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Improving Berry Uniformity in Grape (*Vitis vinifera*): Trait-Based Evaluation and Selection Perspectives

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Abstract This study explores the conceptual framework and evaluation methods of grape berry uniformity, elucidating its multidimensional nature arising from the coordinated contributions of berry size, shape, and cluster structure. Quantitative evaluation approaches based on the coefficient of variation, composite multi-trait indices, and high-throughput phenotyping technologies are systematically summarized. On this basis, key factors influencing berry uniformity are further analyzed, including genetic background, pollination and fertilization processes, berry developmental dynamics, plant growth regulator treatments, and water-nutrient environmental conditions. Integrating breeding strategies with production practices, a framework for improving berry uniformity is proposed, centered on “multi-trait selection, marker-assisted selection, and cultivation regulation.” Meanwhile, with the advancement of machine vision, high-throughput phenotyping, and multi-source data integration technologies, the evaluation of berry uniformity is shifting toward automation, precision, and intelligence. However, challenges remain in the standardization of evaluation systems, elucidation of molecular mechanisms, and integration of multi-source data. Future research directions toward data-driven precision improvement are discussed. This study aims to provide theoretical foundations and technical support for enhancing the quality and standardized production of table grapes.
Keywords Grapevine; Berry uniformity; Phenotypic evaluation; Cluster architecture; Precision breeding

1 Introduction

Grapevine (*Vitis vinifera* L.) is one of the most widely cultivated fruit crops worldwide, and its table grapes are highly favored by consumers due to their attractive appearance and desirable flavor. In the quality evaluation system of table grapes, in addition to intrinsic attributes such as soluble solids content, flavor, and taste, external traits also play a central role. Previous studies have shown that consumers are highly sensitive to visual characteristics such as berry size, shape, color, and overall cluster architecture, among which visual uniformity often plays a dominant role in purchasing decisions (De Oliveira et al., 2026). In this context, berry uniformity, as an important composite indicator reflecting the visual harmony of grape clusters, directly influences consumers’ first impressions and product acceptance, and is therefore a key trait for assessing the commercial quality and market value of table grapes.

Clusters with high uniformity typically exhibit consistent berry size, orderly arrangement, and well-coordinated structure, which not only significantly enhance visual quality but also reflect the combined effects of genetic traits and cultivation management practices (Dobrei and Sala, 2025). In contrast, uneven berry size or irregular distribution is often regarded as an indicator of reduced commercial quality and may negatively affect market evaluation, even when intrinsic quality remains high (De Oliveira et al., 2026). In production practice, such heterogeneity is relatively common and results from the combined influence of genetic factors and environmental regulation. For example, different cultivars show significant variation in fruit set, berry enlargement capacity, and cluster architecture, while seed number, floral characteristics, and cultivation practices (such as thinning, application of plant growth regulators, and water and nutrient management) also affect berry development (Gharate et al., 2025; Milišić et al., 2025). In addition, trade-offs among cluster compactness, berry number, and individual berry size further exacerbate differences in uniformity within and between clusters (Meneses et al., 2025; Sharma et al., 2025).

Berry uniformity not only affects appearance but also leads to spatial heterogeneity in fruit quality. Differences in berry size and structure can alter the ratio of pulp to skin, thereby influencing sugar-acid composition, coloration, and antioxidant capacity, ultimately resulting in uneven eating quality within the same cluster. This heterogeneity increases the difficulty of grading, reduces packaging and transportation efficiency, and may diminish commercial value and cause economic losses. Although grape germplasm exhibits abundant genetic diversity in berry size, shape, and cluster structure (Gharate et al., 2025), most existing studies focus on individual traits such as berry diameter or cluster compactness, while systematic quantitative evaluation of "uniformity" as an integrated trait remains limited. Moreover, inconsistencies in evaluation methods among studies restrict the comparability and practical application of research findings.

This study focuses on berry uniformity as a key trait in grapevine, systematically reviewing its conceptual framework, evaluation methods, and influencing factors, and further exploring its application in cultivar selection and cultivation management strategies. The aim is to provide theoretical foundations and technical references for improving table grape quality and promoting standardized production. In recent years, advances in phenomics and quantitative genetics have provided new approaches for the precise assessment and genetic improvement of berry uniformity. High-throughput quantification of berry size distribution and cluster architecture can be achieved through digital image analysis and two- and three-dimensional segmentation techniques. Meanwhile, QTL mapping and genome-wide association studies have identified multiple genetic loci associated with berry size and cluster structure. Combined with marker-assisted selection and optimized cultivation practices, these approaches offer promising opportunities for the coordinated improvement of berry uniformity.

2 Conceptual Framework of Grape Berry Uniformity

2.1 Conceptual components of berry uniformity

Grape berry uniformity is a comprehensive visual trait that not only reflects the consistency of individual berry size but also involves the coordination of spatial distribution within a cluster. At the intra-cluster scale, uniformity mainly refers to the low variability in berry length, width or diameter, weight, and shape, resulting in high visual consistency among berries located at different positions within the cluster. At the whole-cluster scale, uniformity also encompasses the spatial arrangement of berries along the rachis and its branches, including whether the distribution is balanced and whether local overcrowding, sparsity, or berry deformation due to compression occurs (Torres-Lomas et al., 2024).

In practical production, berry uniformity is the result of the combined effects of genetic background, reproductive development, and cultivation environment. Factors such as pollination quality, fruit set rate, seed development, berry growth rate, and the balance of assimilate distribution all influence berry size and the synchronization of ripening. Studies have shown that berries from different genotypes or with different seed numbers exhibit significant differences in size and uniformity, indicating that uniformity has a strong genetic dependency and developmental basis (De Oliveira et al., 2026). When berry development is synchronized and spatial distribution is well balanced, clusters typically display a full, orderly, and marketable appearance; otherwise, problems such as mixed berry sizes, local crowding, or excessive gaps may occur.

