Journal of Zhejiang University-SCIENCE B 2026 27(5):431-436
www.jzus.zju.edu.cn; www.springer.com/journal/11585
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Editorial
https://doi.org/10.1631/jzus.B2610001

Advancing multi-scale plant phenotyping for precision agriculture and sustainable crop production

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Plant phenotyping captures the integrated structural and functional traits of crops across cellular, tissue, organ, whole-plant, and population scales. It represents the outward expression of genotype–environment interactions and provides essential technological support for precision breeding, smart agriculture, and sustainable crop production. As farming shifts from experience-based to data-driven decision-making, the efficient acquisition and integrated analysis of phenotypic information at multiple spatial scales has emerged as a major research frontier at the intersection of agronomy, plant science, and agricultural engineering.

Recent advances in high-throughput phenotyping platforms, unmanned aerial vehicles (UAVs), satellite remote sensing, and artificial intelligence have propelled the field from single-scale observations toward multi-scale collaborative analysis. This cross-scale integration offers powerful tools for dissecting genotype–environment–management interactions and accelerates the translation of phenotypic insights into practical agricultural decisions. Against this backdrop, the present special issue—entitled "AI in Plant Phenotyping: From Cells to Fields"—features seven original research papers that span organ/plant, plot/field, and regional/large-field scales.

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Received Apr. 14, 2024; Revision accepted Apr. 20, 2025;
Crosschecked Apr. 20, 2026

Organ/plant scale

Research at the organ or individual-plant scale focuses on tasks such as leaf morphology measurement, root-system architecture analysis, fruit counting, and disease detection. These traits are directly linked to growth, development, yield formation, and quality. Non-destructive, continuous monitoring is particularly valuable for uncovering developmental dynamics and environmental responses. Demonstrating this within the special issue, Yao et al. (2026) utilized high-throughput lysimetric arrays to dynamically evaluate environmental responses, ultimately optimizing substrate selection for enhanced orchid growth.

Substantial progress has been made in image-based acquisition and automated analysis of organ phenotypes. Although traditional two-dimensional (2D) visible-light image processing is inexpensive, it often lacks robustness in complex field backgrounds. Deep learning has markedly improved detection accuracy (Kamilaris and Prenafeta-Boldú, 2018; Murphy et al., 2024). In this special issue, Zhang W et al. (2026) report the development of a lightweight convolutional neural network based on the You Only Look Once (YOLO) v8s architecture that achieves a mean average precision of 0.964 for wheat spike detection. Chu et al. (2026) introduce a Rank-Aware YOLO framework that incorporates prior biological knowledge of fruit-cluster maturity, enabling precise localization of cluster-harvested tomatoes across growth stages. Furthermore, targeting the critical task of disease detection, Tao et al. (2026) improved RGB image recognition within the YOLO11n algorithm for the accurate and efficient identification of tea plant diseases.

Most supervised models, however, remain heavily dependent on labelled data and exhibit limited generalization, especially when domain shifts arise across species, imaging modalities, or environments. Foundation models in computer vision now address these limitations by learning generalizable features through large-scale self-supervised pre-training, thereby reducing the need for extensive annotation in plant organ segmentation. Recent work has shown that the Segment Anything Model (SAM), after minimal adaptation, can deliver high-precision leaf segmentation across multiple species (Williams et al., 2024; Zhang et al., 2024).

Traditional 2D approaches also struggle to quantify organ topology and spatial geometry; leaf occlusion, root entanglement, and blurred lesion boundaries limit accuracy. Three-dimensional (3D) reconstruction techniques have opened new avenues. Neural rendering methods such as 3D Gaussian Splatting (3DGS) can reconstruct fine leaf edges and fruit surfaces from ordinary multi-view camera images, outperforming classical point-cloud methods (Li JJ et al., 2026). Three-dimensional foundation models such as Point Transformer excel at handling complex geometry, although computational efficiency and precision must still be balanced. Recent studies have successfully applied 3DGS and Point Transformer to organ-level reconstruction of strawberry and maize, greatly improving topological quantification (Zhao et al., 2025; Li et al., 2026a).

Plot/field scale

The plot or field-plot scale bridges detailed phenotypic analysis and real-world agricultural application. Phenotypic monitoring at this scale integrates canopy structure, resource competition, and multi-stress responses (Sadeh et al., 2025).

From a precision-agriculture perspective, plot-scale studies supply high spatial resolution, multi-temporal crop-growth information that supports data-driven fertilization, irrigation, and pest management (Khoshroo et al., 2014; Zhao et al., 2026). Continuous tracking of vigor, nutritional status, and stress responses enables precise input regulation, higher resource-use efficiency and a reduced environmental impact (Chawade et al., 2019). In breeding programmes, this scale facilitates rapid, objective screening of large germplasm panels (Guo et al., 2021).

