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# Computational Analysis of Growth Traits and Yield Performance of Different Rice Varieties under Zhejiang Paddy Field Conditions

Jin Zhang[1,2]
1 Changshan Yudayuan Agricultural Technology Co., Ltd., Changshan, 324200, Zhejiang, China
2 Zhejiang Agronomist College, Hangzhou, 310021, Zhejiang, China
Corresponding email: 965405023@qq.com
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**Abstract** Rice production in Zhejiang Province is characterized by diverse ecological conditions and complex interactions between genotype and environment, making the selection of suitable rice varieties essential for achieving stable and high yields. This study aims to quantitatively evaluate the growth characteristics and yield performance of different rice varieties under paddy field conditions using computational analysis approaches. A comprehensive framework was established by integrating field observations of growth traits, yield components, dry matter accumulation, and resource utilization efficiency. Dynamic changes in plant height, tillering capacity, leaf area index, canopy structure, and biomass accumulation were analyzed, while statistical models were applied to identify key factors influencing yield formation. Correlation analysis, multiple regression models, and principal component analysis were used to evaluate relationships between growth traits and yield performance. A case study from typical rice-growing regions of Zhejiang Province further demonstrated the applicability of computational approaches for variety evaluation and selection. The results provide insights into the mechanisms underlying varietal differences in growth and productivity and offer a scientific basis for precision rice variety screening and intelligent crop management under modern agricultural systems.
**Keywords** Rice varieties; Growth traits; Yield performance; Computational analysis; Zhejiang paddy fields

## 1 Introduction

Rice is a staple crop central to regional food security, and improving its productivity remains a pressing challenge as demand continues to rise while yield growth has slowed in many rice-growing systems (Saberali and Darzi-Naftchali, 2024). Across production regions, substantial differences in grain yield are shaped not only by climate, soil, and crop management, but also by cultivar choice, which repeatedly emerges as an important determinant of attainable production and yield gaps. Large multi-location evaluations further show that rice genotypes differ significantly in yield performance, adaptability, and genotype-by-environment interaction, making regional testing a prerequisite for selecting varieties suited to specific ecological conditions (Ahmed et al., 2024). In China, long-term regional trial data likewise indicate that variety improvement has substantially raised rice yield and stability, although these gains differ among regions and rice types. Evidence from comparative field studies also shows that yield is significantly affected by variety even under the same latitude, field setting, or management background, confirming that varietal differences remain a practical lever for local production improvement. This issue is especially relevant for paddy-based systems, where yield gaps vary across irrigated, rainfed, and tidal fields and where site-specific intervention packages often need to combine appropriate varieties with optimized management to approach local production potential (Sulaeman et al., 2024). For Zhejiang, a major rice-producing province characterized by humid subtropical conditions, intensive paddy cultivation, and strong ecological heterogeneity across sites, understanding how different rice varieties perform under local field conditions is therefore essential for stabilizing yield, improving resource-use efficiency, and supporting regional grain security. A comparative analysis of varietal performance under Zhejiang paddy conditions is also justified because regional production depends not simply on the highest-yielding genotype in absolute terms, but on identifying cultivars that combine productivity with adaptation to local climate, field environment, and management regimes.

Rice yield is a complex trait formed through the coordinated expression of multiple growth and reproductive characteristics, and substantial progress has been made in clarifying the relationships between these traits and final grain production. Classical trait-association studies have shown that filled grains per panicle, panicles per hill, tillers per hill, and grain weight per hill are positively associated with yield, whereas unfilled grains and, in some materials, excessive plant height are negatively associated with yield formation. Path analyses further indicate that filled grains per panicle can exert the largest direct positive effect on yield, while tillers often contribute indirectly through their influence on panicle number, highlighting the interactive nature of source–sink traits during yield formation (Oladosu et al., 2018). At a broader scale, analysis of 7,686 rice varieties released in China demonstrated that trait–yield relationships are ecotype-dependent: indica types tend to achieve high yield through combinations involving filled grain number, grain weight, seed-setting rate, panicle size, and growth duration, whereas japonica types rely more consistently on panicle number per unit area and longer growth period. Panicle architecture is especially important because it defines sink capacity yet also influences the efficiency of grain filling; large or compact panicles can increase yield potential, but inferior spikelets often suffer poor filling because of weak starch synthesis, unfavorable hormonal balance, and limited endosperm development. Recent work shows that open panicle structure can improve filling in middle and lower spikelets and reduce empty grain rate, while panicle architectural diversity across genotypes provides exploitable variation for yield improvement (Agalya et al., 2023). Tiller type and nitrogen response also shape yield realization, since late-emerging tillers usually show lower spikelets per panicle, poorer grain filling, and weaker assimilate supply than main stems or early tillers, even when nitrogen increases their numerical contribution to population yield. Consistently, recent field experiments comparing panicle types under different nitrogen rates found that large-panicle varieties and medium-panicle varieties may realize yield through different component pathways, with the former relying more on grains per panicle and the latter more on panicle number, while excessive nitrogen can also reduce seed-setting rate and thousand-grain weight. Ecological comparisons reinforce that higher yield is ultimately expressed through coordinated changes in biomass production, panicle number, spikelets per panicle, grain filling, and harvest index under favorable local conditions (Jiang et al., 2025). These findings indicate that evaluating rice varieties in Zhejiang should integrate vegetative growth traits, panicle structure, reproductive efficiency, and yield components rather than relying on grain yield alone.