In addition, different grape cultivars exhibit substantial variation in cluster structure and berry development patterns. Some cultivars naturally produce compact clusters, which may enhance visual fullness but excessive compactness can lead to berry compression and deformation. In contrast, loosely structured clusters may reduce compression but can result in uneven spatial distribution and reduced visual coordination (Torres-Lomas et al., 2024). Therefore, berry uniformity should not be simply interpreted as "larger berries are better" or "more compact clusters are better," but rather as a comprehensive expression of size consistency, shape uniformity, and coordinated cluster architecture.

2.2 Key phenotypic traits of berry uniformity

Among the factors contributing to berry uniformity, berry size traits represent the most direct and fundamental basis for evaluation. Berry length, width (or diameter), and single-berry weight are commonly used descriptors of berry size, and these traits are often positively correlated, meaning that a berry large in one dimension is typically large in others as well (Dobrei and Sala, 2025). When variability in these traits is low within a cluster, the overall appearance is visually uniform; otherwise, noticeable size heterogeneity may occur, reducing uniformity.

Beyond size, berry shape provides an important complementary dimension for evaluating uniformity. The shape index, typically defined as the ratio of berry length to width, is used to distinguish morphological types and reflect shape consistency. More advanced descriptors, such as eccentricity, contour curvature, and elliptical Fourier descriptors, allow a more precise characterization of berry outlines, thereby improving the accuracy of shape evaluation (De Sousa Moreira et al., 2024). Previous studies have shown significant differences in shape stability among grape materials, indicating that shape consistency is also an important component of uniformity.

At the structural level, cluster compactness serves as a key link between individual berry traits and overall cluster appearance. This trait integrates berry number, berry size, and rachis structure, and can be interpreted as the degree of space filling within the cluster (Torres-Lomas et al., 2024). Moderately compact clusters contribute to a full and orderly appearance, whereas excessive compactness may lead to berry deformation and uneven development, and overly loose clusters may result in poor arrangement and visual inconsistency. Therefore, berry size, shape, and cluster structure collectively form the core phenotypic basis of berry uniformity, which is essentially the result of the coordinated interaction of multiple traits.

2.3 Quantitative evaluation methods of berry uniformity

To achieve an objective assessment of berry uniformity, phenotypic traits such as berry size, shape, and cluster structure must be transformed into quantifiable indicators. Among these, the coefficient of variation (CV) is the most widely used statistical metric and is employed to describe the dispersion of traits such as berry weight, length, width, and area within a cluster (Dobrei and Sala, 2025; Milišić et al., 2025). A lower CV value indicates smaller differences among berries and thus higher uniformity, whereas a higher CV reflects greater variability. Due to its simplicity and comparability, CV serves as a fundamental quantitative tool for uniformity evaluation.

Building upon this, composite uniformity indices can be constructed to integrate multiple traits into a comprehensive evaluation. Such indices are typically derived by standardizing variables with different units and assigning weights according to research objectives or commercial grading requirements, thereby reflecting both size and shape consistency. Compared with a single CV metric, composite indices provide a more holistic characterization of uniformity, particularly for comparisons among cultivars and for breeding selection. In addition, structural parameters such as compactness indices, berry number per unit cluster length, and spatial distribution descriptors can be incorporated to quantify berry arrangement within clusters.

With the advancement of digital image analysis and high-throughput phenotyping technologies, the evaluation of berry uniformity is transitioning from manual measurement to automated and intelligent approaches. Two-dimensional image analysis can extract parameters such as berry area, length, width, and shape, while three-dimensional reconstruction techniques can provide additional information on berry volume, cluster volume, and spatial distribution. In recent years, instance segmentation methods based on vision models such as the Segment Anything Model (SAM) have enabled automatic identification of individual berries and extraction of multidimensional phenotypic parameters, providing robust support for high-throughput analysis of uniformity-related traits (Torres-Lomas et al., 2024; Sharma et al., 2025). Overall, berry uniformity evaluation is evolving toward a “multi-indicator integration+high-throughput measurement” paradigm, providing an important technical foundation for precision breeding and standardized production.

3 Evaluation Methods of Grape Berry Uniformity

3.1 Traditional evaluation methods

In grape production, postharvest sorting, and market circulation, the evaluation of berry uniformity has long relied on visual grading methods based on cluster appearance. This approach typically assesses the overall coordination of the cluster by observing whether berry size is uniform, whether the arrangement is orderly, whether cluster structure is appropriate, and whether mixed berry sizes occur, thereby classifying clusters into different commercial grades. Clusters with high uniformity usually exhibit consistent berry size, balanced spatial distribution, a clean appearance, and strong market appeal, whereas clusters with obvious size variation, local overcrowding, or excessive sparsity are more likely to be downgraded.

Within scientific evaluation systems, the descriptors established by the International Organisation of Vine and Wine (OIV) provide a relatively standardized basis for visual grading of grape clusters and berries. For example, OIV 204 is used to evaluate cluster compactness, and OIV 221 is used for berry size classification. Evaluators typically assign compactness levels ranging from very loose to very compact based on cluster appearance and determine berry size grades according to berry diameter ranges. This method is simple to operate, low in cost, and requires minimal instrumentation, and thus remains widely used in field surveys, germplasm characterization, and production grading.

However, visual grading is inherently semi-quantitative and experience-based, making it susceptible to evaluator expertise, interpretation of scoring scales, and subjective bias. Particularly in populations with small phenotypic differences, different evaluators may assign different scores to the same cluster, leading to reduced reproducibility and comparability of data (Sharma et al., 2025). In addition, traditional berry size grading often employs relatively coarse classification scales, making it difficult to detect subtle differences in berry size distribution within clusters and unable to accurately reflect spatial distances among berries, internal void proportions, or local crowding within clusters. Therefore, although visual grading retains practical value in production, it is insufficient for detailed analysis of berry uniformity under the demands of modern grape production, which emphasizes standardization, precision, and efficient breeding selection.

3.2 Quantitative evaluation methods

To overcome the subjectivity of traditional visual grading, the evaluation of grape berry uniformity has gradually shifted from qualitative description to quantitative analysis based on continuous variables. This approach constructs a multi-indicator evaluation system by measuring individual berry traits such as length, width, diameter, weight, area, and volume, as well as structural traits including berry number per cluster, cluster length, width, and weight. Among these, berry size distribution serves as the foundation for assessing size consistency. By analyzing the mean, standard deviation, and range of berry size or weight, the degree of concentration and dispersion within a berry population can be directly quantified, providing a preliminary basis for evaluating uniformity.

