter and yield history and then select Tier I cultivars for high-fertility fields or Tier II for moderate-fertility fields.

Several limitations should be acknowledged: single-location design requiring multi-site validation; incomplete treatment design (N2 not applied in 2021–2022), supplementary analyses (Supplementary Table S4) confirmed the robustness of the main conclusions; lack of plant N measurements (uptake, recovery, NUE) precluding direct N efficiency assessment; and the exploratory nature of the tier system based on a single dataset, requiring independent validation with new trials. While the system has potential to reduce unnecessary N application, direct measurements of N recovery, residual soil N, nitrate leaching, N₂O emissions, and economic returns are needed to confirm environmental benefits. Future research should also examine cultivar $\times$ N $\times$ water interactions and develop diagnostic tools for on-farm use.

5. Conclusions

Cultivar selection is the primary genetic strategy for closing wheat yield gaps in the Huang-Huai region, with a 1.52-fold yield range (3435–5231 kg ha^{−1}) observed among 28 cultivars under identical management. The highly significant cultivar $\times$ T interaction ($p < 0.001$) confirms that cultivars differ fundamentally in their response to fertilizer management, with fertilizer application accounting for the largest proportion of yield variance ($\eta^2 = 0.589$), followed by cultivar $\times$ year ($\eta^2 = 0.244$) and cultivar ($\eta^2 = 0.141$).

Hierarchical clustering of BSPCR enabled fertility-based cultivar matching: Class I (high BSPCR, $n = 7$) for high-fertility fields, Class II (moderate BSPCR, $n = 18$) for conventional management, and Class III (low BSPCR, $n = 3$) for fertilizer-dependent types. Yield-limiting factors differed among cultivars—predominantly spike number (71.4%), followed by kernel number (10.7%) and grain weight (7.1%)—underscoring the need for cultivar-specific management.

Multi-criteria screening (yield, stability, SNRI, BSPCR) identified Tier I cultivars (C20, C1, C21, C14) combining high yield (>5000 kg ha^{−1}) and strong split-N responsiveness (SNRI ≥ 1.10), recommended for high-fertility fields with split-N application. Tier II (C7, C3, C18, C12, C22) offers balanced yield–stability performance for moderate-fertility fields. The proposed diagnostic-to-recommendation framework provides an exploratory, site-specific pathway for narrowing yield gaps through optimized cultivar–fertility–N matching, with broader validation across the Huang-Huai region warranted to strengthen its generalizability.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agronomy16151476/s1>. Supplementary Table S1: Soil properties at two depths (0–20 cm and 20–40 cm). Supplementary Table S2: List of 28 wheat cultivars with their origins and key agronomic traits. Supplementary Table S3: Mean grain yield (kg ha^{−1}) of 28 wheat cultivars under different fertilization treatments and years. Supplementary Table S4: Separate ANOVA results for (a) CK vs. N1 over three seasons and (b) N1 vs. N2 over two seasons. Supplementary Figure S1: Schematic layout of the field experiment (plot dimensions, row spacing).

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