Alongside advances in agronomic and physiological understanding, computational analysis methods have become increasingly important for rice variety evaluation because they can integrate complex, nonlinear relationships among phenotype, environment, management, and yield. Machine learning studies show that models using phenology, climate, and geographic information predict rice yield more accurately than conventional linear regression, and that phenological variables can contribute nearly as much predictive information as climatic variables. In breeding and varietal trial settings, computational approaches are especially valuable because performance must be compared across many genotypes; recent UAV-based multispectral studies report that deep learning models are more robust than feature-based machine learning under multi-variety conditions and can identify the flowering to grain-filling stage as an effective window for pre-harvest prediction. Other forecasting work similarly shows that ensemble or nonlinear models often outperform single statistical models, although the best algorithm can vary by agroecological zone, indicating that local validation remains necessary. At smaller scales, phenotypic modeling based on panicle angle, panicle length, branch length, and grain number has achieved high predictive accuracy, and stacked ensemble models further improve performance over individual learners. Computer vision methods also offer rapid and non-destructive tools for rice variety classification and spikelet extraction, reducing labor intensity and subjectivity in morphological assessment. Remote-sensing analyses across multiple seasons and nitrogen treatments likewise show that tree-based machine learning models can outperform linear approaches for operational in-season yield estimation, with reproductive-stage vegetation indices emerging as stable predictors. Beyond prediction, computational statistics such as random forest, multivariate regression, AMMI, GGE biplot, principal component analysis, and clustering have been used to identify key yield determinants, quantify genotype stability, and classify varietal diversity across environments. Such methods are well suited to Zhejiang paddy systems, where varietal responses are shaped by interactions among genotype, field conditions, climate, and management, and where objective, data-driven evaluation can improve screening efficiency and strengthen recommendations for locally adapted, high-yielding varieties. Accordingly, a study on the computational analysis of growth traits and yield performance of different rice varieties under Zhejiang paddy field conditions can provide both agronomic insight into trait–yield relationships and methodological support for precise variety evaluation and regional rice production planning.

## 2 Data Acquisition and Computational Analysis Framework for Rice Variety Growth and Yield Performance

### 2.1 Ecological characteristics of the experimental region and allocation of rice variety resources

Zhejiang paddy-field experiments should be organized as a regional trial system because rice variety performance is shaped jointly by genotype, environment, and genotype-by-environment interaction, rather than by genotype alone. Multi-site assessment is therefore necessary both to identify high-yielding, stable materials and to distinguish testing locations with strong discrimination and representativeness for varietal screening. In this framework, the experimental region can be divided into ecologically comparable paddy subzones according to local field conditions, and rice variety resources can then be allocated across those subzones to ensure that the comparison reflects actual adaptation differences instead of a single-site yield ranking (Chen et al., 2025). This allocation logic is consistent with field evidence showing that regional trials are essential for breeding guidance and for selecting varieties suitable for specific production areas.

Within each ecological subzone, variety allocation should include materials with contrasting yield potential, stability, and adaptability so that local superiority and broad adaptation can be evaluated simultaneously. A randomized block layout with replication across sites provides the basic design needed to separate varietal effects from field heterogeneity and to support pooled analysis across environments. Because rice quality and agronomic expression both respond strongly to environmental conditions and management, the allocation of germplasm should also preserve diversity in varietal type rather than relying on a narrow set of similar entries. In practice, this means assigning representative indica, japonica, and hybrid materials to matched paddy environments while maintaining consistent agronomic management, so that regional ecological suitability can be inferred from comparable field observations (Shi et al., 2021).

### 2.2 Observation system for growth traits and yield formation indicators

The observation system should cover both visible agronomic traits and the physiological basis of yield formation, because rice grain yield is determined by grain weight, grain number per panicle, and effective tiller number, while these components are further influenced by nutrient-use and photosynthetic efficiency. Accordingly, field records should include vegetative traits, reproductive traits, and final yield-component traits throughout the growth cycle. Existing multi-location evaluations show that these measurements are informative because tillers per hill, panicles per hill, filled grains per panicle, and grain weight per hill are positively associated with yield, whereas unfilled grains per panicle and excessive plant height can reduce yield performance. This supports an observation framework in which seedling establishment, tillering, plant height, flowering, panicle structure, grain filling, and harvest output are tracked as an integrated trait set rather than as isolated endpoints.

For reproductive-stage monitoring, panicle architecture deserves special emphasis because it captures important variation in sink formation and yield realization (Agalya et al., 2023). Measurements can therefore include panicle length, primary and secondary branch number, filled grain number, panicle weight, productive tillers, and thousand-grain weight, as these traits have shown substantial variation among genotypes and strong positive links with single-plant yield. Trait prioritization can also be informed by direct and indirect effect analysis: filled grains per panicle often has the largest direct positive effect on yield, while tillers contribute indirectly through panicle number. Where computational prediction is intended, biomass, straw weight, plant number per square meter, and panicle number should also be recorded, because model-based analyses identify them as major explanatory variables for yield formation under field conditions.

### 2.3 Multidimensional data standardization and statistical computational analysis methods

Because varietal evaluation generates multidimensional data from morphology, yield components, and environment, the dataset should be standardized before modeling so that indicators with different units and ranges can be compared within a common analytical framework. A practical workflow is to summarize replicated observations by genotype mean, compute descriptive statistics and coefficients of variation, and then subject the normalized matrix to inferential and multivariate analysis. This approach is widely aligned with rice evaluation studies that use ANOVA to detect varietal differences and then extend the analysis to correlation, PCA, and clustering for trait reduction and pattern recognition. In germplasm-scale datasets, PCA has been effective because the first two principal components can explain a large share of total variation, making it useful for condensing many agronomic traits into a smaller set of synthetic evaluation axes.

The computational analysis stage should combine classical statistics with predictive and interaction-focused models. ANOVA can first test genotype effects and trait variability, while correlation and path analysis can identify traits with direct or indirect yield contributions (Agalya et al., 2023). PCA, cluster analysis, and discriminant approaches are then suitable for comprehensive classification, authenticity-style discrimination, and variety grouping in complex rice datasets. For multi-environment trials, AMMI and GGE biplot analysis are appropriate for quantifying stability and genotype-by-environment interaction (Chen et al., 2025), whereas nonlinear models such as random forest can be added when the objective is yield prediction or estimation of relative trait importance, since they have outperformed traditional regression models in agronomic rice datasets. In sum, the data acquisition and computational analysis framework for Zhejiang rice variety evaluation should link ecologically stratified field trials, systematic observation of growth and yield traits, and integrated statistical-computational methods. That combination best fits the goal of comparing different rice varieties under Zhejiang paddy field conditions.

## 3 Dynamic Analysis of Growth Trait Changes among Different Rice Varieties

### 3.1 Comparison of growth characteristics during the vegetative growth stage

Different rice varieties showed clear dynamic divergence during the vegetative growth stage, especially in plant height development, leaf expansion rhythm, and early biomass establishment. Comparative studies of contrasting genotypes found that height differences can appear as early as the seedling stage, while some varietal gaps narrow temporarily around tillering and then reappear by later development, indicating that vegetative growth is not a linear process but a stage-dependent expression of genotype (Akter et al., 2019). Across broader germplasm sets, significant variability has also been reported in leaf appearance rate, leaf elongation rate, and final leaf length, showing that varietal differences in early canopy construction are rooted in distinct developmental kinetics rather than only in final plant size.