Among various statistical indicators, the coefficient of variation (CV) is one of the most widely used parameters for uniformity evaluation. CV describes trait dispersion as the ratio of standard deviation to mean, effectively eliminating the influence of different measurement scales and mean values, thereby improving comparability among materials. For a given cluster, smaller CV values for berry diameter, weight, or volume indicate more concentrated distributions and higher uniformity, whereas larger CV values indicate greater variability. Somogyi et al. (2021), in a study on 'Italia' grapes, found significant differences in the CV of berry weight and circumference among berries with different seed numbers, with seedless berries showing higher variability and seeded berries generally exhibiting greater uniformity, highlighting the important biological role of seed number in determining berry uniformity.

Beyond berry size, cluster compactness provides a critical structural dimension for evaluating uniformity. Compactness reflects the integrated relationship among berry number, berry volume, and rachis structure, and can be quantified using metrics such as berry number per unit cluster length, the ratio of berry area to projected cluster area, or the ratio of total berry volume to cluster volume (Meneses et al., 2025). Compared with single size metrics, compactness better captures the spatial arrangement of berries. For instance, clusters with similar average berry size may exhibit different levels of uniformity due to differences in berry number or internal void space. Therefore, uniformity evaluation should be based on multi-indicator integration, considering both size consistency and spatial structural coordination.

3.3 Modern technological approaches

With the development of computer vision and intelligent agricultural technologies, high-throughput phenotyping methods based on digital image analysis have become important tools for evaluating berry uniformity.

Two-dimensional image analysis typically uses RGB images to identify berry contours and extract parameters such as berry number, projected area, length, width, aspect ratio, and cluster dimensions. The tools such as the Berry Analysis Tool (BAT) and Cluster Analysis Tool (CAT) can achieve automatic berry counting and size estimation, with results highly consistent with manual measurements, providing an efficient and objective basis for uniformity evaluation.

Building upon 2D image analysis, deep learning-based segmentation models have significantly improved the accuracy of berry detection under complex conditions. Instance segmentation methods such as Mask R-CNN, as well as foundation vision models like the Segment Anything Model (SAM), can automatically identify individual berries under varying lighting, occlusion, and background interference, and extract key parameters such as size distribution and compactness (Figure 1) (Kim et al., 2023; Torres-Lomas et al., 2024; Sharma et al., 2025). These approaches enable the transition from manual sampling to high-throughput measurement at the whole-cluster or population scale, providing more reliable phenotypic data for breeding selection and genetic analysis.

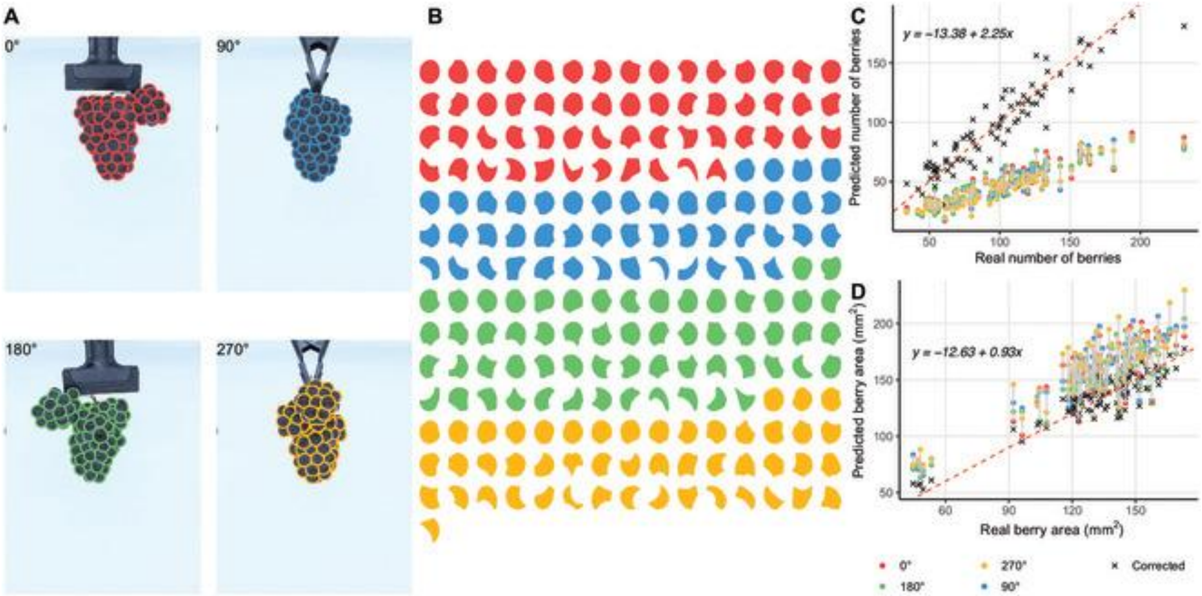

Figure 1 Prediction of berry number using SAM from cluster images (Adopted from Torres-Lomas et al., 2024)

Image caption: (A) Identification of individual berries from 4 angles on the same cluster. (B) Berry masks from cluster images in panel A, color-coded by angle view. (C) Correlation between real and predicted berry counts from SAM; predicted counts for each angle view in panel A are displayed. Points marked with an X represent corrected counts using the angle view with the maximum berries, adjusted with a linear model. (D) Correlation between real and predicted berry area; color and shape patterns are similar to panel C; corrected points were generated with a linear model of the form $y \sim \beta 0 + \beta 1x$. The vertical red line indicates a one-to-one relationship between variables (Adopted from Torres-Lomas et al., 2024)

Furthermore, three-dimensional modeling techniques overcome the limitations of 2D image analysis in representing spatial structure. Through 3D scanning, stereo vision, or point cloud reconstruction, parameters such as berry number, average diameter, individual berry volume, cluster envelope volume, and spatial compactness can be obtained. Compared with 2D methods, 3D analysis provides a more accurate description of inter-berry distances, internal voids, and cluster closure, and is suitable for dynamic monitoring of cluster development (Trivedi et al., 2023). Combined with mobile devices and field platforms, these technologies are driving berry uniformity evaluation toward automation, scalability, and intelligent applications.

4 Factors Affecting Grape Berry Uniformity

4.1 Genetic factors

Grape berry uniformity is primarily influenced by genetic background. Different cultivars exhibit inherent differences in berry size, shape, and cluster structure, which arise from genetic traits such as berry developmental potential, fruit set stability, seed formation capacity, and cluster architectural formation. Studies have shown that berry size and cluster structure display extensive variation within grape germplasm, with berry weight ranging from less than 1 g to approximately 10 g, closely associated with cell division and expansion before and after flowering as well as pericarp tissue development. Therefore, the performance of berry uniformity among cultivars has a strong genetic basis.

In table grape breeding, genetic selection plays a decisive role in improving berry size and uniformity standards. Breeding programs represented by 'Kyoho' and its derivatives have significantly increased berry size, while 'Shine Muscat' has further achieved a combination of large berries, excellent flavor, and good resistance. This cultivar has an average berry weight of approximately 10-12 g and can achieve seedless production through gibberellic acid (GA_3) treatments at full bloom and post-bloom stages, resulting in high berry consistency through the synergistic effects of genetic potential and cultivation practices. This demonstrates that the selection of superior cultivars is one of the core approaches to improving berry uniformity.

In addition to varietal differences, clonal variation is also an important genetic source of uniformity. Studies have shown that different clones may exhibit stable differences in seed number, fruit set rate, berry size, and cluster density, with seedless or low-seed types often displaying distinct berry developmental patterns and structural characteristics (Alañón-Sánchez et al., 2026). Overall, berry uniformity is a typical quantitative trait controlled by multiple genes and influenced by genotype-environment interactions, requiring multi-trait selection and long-term breeding efforts to achieve stable improvement.

4.2 Physiological factors

Berry uniformity largely depends on key physiological processes from flowering to early fruit development, among which the adequacy and synchrony of pollination and fertilization are fundamental for uniform berry development. Insufficient pollen viability or uneven pollination conditions may result in poor fertilization of some flowers, leading to the formation of underdeveloped small berries and increased variability within clusters. Sabir et al. (2020) demonstrated that supplementary or cross-pollination can significantly improve fruit set and berry development, indicating a direct effect of pollination quality on uniformity.

Pollination and fertilization further influence berry enlargement by regulating hormonal signaling and cellular development processes. Dauelsberg et al. (2011) reported that successfully pollinated berries exhibit larger diameters and faster flesh expansion, whereas berries formed from unpollinated flowers remain smaller and developmentally restricted. These differences are closely associated with the expression of genes related to gibberellins, auxins, and cytokinins, indicating that fertilization activates hormone-mediated regulation and cell division required for early fruit development. In addition, differences in pollen source and viability can influence berry size and uniformity through metaxenia effects (Dhakad et al., 2024).

During the berry enlargement stage, developmental synchrony becomes a key determinant of uniformity. Berry growth depends on assimilate supply, water transport, and hormonal regulation, and differences among berries in seed number, hormone levels, and competitive ability for resources can lead to asynchronous development, resulting in size variability. Therefore, berry uniformity is the cumulative outcome of multiple developmental stages, including pollination, fertilization, seed development, and berry enlargement, and is fundamentally determined by the synchrony of berry development.

4.3 Cultivation and environmental factors

In production practice, cultivation management is the most direct and controllable factor affecting berry uniformity. Practices such as flower thinning, cluster thinning, and berry thinning reduce berry number, optimize the source-sink relationship, and decrease competition among berries, thereby promoting balanced development of the remaining berries. Khalil et al. (2023) reported that cluster thinning can significantly increase berry weight and diameter in certain cultivars, although responses vary among genotypes, indicating that cultivation practices must be adapted to genetic background. For compact clusters, thinning also improves spatial distribution, reduces compactness, and enhances visual quality (Alshallash et al., 2023; Choi et al., 2023).

Plant growth regulators, particularly gibberellic acid (GA_3), play an important role in regulating berry uniformity. Appropriate GA_3 treatments can promote berry enlargement and improve uniformity, whereas improper applications may exacerbate size variability. Studies have shown that multi-stage GA_3 applications enhance vascular development and sugar transport, thereby promoting berry growth (Cai et al., 2024), while combined treatments of GA_3 and CPPU regulate endogenous hormone levels to influence cell division and expansion in berries (Figure 2) (Choi et al., 2023; Chen et al., 2025). However, such regulation is highly cultivar-dependent. For example, Acharya et al. (2025) reported that low concentrations of GA_3 had limited effects in ‘Cabernet Sauvignon’, indicating the need for cultivar-specific optimization.