The growth advantage of superior varieties at this stage usually reflects coordinated morpho-physiological performance rather than a single external trait. Rapid early growth has been associated with higher chlorophyll content, stronger photosynthetic rate, longer flag leaves, and more grains per panicle later in development, suggesting that vigorous vegetative establishment supports subsequent reproductive potential. At the same time, varietal comparisons under field conditions show that some cultivars maintain stronger leaf area index, crop growth rate, and dry matter accumulation even when they are not the tallest, indicating that Zhejiang variety evaluation should emphasize integrated growth efficiency rather than relying only on plant height as a screening criterion (Figure 1).

### 3.2 Tillering dynamics and population structure development characteristics

Tillering dynamics among rice varieties generally follow a single-peak trajectory, with stem and tiller numbers increasing after transplant establishment, reaching a maximum tillering stage, and then declining as ineffective tillers die off and the productive population structure stabilizes. This process is now commonly described as two linked phases, tiller occurrence and tiller extinction, and dynamic modeling shows that varietal differences can be quantified through indices such as inherent tillering rate, peak tillering time, tillering duration, and retained tiller number (Wang et al., 2024). These features are important because effective tiller number directly determines the number of effective panicles and therefore strongly affects final yield formation.

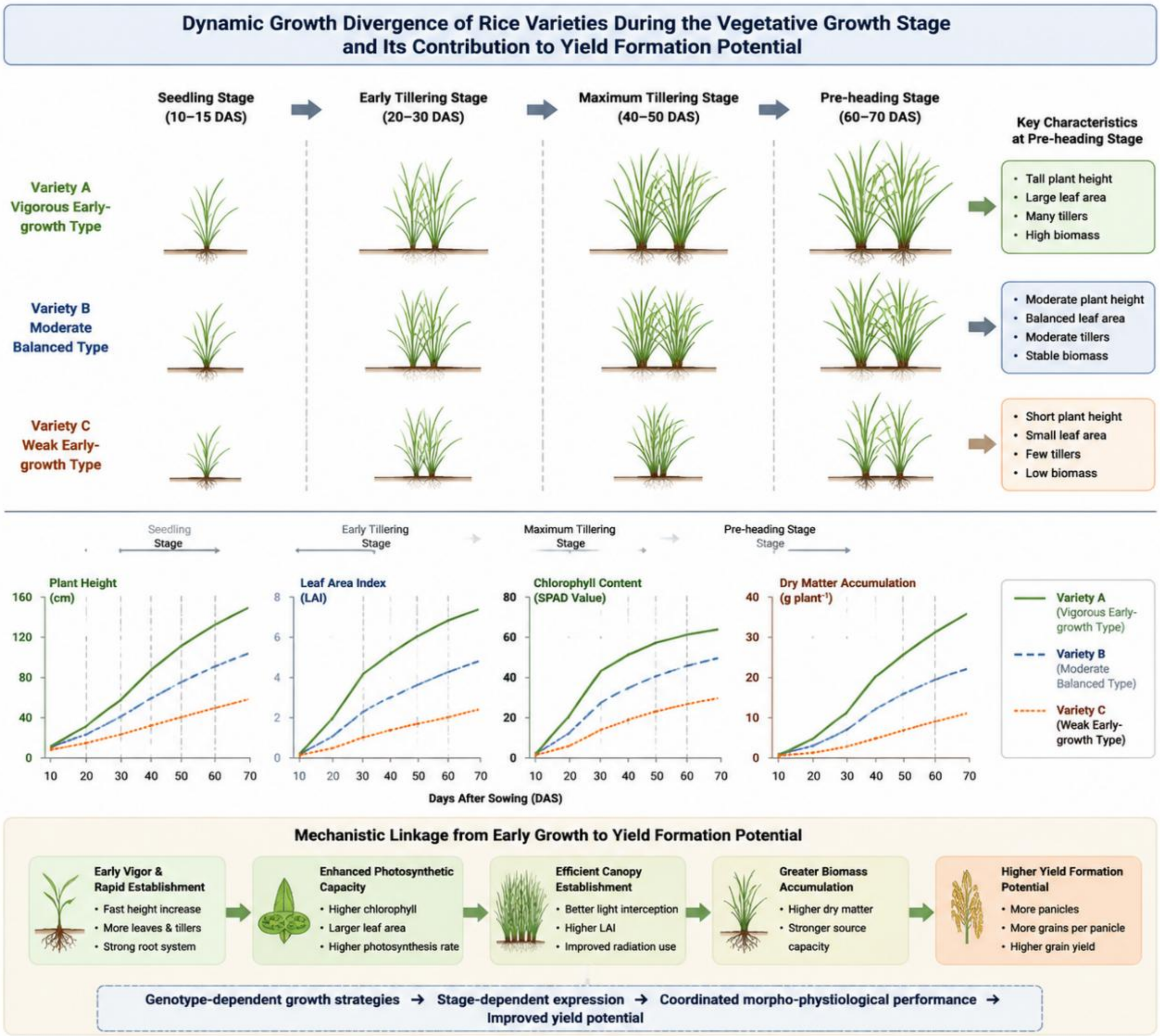


Figure 1 Conceptual model of growth dynamics differences in the vegetative stage among different rice varieties

Varietal comparison indicates that high tiller number alone does not guarantee a superior population structure, because cultivars with strong tillering often also produce more dead tillers and a lower percentage of productive tillers when competition for assimilates and nitrogen intensifies. Evidence from node-level and tiller-order studies further shows that early tillers contribute much more to yield than late tillers, and that promoting early tillering while suppressing excessive late tiller emergence is a more efficient strategy for forming a productive canopy population. Consistent with this, recent cultivar comparisons found that main stems and primary tillers repeatedly outyield later tillers, so population quality depends more on early tiller productivity and resource partitioning than on maximizing total tiller number (Kalaitzidis et al., 2025).