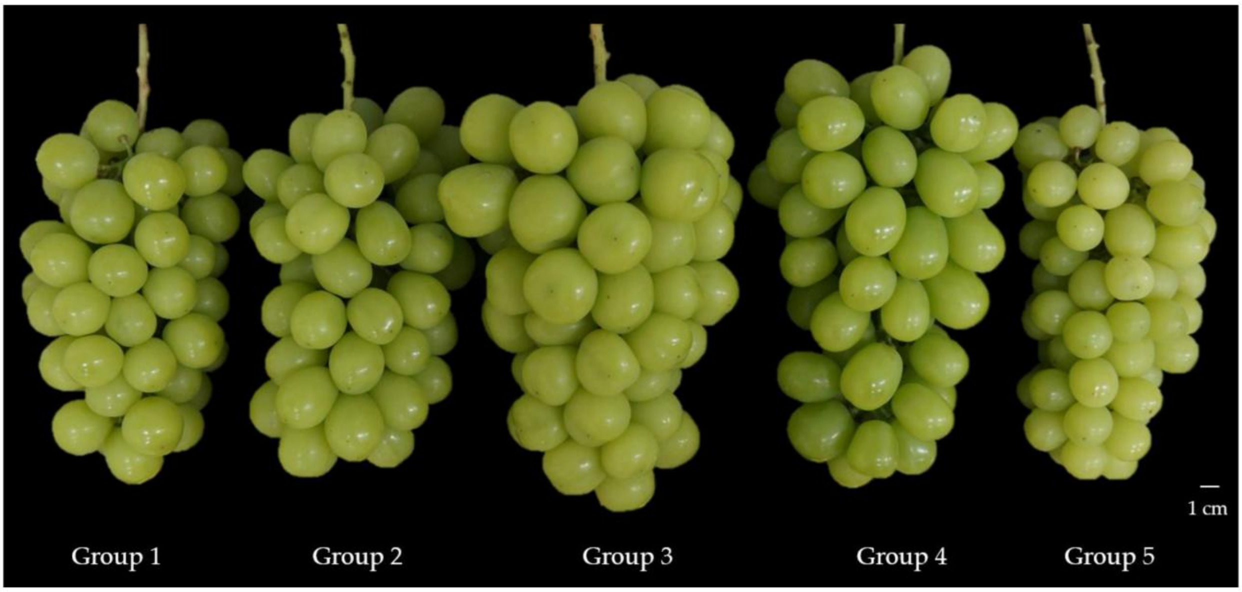

Figure 2 The shape of ‘Shine Muscat’ grapes at harvest according to PGR treatment (Adopted from Choi et al., 2023)
Image caption: The combinations of PGR treatments applied at full bloom (F) and 12 days after full bloom (DAFB) are as follows; Group 1: F: GA3 12.5+TDZ 2.5, 12 DAFB: GA3 25. Group 2: F: GA3 25 + CPPU 5, 12 DAFB: GA3 25. Group 3: F: GA3 25 + TDZ 5, 12 DAFB: GA3 25. Group 4: GA3 25 + CPPU 5, 12 DAFB: GA3 25+ CPPU 5. Group 5: F: GA3 25 + CPPU 5, 12 DAFB: untreated. The numbers that appear with the PGR are concentrations and their unit is mg/L. Abbreviations: gibberellic acid 3 (GA3), thidiazuron (TDZ), forchlorfenuron (CPPU) (Adopted from Choi et al., 2023)

Water and nutrient management, as well as climatic conditions, also have significant effects on berry uniformity. Stable water and nutrient supply helps maintain synchronized berry growth, whereas water stress or nutrient fluctuations may disrupt developmental balance. Environmental factors such as temperature, light, and precipitation not only affect pollination and seed formation but also influence berry growth rate and cluster structure, leading to inter-annual variation in uniformity. Therefore, improving berry uniformity requires an integrated consideration of genetic background, physiological processes, and cultivation environment, with coordinated regulation of multiple factors to achieve stable optimization.

5 Selection Strategies for Improving Grape Berry Uniformity

5.1 Trait selection

The first step in improving grape berry uniformity is to establish clear, quantifiable, and selection-oriented trait criteria. For table grapes, the combination of large berry size, uniform appearance, and coordinated cluster structure plays a crucial role in consumer preference, commercial grading, and market competitiveness. Therefore, selection should not focus solely on average berry size but should emphasize berry size uniformity, stability of berry morphology, and the coordination of spatial structure within clusters.

At the berry level, the coefficient of variation (CV) of berry size can serve as a key indicator for assessing size uniformity. A lower CV indicates a more concentrated distribution of berry size within a cluster and thus higher uniformity. Consequently, in cultivar screening, germplasm evaluation, and progeny selection, priority should be given to materials with higher mean values of berry weight, length, width, and volume, combined with lower CV values. Previous studies have shown that grape germplasm resources and breeding populations exhibit wide variation in berry weight, length, diameter, seed number, and cluster structural traits, providing a genetic basis for selecting genotypes with uniform berries and coordinated cluster architecture (Güler and Karadeniz, 2023; Gharate et al., 2025).

At the cluster level, an ideal cluster should maintain a balance between compactness and openness. Overly loose clusters may exhibit large gaps and uneven berry distribution, whereas excessively compact clusters are prone to berry compression, deformation, and uneven development. Therefore, selection for uniformity should comprehensively consider cluster length, width, berry number, berry density, compactness, and overall cluster regularity (Thorat et al., 2024; Sharma et al., 2025). Genome-wide association studies (GWAS) and QTL analyses have shown that berry size and cluster structure traits are controlled by multiple genes but generally exhibit moderate to high heritability, enabling gradual improvement through continuous selection and the utilization of stable genetic loci (De Oliveira et al., 2026).

5.2 Breeding strategies

From a genetic improvement perspective, enhancing grape berry uniformity requires an integrated strategy combining high-quality germplasm evaluation, hybridization design, and marker-assisted selection. It is essential to systematically identify superior genetic resources from existing cultivars, local germplasm, and breeding materials that exhibit high berry uniformity, stable cluster structure, and consistent fruit set performance, and to use these as parental lines in hybrid breeding. Germplasm studies indicate that grape berry size, cluster density, berry number, and seed traits show substantial variation, providing a foundation for targeted selection of uniformity-related traits (Güler and Karadeniz, 2023; Gharate et al., 2025).

Because berry uniformity is a complex quantitative trait, relying solely on phenotypic selection is often time-consuming and susceptible to environmental interference. In recent years, technologies such as QTL mapping, GWAS, RNA-Seq, and high-density SNP genotyping have provided powerful tools for dissecting the genetic basis of uniformity-related traits. Multiple studies have identified QTLs associated with berry weight, length, diameter, seed traits, and cluster structure, with some loci showing stable expression across years and populations (García-Abadillo et al., 2024). For example, QTLs associated with berry weight have been located on chromosomes 11, 17, and 18, while major loci for berry length and width have been identified on chromosomes 14 and 3-5 (Figure 3) (Thorat et al., 2024; De Oliveira et al., 2026).

Marker-assisted selection (MAS) enables the early identification of progeny carrying favorable alleles, thereby improving breeding efficiency for uniformity-related traits. Studies based on RNA-Seq and GWAS have identified multiple SNP and InDel markers associated with berry size, some of which co-localize with candidate genes involved in cell number, cell wall modification, and hormone signaling pathways. In practice, a strategy integrating “phenotypic pre-screening + marker-assisted selection + multi-year stability validation” can be adopted: first selecting materials with low CV, large average berry size, and coordinated cluster structure, then enriching favorable alleles through MAS or genomic prediction, and finally validating the stability of uniformity across multiple environments.

5.3 Cultivation regulation

At the production level, cultivation practices represent the most direct and rapidly effective approach for improving berry uniformity. Even when cultivars possess favorable genetic potential, inappropriate cluster load, thinning intensity, growth regulator application, or water and nutrient management may still result in uneven berry size, excessive compactness, or localized developmental imbalance. Therefore, uniformity optimization should be based on cultivar-specific genetic characteristics and achieved through coordinated regulation of cluster shaping, quantitative thinning, and appropriate application of plant growth regulators to ensure balanced and stable berry development.

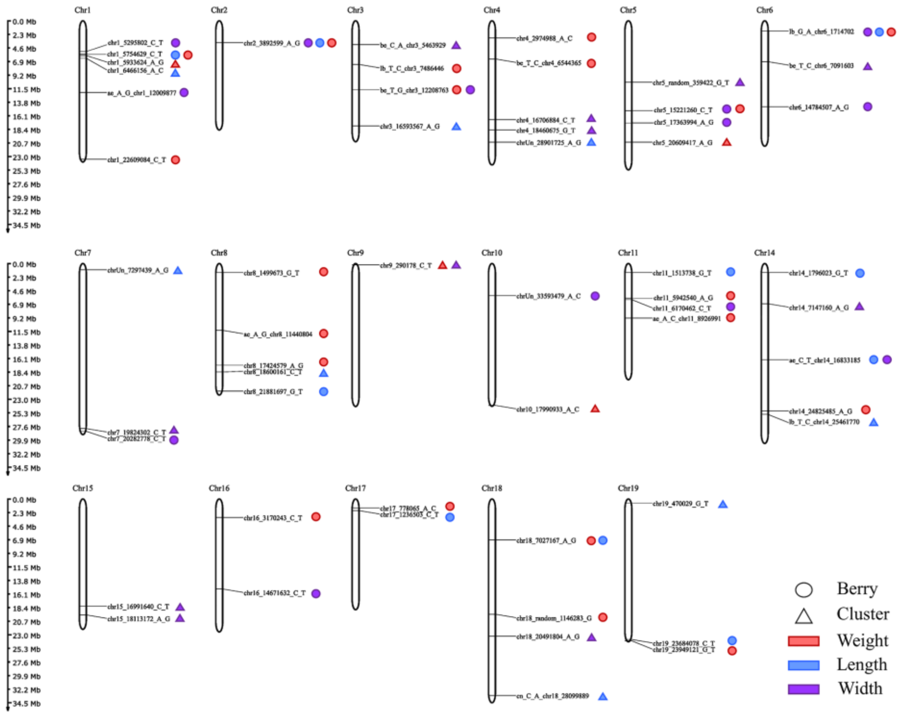

Figure 3 Chromosomal localization of significant SNPs associated with berry- and cluster-related traits (Adopted from De Oliveira et al., 2026)

Image caption: The chromosome number is shown at the top of each chromosome, and chromosome sizes are depicted on a vertical scale (Mb) (Adopted from De Oliveira et al., 2026)

Cluster shaping and quantitative thinning are key techniques for improving cluster structure and berry uniformity. By adjusting inflorescence length, secondary cluster number, and branching density before and after flowering, berry crowding at later stages can be effectively reduced, creating space for uniform berry enlargement. For compact cultivars, shortening inflorescences or removing secondary clusters can reduce berry density, whereas for loose cultivars, excessive thinning should be avoided to maintain cluster fullness. Implementing quantitative berry thinning during the early fruit stage removes underdeveloped or overly dense berries, reduces resource competition, and ensures a more balanced assimilate supply to the remaining berries. Studies have shown that mechanical or chemical thinning can significantly improve berry size and cluster structure in compact cultivars. In ‘Shine Muscat’, moderate thinning promotes berry enlargement and maintains sugar-acid balance, whereas excessive thinning may reduce fruit quality (Choi et al., 2023), indicating that thinning intensity must be carefully adjusted according to cultivar characteristics and production objectives.

Plant growth regulators, particularly gibberellic acid (GA_3), play an important role in regulating berry uniformity. Appropriate timing and concentration of GA_3 treatments can promote berry enlargement, increase berry diameter and cluster weight, and act synergistically with thinning practices. However, the effects of GA_3 are highly cultivar-dependent and sensitive to dosage, and improper application may result in uneven berry development, altered skin characteristics, or delayed ripening. Therefore, GA_3 application should be integrated with cluster shaping, thinning, and water and nutrient management to form a systematic regulation strategy. Overall, the coordinated optimization of multiple cultivation practices can effectively enhance developmental synchrony and represents a key pathway for achieving stable improvement in berry uniformity.

6 Digitalization and Intelligent Development Trends

6.1 Machine vision-based automatic identification and evaluation systems for berry uniformity

With the rapid development of artificial intelligence, machine vision, and high-throughput phenotyping technologies, image-based automatic evaluation systems for grape berry uniformity have become a key direction for improving efficiency, objectivity, and reproducibility. These systems typically acquire cluster information using high-resolution RGB images, mobile device images, or field close-range images, and integrate image segmentation, object detection, edge reconstruction, and geometric analysis to achieve automatic identification and parameter extraction of individual berries, including berry number, diameter, area, shape, spatial coordinates, and distribution density.

Early machine vision approaches mainly relied on two-dimensional image processing. For example, methods based on edge detection and geometric analysis can identify berry contours and estimate berry diameter, with an average error of approximately 2-3 mm and good stability across different grape types (Luo et al., 2021). Automated frameworks based on conditional random fields can classify approximately circular structures in images as “berries” or “non-berries,” with high correlation between image-derived and manually measured diameters ($\rho \approx 0.88$) (Roscher et al., 2017). In addition, field-scale berry size mapping systems can control diameter estimation errors within 6% and show strong correlations with berry weight ($R^2 \approx 0.96$), providing a foundation for automated evaluation of spatial variation and uniformity (Mirbod et al., 2016).