### 3.3 Changes in leaf area index and canopy structure

Leaf area index and canopy structure changed markedly across developmental stages and differed substantially among rice varieties, making them key indicators for dynamic evaluation of growth performance. Time-series observations show that after transplanting, plant height and leaf number increase progressively, LAI rises through the vegetative phase, and it approaches its maximum around booting to heading as the flag leaf fully expands. In farmer-field and cultivar monitoring studies, the timing of maximum LAI has likewise been found to coincide approximately with heading, although the shape of the growth curve varies across environments and management conditions (Hashimoto et al., 2023).

After heading, canopy structure becomes more complex because panicle exsertion, leaf senescence, and panicle drooping alter both vertical organization and light distribution within the stand. Non-destructive stratified measurements have shown that the vertical distribution of LAI varies with growth stage, cultivar, and cultivation management, and that cultivar × growth stage interaction is an important source of canopy heterogeneity. Studies of canopy architecture further indicate that more erect leaves reduce the extinction coefficient, improve light penetration into lower canopy layers, and support greater biomass or photosynthetic potential than flatter canopies, which provides a useful structural basis for computational comparison of Zhejiang rice varieties (Mubarak et al., 2022). Overall, different rice varieties under Zhejiang paddy field conditions should be compared dynamically across vegetative growth, tillering regulation, and canopy development rather than by final yield alone. That approach best captures how growth traits change over time and how those changes shape yield performance.

## 4 Computational Analysis of Dry Matter Accumulation and Resource Utilization Characteristics in Rice

### 4.1 Dynamic simulation of dry matter accumulation

Dry matter accumulation in rice shows a clear dynamic process that can be quantitatively characterized by normalized growth models. Simulation studies based on field observations indicate that aboveground dry matter accumulation usually follows a slow–fast–slow S-shaped trajectory, and the relative accumulation process can be accurately fitted by Richards or Logistic equations across different cultivars, eco-sites, and nitrogen regimes. Model-based analysis further shows that the accumulation curve can be divided into early, middle, and late phases according to inflection points in growth rate, which provides a practical computational basis for comparing varietal growth rhythms under Zhejiang paddy conditions.

Varietal and environmental differences shift both the shape and timing of this accumulation process rather than changing only the final biomass value. Knowledge-based modeling has shown that dry matter accumulation varies with cultivar genetic characteristics and climatic conditions, with relatively small increases early in development, rapid growth after internode elongation, and peak accumulation during booting and grain filling. Recent quantitative analysis in machine-transplanted rice likewise found that field-stage dry matter accumulation conforms to an S-shaped curve over developmental time, but treatment differences in growth parameters remain significant, indicating that simulation parameters should be estimated separately for different variety and management combinations (Wang et al., 2024).

### 4.2 Analysis of photosynthetic productivity and dry matter translocation

Photosynthetic productivity after heading is a major determinant of varietal differences in dry matter formation and final yield. Comparative studies of rice varieties with different yield levels show that post-anthesis dry matter accumulation and the apparent transfer of stem non-structural carbohydrates are both significantly positively correlated with yield, while super high-yielding varieties maintain higher root oxidation activity, cytokinin status, and leaf photosynthetic rate during 0–20 days after anthesis. Hybrid–inbred comparisons further indicate that the higher yield of super hybrid rice is associated with greater radiation use efficiency before heading, stronger leaf photosynthesis, and higher dry matter translocation from stem and leaf to panicle during grain filling (Meng et al., 2024).

Dry matter translocation efficiency depends not only on genotype but also on nitrogen supply, ecological conditions, and stress during the grain-filling period. Under optimized nitrogen management, rice can maintain a longer leaf stay-green duration, higher photosynthetic potential, greater late-stage dry matter accumulation, and a higher matter translocation rate from stem and leaf to panicle, all of which benefit yield formation. By contrast, severe drought markedly restricts dry matter accumulation and post-anthesis translocation, leaving more assimilates in vegetative organs and reducing the capacity to satisfy grain-filling demand, although mild or moderate drought can temporarily increase translocation efficiency.

### 4.3 Calculation of nutrient use efficiency

Nutrient use efficiency in rice should be calculated as an integrated performance index linking nitrogen input with dry matter production, grain yield, and plant uptake capacity. Review-based synthesis defines NUE as the relationship between dry matter production or economic yield and the quantity of nitrogen applied, and emphasizes that root morphological and physiological traits are central to varietal differences in N absorption and utilization (Zhang et al., 2023). Field comparison of near-isogenic lines similarly shows that high-yielding, high-NUE materials achieve their advantage through stronger dry matter production, better canopy structure, improved root traits, and enhanced carbon and nitrogen translocation during grain filling.

In computational analysis, NUE should therefore be assessed together with N uptake, N recovery, and yield-scaled loss indicators rather than by fertilizer input alone. Field experiments across nitrogen rates show that recovery efficiency declines as total N application increases, even when yield rises to an optimum range, indicating that maximum yield and maximum NUE do not coincide exactly. Rhizosphere-scale evidence from ^15N tracing adds that NUE differs among rice varieties and is mainly controlled by ammonium uptake, while reduced NH4+ oxidation and slower organic N release favor N absorption efficiency and lower N loss in flooded paddy systems (Chen et al., 2025). In sum, dry matter accumulation, photosynthetic production, translocation efficiency, and NUE should be analyzed jointly when evaluating different rice varieties under Zhejiang paddy field conditions. This integrated computational perspective best captures how resource utilization characteristics support yield formation.

## 5 Analysis of Yield Formation Characteristics and Influencing Factors among Different Rice Varieties

### 5.1 Comparison of yield components

Differences in rice yield among varieties are mainly expressed through different combinations of panicles per unit area, spikelets per panicle, grain filling percentage, and grain weight rather than through one fixed component pathway. Comparative analyses further show that the relative importance of these components changes with varietal type, growth duration, and cultivation background, so high-yielding varieties in Zhejiang should be identified by their component coordination rather than by a single indicator. In varietal populations, high yield is often associated with a larger total number of spikelets per unit area, but this advantage can be achieved through different structural routes, such as more panicles, larger panicles, or a better balance between the two. Developmental comparisons support this interpretation because panicle-number types usually maintain higher panicle density, whereas panicle-weight types tend to reduce panicle number but increase spikelets per panicle.

The trade-off among yield components is a central feature of varietal differentiation. Increasing panicles per square meter, spikelets per panicle, and total spikelets usually promotes yield potential, but excessive expansion of sink size often reduces filled grain percentage and grain weight. Long-term data from southern China likewise show that the increase in spikelets per panicle is frequently accompanied by a decline in seed-set percentage, indicating that varieties with large sink capacity do not automatically realize high effective yield. For Zhejiang conditions, this point is especially important because provincial comparisons found that Zhejiang achieved high grain yield through the simultaneous improvement of spikelets per panicle and seed-set percentage over time, implying that local varietal selection should emphasize both sink expansion and reproductive stability. Varietal optimization therefore needs to distinguish whether a genotype depends primarily on panicle number, spikelet number, or grain weight, since these yield-formation patterns are not interchangeable across cultivar groups (Zhao et al., 2025).

### 5.2 Analysis of panicle structure and grain filling characteristics

Panicle structure is one of the most direct determinants of varietal differences in yield formation because branch number, panicle length, seed distribution, and panicle weight jointly determine the size and spatial organization of the sink (Agalya et al., 2023). Among diverse rice genotypes, secondary branch number, panicle weight, and filled grains per panicle show particularly large variation and strong positive relationships with single-plant yield, indicating that panicle architecture is a suitable structural basis for computational variety evaluation. However, larger panicles also intensify internal heterogeneity in grain filling. Large-panicle cultivars often fail to achieve their apparent yield potential because inferior spikelets fill later and more poorly than superior spikelets. This pattern is consistent with broader evidence from super rice showing that poor grain filling of later-flowering inferior spikelets remains a major constraint on realizing the yield potential of spikelet-rich panicles.

The mechanism behind this constraint is not explained by panicle size alone, but by differences in transport capacity and physiological activity within the panicle. In large-panicle japonica materials, inferior spikelets had significantly lower grain weight and seed-setting rate than superior spikelets, showing that positional disadvantage is directly reflected in effective grain formation. Structural evidence further indicates that inferior spikelet rachillae have smaller vascular bundle areas and weaker transport capacity, which likely limits assimilate delivery during the initial filling stage. Physiological manipulation experiments support this source–sink interpretation: removing superior spikelets improved seed-setting rate, grain weight, sucrose content, and hormone levels in inferior spikelets, thereby enhancing their filling process. At the same time, compact panicles appear especially vulnerable because poor filling in inferior spikelets is associated with unfavorable hormonal regulation and reduced starch-synthesis activity rather than simple carbohydrate shortage alone (Parida et al., 2022).

### 5.3 Thousand-grain weight and grain filling characteristics

Thousand-grain weight is a final expression of grain filling performance, but its contribution to yield differs among varietal groups. In ultrashort-duration rice, grain weight contributed 42.8% of yield variation, exceeding the contribution of panicles per square meter and spikelets per panicle, whereas in short-duration rice it remained important but ranked below spikelets per panicle (Zhao et al., 2025). This indicates that grain weight should be treated as a core screening trait for some variety types, but not as a universal dominant factor across all rice materials. Controlled-environment comparisons also showed significant varietal differences in grain-filling rate and duration, and both parameters were positively associated with grain size. In field-grown irrigated rice, however, final grain weight on an area basis was more consistently associated with longer grain-filling duration than with faster filling rate, suggesting that duration often contributes more to stable grain mass accumulation under production conditions.

The relationship between thousand-grain weight and grain filling is further shaped by panicle position, temperature, and nutrient regulation. Earlier work found that grain-filling rate was positively correlated with actual panicle weight and 100-grain weight, indicating that heavier grains are often linked to stronger assimilate accumulation per unit time. Yet large-grain genotypes do not always achieve higher yield, because increases in thousand-grain weight can be offset by fewer panicles, lower filled grain percentage, or higher sterility. Nitrogen application adds another layer of variation: it can prolong the grain-filling duration of superior and inferior grains, but excessive nitrogen may simultaneously reduce thousand-grain weight while improving sink size, creating a trade-off between grain number and individual grain mass (Zhang et al., 2021). In addition, the grain weight and seed-setting rate of inferior grains are inherently lower than those of superior grains in large-panicle materials, confirming that thousand-grain weight differences among varieties are partly determined by the synchronization and completeness of grain filling within the panicle. Overall, yield formation among different rice varieties under Zhejiang paddy conditions depends on the coordination of yield components, panicle architecture, and grain filling efficiency. A computational comparison should therefore evaluate not only final yield, but also the structural and physiological pathways through which each variety forms that yield.

## 6 Construction of Computational Models for the Relationship between Growth Traits and Yield Performance

### 6.1 Correlation analysis between growth indicators and yield

Correlation analysis showed that rice yield is jointly shaped by multiple growth indicators rather than by any single trait, so the first step in model construction should be to identify those vegetative and reproductive variables that maintain stable associations with yield under Zhejiang paddy conditions. Existing rice studies indicate that productive tiller number, panicle length, grain number per panicle, and 1000-grain weight are positively correlated with grain yield, while the strength of these relationships can differ between phenotypic and genotypic levels. Evidence from broader morpho-physiological evaluation further suggests that flag leaf area and productive tillers contribute positively to high yield, whereas some canopy traits such as large leaf angles or delayed panicle initiation tend to show negative correlations, which means that correlation matrices should include both favorable and constraining traits in the same analytical framework (Banjare et al., 2024).

Simple correlation is useful for screening candidate indicators, but it cannot distinguish whether a trait affects yield directly or through its association with other variables. For that reason, correlation analysis should be combined with path-based decomposition, because yield-related traits often exert indirect effects through biomass formation, panicle development, or harvest index (Saketh et al., 2023). Empirical results support this modeling logic: biological yield, dry matter, effective tillers, and filled grains per panicle repeatedly emerge as traits with strong direct or total effects on grain yield, making them suitable core predictors in a growth–yield relationship model.

### 6.2 Yield prediction based on multiple regression models

Multiple regression models provide an interpretable way to predict rice yield from observed growth traits, especially when the goal is to quantify the relative contribution of several indicators at once. Agronomic modeling studies show that aboveground biomass, straw weight, plant number per square meter, and plant height can explain substantial variation in yield, confirming that regression models can translate field-measured growth traits into explicit yield estimates. Remote-sensing regression work likewise found that a multiple linear regression model using four vegetation and water indices predicted rice yield more accurately than single-index linear models, indicating that integrating several complementary predictors is preferable to relying on one indicator alone (Htun et al., 2023).