In recent years, deep learning models have further improved berry detection accuracy under complex backgrounds. The Segment Anything Model (SAM) enables high-precision segmentation of individual berries in large sets of 2D cluster images, showing strong agreement with manual annotations (Pearson correlation $r = 0.96$), and can generate over 150,000 berry masks with spatial coordinates for analyzing berry size distribution, cluster compactness, and spatial structure (Torres-Lomas et al., 2024). Moreover, instance segmentation models based on AS-SwinT and end-to-end berry counting algorithms can automatically detect and count berries before thinning, supporting intelligent thinning decisions in high-value table grapes such as ‘Shine Muscat’ (Du and Liu, 2023). Mobile vision systems integrating Mask R-CNN and calibration objects can achieve sub-millimeter accuracy in berry diameter measurement and dynamically track berry growth, providing a technical basis for temporal monitoring of berry uniformity (Upadhyaya et al., 2023).

6.2 Trait association analysis and predictive modeling based on big data

In the context of digitalization, research on grape berry uniformity is shifting from single-point measurements to multi-source data integration and large-scale modeling. By integrating phenotypic data across different cultivars, years, ecological regions, and cultivation conditions, it is possible to systematically analyze the relationships between berry uniformity and yield, fruit quality, stress resistance, and marketable fruit rate. For instance, questions such as whether lower berry CV corresponds to a higher proportion of marketable fruit, whether optimal cluster compactness reduces disease risk, or whether uniform berry size affects sugar and acid accumulation can be addressed through big data modeling.

High-throughput phenotyping platforms provide the foundation for such analyses. Automated berry imaging systems can extract over 100 traits per fruit within approximately one second, including size, shape, and color parameters, and store the data in standardized formats for subsequent genetic analysis and model training. When combined with genome-wide SNP data, these high-density phenotypic datasets can be used for GWAS, haplotype analysis, and multi-trait selection, enabling the dissection of the genetic basis of complex traits such as berry shape, sugar content, organic acids, and stress tolerance (Zhang et al., 2025).

At the vineyard scale, multimodal sensing and machine learning models can be used to establish predictive relationships among environment, plant status, yield, and fruit quality. By integrating hyperspectral vegetation indices, thermal infrared indices, photosynthetically active radiation interception, stem water potential, chlorophyll content, and gas exchange parameters, and applying algorithms such as random forest and gradient boosting, it is possible to accurately predict traits such as average berry weight, berry number per cluster, cluster weight, total yield, soluble solids content, pH, titratable acidity, and maturity index, with some models achieving R^2 values greater than 0.9 (Jewan et al., 2024). UAV-based multispectral and thermal remote sensing studies have also shown that vegetation indices are positively correlated with yield and berry weight, while canopy temperature is related to berry pH, polyphenol content, and anthocyanin levels, providing a basis for zone management and selective harvesting (Lee et al., 2024). In addition, artificial neural networks can use CIELab color parameters to accurately predict berry physicochemical properties, with correlation coefficients reaching $R \approx 0.98\text{-}0.99$, indicating that color information is also an important variable for modeling fruit maturity and quality.

6.3 Application of intelligent management in precision regulation

Digital and intelligent technologies are not only used for evaluating berry uniformity but are also transforming vineyard resource management. Precision viticulture systems integrate satellite remote sensing, UAVs, ground-based sensors, soil moisture monitoring, and plant physiological data to spatially identify variations in plant growth, water stress, nutrient supply, and canopy status within vineyards, thereby enabling variable-rate irrigation, fertilization, and zone-based management strategies (Mucalo et al., 2024). This management approach helps reduce internal variability in resource supply and minimizes uneven berry development caused by water or nutrient stress.

Internet of Things (IoT)-based fertigation systems represent an important tool for precise regulation of berry uniformity. These systems automatically adjust irrigation volumes and nutrient solution compositions based on soil moisture, irrigation water quality, nutrient status, and plant demand, thereby maintaining stable water and nutrient supply during the berry enlargement stage. Smart fertigation platforms such as NutriBalance can automatically calculate optimal nutrient formulations based on water source quality and reduce fertilizer input by approximately 40% while maintaining nutrient supply accuracy (Imbernón-Mulero et al., 2023). Furthermore, irrigation and fertilization decision models based on mathematical optimization and genetic algorithms can improve economic returns while reducing environmental impacts, demonstrating the dual benefits of intelligent water-fertilizer management.

Intelligent environmental monitoring systems can also support regulation during critical growth stages. Temperature, humidity, and wind speed during flowering affect pollination uniformity; water supply and canopy light conditions during berry enlargement influence developmental synchrony; and microenvironmental variation during veraison and ripening may affect sugar-acid accumulation and maturity consistency. By continuously monitoring these parameters and integrating predictive models for early warning and regulation, it is possible to reduce asynchronous berry development at the source. In the future, improvements in grape berry uniformity will increasingly rely on an intelligent closed-loop system of “perception-diagnosis-prediction-decision-execution.” This involves evaluating berry uniformity through machine vision, predicting risks through multi-source data modeling, implementing regulation via intelligent water-fertilizer and environmental control systems, and continuously optimizing models based on feedback data. Such a framework enables the transition from experience-based management to data-driven precision management, providing sustainable technical support for the production of high-quality table grapes.

7 Challenges and Future Perspectives

7.1 Lack of a unified evaluation system

Currently, research on grape berry uniformity still lacks a unified and standardized evaluation system. Existing grape trait description systems mainly focus on individual traits such as berry size, berry shape, cluster compactness, and cluster color, while the composite trait of “intra-cluster berry uniformity” lacks a dedicated definition and standardized quantitative framework. Different studies and germplasm databases often employ OIV descriptors, self-defined trait systems, or output indicators from high-throughput phenotyping platforms, leading to inconsistencies in indicator definitions, measurement methods, and grading standards. These discrepancies limit cross-study comparisons and hinder industrial application (García-Abadillo et al., 2024; Liu et al., 2024; Zhang et al., 2025).