At the same time, multiple regression should be treated as a baseline rather than a complete solution, because rice yield reflects complex interactions among variety, environment, and management. Studies in East China showed that both agronomic traits and climate data were significantly related to yield and that fusing these data sources improved predictive performance beyond single-source models, which is highly relevant for Zhejiang's ecologically diverse paddy systems. Other forecasting studies also show that feature-selected MLR can remain stable and useful for agricultural decision-making, but nonlinear methods such as random forest or neural networks often outperform conventional linear regression when trait interactions become stronger and less additive (Ingio et al., 2024).

### 6.3 Principal component analysis and comprehensive evaluation models

Principal component analysis is well suited to rice variety evaluation because it reduces many correlated growth and yield variables into a smaller number of synthetic components while retaining most of the biological variation. In multi-season varietal studies, the first few principal components explained a large share of total variation, and traits such as grain yield per plant, productive tiller number, panicle grain density, plant height, and panicle length contributed strongly to the leading axes (Sruthi et al., 2024). Similar germplasm-scale analyses found that productive tillers, filled grains, flowering time, and panicle-related traits are major contributors to overall variability, which supports the use of PCA to identify compact indicator sets for comprehensive evaluation under Zhejiang field conditions.

Beyond dimensionality reduction, PCA can be used to rank varieties, classify performance groups, and construct composite evaluation scores for recommendation. Studies of rice landraces and nitrogen-response experiments show that PCA biplots can identify representative traits and distinguish superior genotype or treatment combinations, with productive tillers, flag leaf length, panicle-bearing tillers, filled grain percentage, and plant height repeatedly appearing as influential evaluation variables. Comprehensive evaluation research further shows that PCA can be combined with clustering to categorize rice materials and identify those with better overall performance, suggesting that a Zhejiang variety assessment model should integrate PCA-derived weights with cluster grouping and field yield data to produce a more robust ranking than yield alone. Overall, the relationship between growth traits and yield performance is best modeled through a layered strategy: correlation and path analysis for trait screening, multiple regression for quantitative prediction, and PCA-based comprehensive evaluation for dimensional reduction and varietal ranking. This combination fits the objective of comparing different rice varieties under Zhejiang paddy field conditions.

## 7 Case Study: Computational Evaluation of Yield Performance of Different Rice Varieties in Typical Paddy Regions of Zhejiang Province

### 7.1 Case study region and rice variety selection

The case study region should be defined as representative paddy areas of Zhejiang with clear ecological comparability and strong varietal discrimination, because rice yield in East China is shaped not only by genotype but also by environment and genotype-by-environment interaction. Multi-site regional testing is therefore necessary before varietal recommendation, and it is especially suitable for Zhejiang because the province has shown high rice yield performance associated with sustained improvements in spikelets per panicle and seed-set percentage. In practical terms, typical case-study sites can be selected from major rice-growing counties with stable paddy management conditions, following the same principle by which optimal trial environments are identified according to discrimination and representativeness (Figure 2). This regional design is also consistent with long-term Chinese cultivar evidence showing that agronomic traits and yield expression differ significantly across regions, making region-specific evaluation essential for accurate variety selection (Hang et al., 2024).

Rice variety selection for the case study should include high-yield japonica hybrids, indica–japonica hybrids, and locally relevant comparison cultivars so that both yield potential and regional adaptability can be assessed. Field evidence from Fenghua and Yuyao showed that Yongyou1540 reached 13.9 and 14.5 t ha<sup>−1</sup> in two seasons, while CHY83 and CHY112 also achieved yields not significantly different from the control high-yield cultivar, confirming that Zhejiang-adapted japonica hybrid materials can perform at a super-high-yield level. Variety choice should also reflect adaptation to the lower Yangtze River plain, where indica–japonica hybrid rice outperformed japonica hybrid rice by 15% under normal nitrogen and 25% under low nitrogen in Hangzhou, indicating stronger yield resilience under reduced input. At the same time, varietal portfolios should retain diversity in growth duration and ecotype, because closely related materials can face a genetic bottleneck and limited yield advantage, as shown in Hangzhou early-season trials where hybrid superiority over inbreds averaged only 0.62% to 3.20%.

### 7.2 Analysis of case study results and variety performance evaluation

The case-study results should be analyzed first by comparing grain yield and major yield components across sites and varieties, and then by evaluating stability and adaptability through computational models. Across East Coast hybrid japonica trials, significant effects of genotype, environment, and G×E interaction were detected for yield, indicating that simple mean yield is insufficient for varietal ranking. AMMI and GGE analyses therefore provide the necessary second layer of evaluation, because they distinguish high-yielding varieties from broadly adapted or specifically adapted ones; in one regional trial, Zhegengyou2035 and Changyou20-2 combined strong yield potential with stability, whereas Huazhongyou9413 showed broader adaptability. This type of result is directly relevant to Zhejiang case analysis, where recommendation should prioritize varieties that maintain high output across multiple paddy ecologies rather than only at one favorable site (Ahmed et al., 2024).

At the trait level, high-yielding varieties in Zhejiang-like environments usually express a coordinated sink structure rather than extreme values for one component alone. In Yangtze River japonica hybrid trials, high-yield cultivars typically had more spikelets per panicle, more spikelets per square meter, and a higher harvest index, while longer total growth duration contributed little to yield improvement. Complementary evidence from large Chinese cultivar datasets shows that Zhejiang’s historically high yield was associated with increased spikelets per panicle and seed-set percentage, whereas Shanghai high-yield indica–japonica hybrids relied more on larger spikelet number despite lower effective panicle number and 1000-grain weight. Accordingly, computational performance scores in the case study can integrate yield, spikelet density, seed-set rate, harvest index, and post-heading productivity to separate high-yield unstable types from high-yield stable types.

### 7.3 Implications and application of the case study findings

The main implication of the case study is that Zhejiang rice recommendation should move from single-index yield comparison to integrated computational evaluation combining productivity, stability, and resource-use efficiency. Model-based research shows that yield prediction improves when multiple agronomic indicators are evaluated together, and that aboveground biomass, plant number per square meter, and plant height can explain substantial variation in rice yield (Liu et al., 2023). This supports the use of a composite evaluation framework in which field observations are standardized and then analyzed jointly through regression, random forest, and multivariate stability tools rather than by conventional descriptive statistics alone. It also aligns with comprehensive evaluation work showing that membership-function methods can identify varieties that balance high yield with other production targets, including grain quality.