In recent years, two-dimensional and three-dimensional high-throughput phenotyping technologies have enabled precise extraction of traits such as berry diameter, berry volume, cluster length, cluster width, berry number, and compactness. However, these technologies are primarily applied to cluster architecture or single morphological traits and have not yet formed a dedicated core indicator system specifically for berry uniformity evaluation. Therefore, future efforts should focus on developing a standardized multi-indicator evaluation framework, while retaining the simplicity of traditional methods, with key components including berry size CV, shape consistency, spatial distribution uniformity, and appropriate cluster compactness.

7.2 Insufficient understanding of molecular mechanisms

Although considerable progress has been made in QTL mapping, GWAS, and candidate gene identification for traits related to berry size, shape, and cluster structure, research on the genetic mechanisms underlying the composite trait of berry uniformity remains limited. Most existing studies focus on mean values of traits such as berry weight, length, diameter, cluster compactness, or berry number, whereas relatively few directly use intra-cluster variability (e.g., CV) or spatial uniformity as core phenotypic traits for genetic mapping (García-Abadillo et al., 2024; Thorat et al., 2024).

Previous studies have shown that berry size and cluster structure are controlled by multiple genes, with candidate genes involved in processes such as cell division, cell expansion, hormone signaling, cell wall modification, and stress responses (De Sousa Moreira et al., 2024; Meneses et al., 2025). Pangenome studies further indicate that complex traits in grapevine are influenced not only by single nucleotide polymorphisms (SNPs) but also by structural variations, and that integrating SNP and structural variation analyses can improve the explanation of heritability (Liu et al., 2024). However, how these genetic variations regulate developmental synchrony, intra-cluster resource allocation, and spatial distribution of uniformity remains largely unclear.

Future research should treat berry uniformity as an independent core phenotype and integrate multi-stage developmental phenotypes with transcriptomic, metabolomic, hormonal, and genomic data to elucidate the regulatory networks underlying synchronous and asynchronous berry development. At the same time, functional validation of key candidate genes should be strengthened to facilitate the transition from empirical selection to molecular design breeding for uniformity improvement.

7.3 Insufficient integration of multi-source data

With the advancement of high-throughput phenotyping, genomics, and intelligent agriculture technologies, grape uniformity research is entering a data-driven era. However, the integration of phenotypic, genomic, environmental, and management data remains insufficient. Most existing studies focus on a single data type, such as phenotypic measurement, QTL mapping, or GWAS, while integrated modeling of genotype × environment × management interactions is still limited. This restricts the comprehensive understanding of the stability of berry uniformity across years, regions, and management conditions (Herzog et al., 2025; Zhang et al., 2025).

The integration of high-density genotyping with high-throughput phenotyping has already demonstrated significant value in the study of complex traits such as berry morphology, quality, and stress resistance (Liu et al., 2024; Zhang et al., 2025). Meanwhile, genomic selection and multi-trait selection indices are becoming important approaches to improve breeding efficiency in grapevine (Bharati et al., 2023; Brault et al., 2024). However, in practical production, management variables such as thinning intensity, GA_3 application, water status, microclimate, and vine load are often not recorded and modeled alongside genetic and phenotypic data, limiting the development of predictive models and precision regulation strategies for berry uniformity.

In the future, it will be necessary to establish a multi-source data platform specifically for berry uniformity, standardize data collection protocols, and integrate phenotypic, genotypic, environmental, and management information. By leveraging machine learning, genomic prediction, and digital twin technologies, dynamic predictive models can be developed. On this basis, uniformity-related traits can be incorporated into ideotype design and multi-trait selection indices, enabling the coordinated improvement of high uniformity, high yield, superior quality, and strong adaptability.

8 Concluding Remarks

Berry size, shape, and cluster structure are core components of grape quality, directly influencing consumer acceptance, suitability for fresh consumption or processing, and ultimately economic returns. With the advancement of high-throughput image analysis and machine vision technologies, researchers are now able to quantify berry and cluster traits at large scales and to elucidate the relationships between berry size, compactness, structural variation, and yield and quality attributes. Genomic and association studies have demonstrated that most berry-related traits, including size, weight, texture, and shape, are controlled by multiple genes. Nevertheless, stable genetic loci and selection signals associated with fruit quality and morphology have been identified in grape germplasm, providing a foundation for targeted improvement. Collectively, these findings indicate that berry uniformity is a multidimensional trait with significant economic value that can be clearly defined, accurately measured, and genetically dissected.

Improving berry uniformity requires coordinated efforts in cultivar selection, molecular breeding, and field management. High-density genotyping, genome-wide association studies, and SNP array technologies, combined with high-throughput phenotyping, enable precise identification of genetic loci associated with berry size, cluster structure, and stress resistance, thereby supporting marker-assisted selection and future gene-editing approaches. Meanwhile, advanced breeding strategies such as genomic selection, clonal selection, and polyploidization, together with the integration of multi-omics data, can effectively accumulate favorable alleles and achieve the coordinated improvement of berry traits, fruit quality, and stress tolerance. In addition, digital phenotyping and remote sensing technologies can guide thinning practices, canopy management, and water-nutrient regulation, ensuring that cultivation practices are aligned with genetic potential and promoting synchronized berry development and stable fruit quality. Future progress in improving grape berry uniformity will depend on advancing standardized trait evaluation, precision management, and intelligent production systems. On the one hand, intelligent algorithms based on foundation models such as SAM and deep learning techniques (e.g., AS-SwinT and Mask R-CNN) have enabled automated berry segmentation, counting, and size measurement, laying the groundwork for standardized, machine-readable phenotypic data systems for uniformity and cluster compactness. On the other hand, integrating phenomics, genomics, and environmental monitoring data with machine learning models will enhance the prediction of yield and fruit quality, enabling precision management and selective harvesting based on spatial variability. Furthermore, combining variable-rate irrigation and fertilization technologies with optimization algorithms and IoT-based control systems can improve resource use efficiency and stabilize berry development. Overall, establishing unified data standards, shared trait ontologies, and integrated “perception-decision-execution” systems will be essential pathways for achieving stable improvements in grape berry uniformity and advancing intelligent production systems.

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Conflict of Interest Disclosure

The authors affirm 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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