Figure 2 Ecological zoning and rice variety case study layout in typical rice-growing regions of Zhejiang

A second implication is that the case-study findings can be translated directly into variety deployment and breeding strategy for Zhejiang's typical paddy regions. Long-term national evidence shows that variety improvement has raised both yield and yield stability in China, but the magnitude of progress differs by region and rice type, so local recommendation systems remain necessary. In the Yangtze River Delta context, broad regional adaptability can be enhanced by selecting ecotype-differentiated japonica materials whose combined planting range covers the middle and lower Yangtze region, reducing the problem of narrow adaptation (Zeng et al., 2025). At the same time, lower-input suitability should be considered in variety release because indica–japonica hybrids in Hangzhou maintained clear yield advantages under low nitrogen through higher productive tiller percentage, larger sink size, and stronger post-heading physiological activity. In sum, this

Zhejiang case study supports a recommendation framework based on multi-site yield performance, trait coordination, and computational stability analysis. That approach best fits the goal of evaluating different rice varieties under typical Zhejiang paddy field conditions.

## 8 Discussion

### 8.1 Mechanisms underlying growth differences among rice varieties

The growth differences observed among rice varieties under Zhejiang paddy conditions are fundamentally the result of coordinated variation in sink construction, dry matter accumulation, and physiological efficiency rather than differences in single external traits alone. Large comparative datasets show that the association between agronomic traits and yield is ecotype-dependent, indicating that the same growth indicator does not contribute equally across indica and japonica backgrounds. At the same time, yield formation is governed by three visible components—grain weight, grain number per panicle, and effective tiller number—that are themselves controlled by less visible processes such as photosynthetic efficiency and nutrient use efficiency. This explains why varietal differences in field performance often emerge from the interaction of canopy development, population quality, and assimilate supply rather than from plant stature alone.

A second mechanism concerns the capacity to maintain biomass production and assimilate translocation after heading, which appears to distinguish high-yielding from ordinary varieties. Super-high-yielding rice varieties showed significantly higher post-anthesis dry matter accumulation and stem non-structural carbohydrate translocation, both of which were positively associated with final yield. In indica–japonica hybrid rice, superior yield was likewise mainly attributed to higher total spikelets and greater dry matter accumulation, while high planting density could simultaneously increase effective panicles yet also accelerate leaf area decline and constrain panicle development if excessive (Mi et al., 2025). Under stress conditions, these differences become more explicit, because salt-tolerant genotypes retained more biomass accumulation, stronger antioxidant and osmotic adjustment capacity, and better grain filling than salt-sensitive materials. Taken together, the mechanism behind varietal growth divergence is best understood as a dynamic balance among source strength, sink size, transport efficiency, and stress adaptability (Ren et al., 2023).

### 8.2 Application value of computational models in rice production prediction

The practical value of computational models in rice production prediction lies in their ability to convert complex trait, climate, and image data into timely and quantitative estimates of yield performance. Machine learning studies consistently show that nonlinear models outperform conventional linear regression when predicting rice yield, especially when phenology, climate, and geographical information are integrated in the same framework (Guo et al., 2020). Phenological variables are particularly important because their predictive contribution can be comparable to that of climatic variables, which is highly relevant for Zhejiang where varietal growth rhythm strongly affects final productivity. This means that computational prediction should not rely only on end-of-season agronomic observations, but should incorporate dynamic developmental indicators throughout the growing period.

Recent deep learning and multi-source modeling work further demonstrates that prediction accuracy improves when spatial, temporal, and environmental information are fused. Across China, LSTM and random forest models using satellite vegetation indices, meteorological indices, and soil properties outperformed LASSO regression, and optimal prediction could be achieved about one to two months before maturity. In multi-variety breeding trials, UAV-based image models showed strong robustness across genotypes, with the best predictions emerging from the flowering to grain-filling stage and with an effective lead time of about one month before harvest. Hybrid deep learning models based on drone environmental data also improved the discrimination of high- versus low-yield fields, showing that prediction systems can support both yield estimation and decision classification in practice (Chang et al., 2024). Therefore, for Zhejiang paddy production, computational models have clear application value in early warning, variety screening, and management optimization.

### 8.3 Future development of intelligent rice variety evaluation systems

The future development of intelligent rice variety evaluation systems should move beyond simple grain-image classification toward integrated platforms that combine seed traits, field phenotypes, environmental variables, and yield outcomes. Existing deep learning studies have already shown that rice variety classification can achieve very high accuracy under controlled image conditions, with real-time systems and optimized networks reaching about 98% accuracy or above (Jeyaraj et al., 2022). More recent Japonica-focused work further improved varietal classification accuracy to 98.81% while reducing computational demand, showing that intelligent evaluation tools are becoming more efficient as well as more precise. However, classification alone is insufficient for agronomic recommendation, because Zhejiang variety selection also requires adaptability, stability, and field productivity to be evaluated together.

Future systems will therefore need stronger generalization ability, richer training data, and closer integration with agronomic knowledge. Reviews of AI in rice agriculture emphasize that current bottlenecks include limited standardized datasets, sensitivity to environmental variation, and the need for resilient, scalable systems that can work outside laboratory conditions (Islam et al., 2025). Yield-prediction research supports the same conclusion: model performance declines when tested on regional datasets not represented in training, indicating that diverse data are essential for robustness. Small-sample deep learning studies likewise note that model potential depends heavily on data volume and may require augmentation strategies to overcome field-data scarcity. In this sense, the next generation of intelligent rice variety evaluation systems in Zhejiang should combine multi-site field trials, remote sensing, machine learning, and standardized databases to form a decision-oriented platform for breeding and production. Overall, the discussion supports a unified conclusion: growth differences among rice varieties arise from integrated physiological and structural mechanisms, while computational models provide an effective way to predict, compare, and operationalize those differences under Zhejiang paddy field conditions.

## 9 Conclusions and Perspectives

This study systematically examined the growth traits and yield performance of different rice varieties under Zhejiang paddy field conditions through a computational analysis framework integrating field observation, statistical analysis, and model-based evaluation. The results showed that significant differences existed among varieties in vegetative growth rate, tillering dynamics, canopy development, dry matter accumulation, and yield component formation. These differences were not isolated trait expressions, but rather reflected coordinated variations across the whole growth process. Varieties with stronger early vigor did not always achieve the highest final yield, whereas those with more balanced population development, stable post-heading dry matter production, and stronger grain filling capacity generally displayed better yield performance under the ecological conditions of Zhejiang. The analysis further demonstrated that yield formation in rice is the result of the joint regulation of multiple agronomic traits rather than the simple effect of a single indicator.

Panicle number, effective spikelet formation, seed-setting stability, and thousand-grain weight together determined final productivity, but their relative contributions varied across genotypes and growth environments. Computational models such as correlation analysis, multiple regression, and principal component evaluation effectively revealed the internal relationships between growth characteristics and yield outcomes. These methods improved the objectivity of varietal comparison and provided a more comprehensive basis for identifying rice varieties with superior adaptability, higher resource-use efficiency, and greater production potential in regional paddy ecosystems. This research also confirmed the practical value of dynamic trait analysis in rice performance evaluation. Compared with traditional assessments based only on final yield or a few phenotypic indices, a dynamic computational perspective better captured the temporal characteristics of variety performance, especially the continuity between pre-heading growth, post-heading assimilation, and final grain formation. This is particularly important in Zhejiang, where climatic variability, soil heterogeneity, and management differences can influence the expression of varietal advantages.

By incorporating multidimensional indicators into an integrated evaluation process, the study provided a more scientifically grounded approach for understanding why certain varieties perform better than others under local production conditions. At the same time, the findings indicated that high-yielding rice varieties suitable for Zhejiang are characterized not only by strong biological productivity but also by coordinated growth rhythm and stable adaptation to field conditions. Varieties showing excessive vegetative growth did not necessarily maintain efficient translocation of assimilates to reproductive organs, while some varieties with moderate vegetative performance achieved higher final yields through improved source–sink coordination and stronger grain filling efficiency. This suggests that future rice variety selection in the region should pay closer attention to overall developmental balance, stress buffering capacity, and the synergy between growth traits and yield formation mechanisms, rather than relying solely on single-season output performance.

Although this study generated useful insights into the growth and yield differences among rice varieties in Zhejiang paddy fields, several limitations should be acknowledged. First, the research scope was constrained by the number of tested varieties, the spatial distribution of experimental sites, and the observation period. Rice performance is strongly influenced by year-to-year climatic fluctuations, local soil fertility, water management, and cultivation practices. Therefore, the current results mainly reflect varietal responses under the specific experimental conditions included in this study, and caution is needed when extending these conclusions to broader ecological zones or production systems without further verification. Second, while the computational analysis framework improved the interpretation of complex trait interactions, some biological processes were still simplified during modeling. For example, the effects of genotype-by-environment interaction, physiological regulation during critical developmental stages, and stress responses under extreme weather conditions were not fully incorporated into the present analysis. In addition, certain important traits such as root system activity, photosynthetic resilience, and nutrient remobilization efficiency were difficult to quantify continuously in field conditions, which limited the explanatory depth of the models.

As a result, although the constructed models showed value for comparative evaluation and yield prediction, their generalizability and mechanistic precision remain to be improved. Future research should strengthen both the breadth and depth of data collection. Multi-year, multi-location, and multi-variety experimental networks should be established to improve the representativeness of rice performance evaluation under diverse Zhejiang production conditions. At the same time, future studies should integrate more detailed environmental, physiological, and management variables into the analytical framework, including meteorological dynamics, soil nutrient status, irrigation patterns, and pest or disease pressure. Such expansion would allow researchers to more accurately identify the key drivers of varietal adaptation and to distinguish stable genetic advantages from environment-dependent responses. Further methodological development is also necessary. Advanced machine learning, time-series modeling, and data fusion approaches could be introduced to enhance the prediction of growth trajectories and yield performance. In addition, combining field phenotyping with remote sensing, sensor-based monitoring, and genomic or transcriptomic information would help build a more mechanistically informed evaluation system. Future studies should not only pursue higher predictive accuracy, but also improve model interpretability so that computational outputs can be translated into practical guidance for breeders, agronomists, and producers. In this way, rice variety evaluation can move from descriptive comparison toward intelligent diagnosis, targeted optimization, and adaptive decision support.

Under the rapid development of smart agriculture, precision rice evaluation is expected to become an important direction for improving varietal selection, cultivation management, and regional production planning. Traditional rice evaluation methods have played an important role in variety screening, but they often depend on periodic manual measurements and relatively static indicators. In contrast, smart agriculture provides the technical foundation for continuous, high-resolution, and multidimensional data acquisition. Through digital field monitoring, unmanned platforms, image-based phenotyping, and environmental sensing, researchers can capture the dynamic expression of growth traits throughout the rice life cycle with much greater temporal and spatial precision. This transformation will significantly improve the scientific basis of varietal evaluation under Zhejiang paddy conditions. Rice varieties differ not only in visible agronomic performance but also in their responses to temperature, water, nutrients, and microenvironmental variation. Precision evaluation systems supported by smart agriculture can detect these subtle response differences earlier and more accurately than conventional methods. As a result, variety performance can be judged not merely by final harvest data, but by a full-process profile including early establishment, canopy development, stress adaptation, biomass accumulation, and reproductive stability.

This will provide a stronger foundation for selecting varieties suited to specific ecological zones, planting systems, and management targets. Looking ahead, the integration of computational analytics with intelligent agricultural infrastructure will likely reshape the entire pathway of rice variety assessment.

A future precision evaluation system may combine field sensors, satellite or drone imagery, automated data processing, and predictive models into a unified decision platform. Such a system could support real-time monitoring of varietal growth status, early warning of performance risks, and dynamic adjustment of agronomic strategies. For breeders, it would improve the efficiency of identifying superior genotypes. For farmers and extension personnel, it would provide more targeted recommendations based on local field conditions and varietal characteristics. The broader prospect is the establishment of a data-driven, adaptive, and region-specific rice evaluation paradigm. In Zhejiang, where production conditions are diverse and agricultural modernization is advancing rapidly, this approach has strong practical significance. Precision rice evaluation can promote the matching of varieties with environments, optimize the allocation of agricultural resources, and improve the stability and sustainability of grain production. As smart agriculture technologies continue to mature, rice research will increasingly shift from isolated trait measurement to integrated system analysis, enabling more accurate evaluation, more efficient cultivation, and more resilient regional food production.

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The author affirms that this research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

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