Papers in this special issue illustrate recent advances. One study tackled the difficult pre-harvest estimation of biomass and yield in oilseed rape using UAV multispectral and RGB imagery. Systematic evaluation of the synergistic contributions of spectral, textural, and structural features showed that spectral–textural combinations performed best for biomass (R^2=0.72), while yield estimation (R^2=0.68) required multidimensional fusion. Ensemble learning and Shapley additive explanation (SHAP) interpretability further enhanced robustness across years, varieties, and planting densities (Zhang YN et al., 2026). Another contribution addressed the high-precision extraction of crop residue cover (CRC) in conservation agriculture by developing RCTUnet, a deep-learning model built on a U-Net backbone with ResNet50 encoder, CBAM attention, and Transformer global-context fusion. The model achieved 88.11% mean intersection over union (mIoU), 90.32% recall for residues, and reduced the CRC root mean square error (RMSE) from 8.94% to 4.88%, offering an efficient tool for evaluating conservation-tillage performance (Li T et al., 2026).

Despite these gains, challenges persist: complex field environments hinder stable data collection; heterogeneous multi-source data complicate analysis; model generalization across regions and years remains limited; and high-throughput data processing has become a bottleneck. UAVs typically provide broad vertical canopy views, whereas ground robots and handheld devices capture close-range or local information (Khoshroo et al., 2014; Tanaka et al., 2024). Unified multi-view, multi-scale data registration and fusion methods are still lacking.

Plot-scale phenotyping is therefore moving rapidly toward integration and intelligence. Multi-source fusion of RGB, multispectral, hyperspectral, and light detection and ranging (LiDAR) data now yields comprehensive structural and physiological characterizations, improving trait estimation accuracy and model stability (Mu and Lu, 2025; Yan et al., 2025; Saif et al., 2026). Artificial intelligence is reshaping workflows: deep learning combined with feature selection and ensemble methods produces more robust predictors; time-series modeling captures growth dynamics (Tanaka and Gislum, 2025); 3D analysis extracts canopy height, volume, and spatial distribution (Dong et al., 2025); and joint assimilation with crop models and multi-source agricultural data shifts the paradigm from empirical statistics to mechanism-driven understanding (Omia et al., 2023). The result is an emerging "aerial–space–ground" integrated data-acquisition and analysis system.

Regional/large-field scale

Crop phenotyping is expanding rapidly from single plants and experimental plots to whole fields, regions, and even multi-regional scales. Internationally, remote-sensing-based field-scale monitoring has evolved from static classification to dynamic characterization, expanding from crop-type identification to phenological processes, canopy structure, leaf-area index, biomass, and environmental responses. Data sources have progressed from single-sensor, single-date acquisitions to multi-sensor, multi-platform, and multi-temporal systems. Satellite remote sensing, with its synoptic coverage, repeat observations, and long-term continuity, remains the cornerstone of regional-scale phenotyping. Research paradigms are shifting from trait extraction toward time-series modelling and process-based expression, with growing emphasis on coupling multi-temporal remote sensing, deep-learning representations, and crop-growth processes (Shojaeezadeh et al., 2025).

At the data level, multi-satellite synergy and fusion improve temporal continuity. Methodologically, the field is moving from empirical vegetation indices and radiative-transfer models to spatio-temporal deep learning, phenology-constrained modelling, and multi-source joint inversion. For example, fusion of Sentinel-1, Sentinel-2, and high-resolution meteorological data has enabled accurate crop-phenology estimation (Cyran et al., 2025); Sen2Like fusion products outperform single Sentinel-2 data in complex cropping systems (Zhang et al., 2025); and alignment of satellite-derived field-scale phenology with deep-learning yield models reduces estimation error while improving disaster-signal interpretability. In this special issue, Wang et al. (2026) describe the development of a deep-learning framework that jointly extracts phenology and classifies crop types in the complex oasis agroecosystem of Tumushuke, Xinjiang, China, using Sentinel-2 multi-temporal imagery and normalized difference vegetation index (NDVI) time series. Multi-scale window combinations achieved an optimal trade-off between classification accuracy and computational efficiency, yielding F1-scores of 94.37%, 87.75%, and 86.35% for three target crops, respectively.

Common challenges remain: cloud cover, data gaps, phenological overlap in multi-cropping systems, and ecological-zone differences that hinder model transfer. Multi-scale integration is still transitioning from simple data stitching to true information fusion. The future lies in building cross-scale, transferable, interpretable, and operationally ready phenotypic-analysis frameworks.

Summary and outlook

Crop-phenotyping technologies continue to evolve toward multi-source, multi-scale, intelligent, and application-oriented systems. Deep integration of high-performance sensors, intelligent platforms, artificial intelligence, and bioinformatics will enable phenotyping to play an even more pivotal role in complex-trait dissection, genetic improvement, and precision management. Persistent bottlenecks include fragmented sensing systems, weak cross-scale linkages, limited adaptability to complex environments, and insufficient data sharing and standardization. Future efforts should therefore focus on four priority directions.

First, at the organ/tissue level, computer-vision foundation models and 3D neural-rendering techniques should enable zero-shot/few-shot organ segmentation, topological quantification, and dynamic growth monitoring, overcoming annotation dependence and domain-shift problems while enhancing cross-species and cross-environment generalization through multi-modal fusion.

Second, UAV-based phenotyping has matured from a data-acquisition tool into a central hub for data and information in precision agriculture. Its high spatial and temporal resolution, combined with multi-temporal observations, delivers rapid information on growth status, structural traits, and physiology for yield forecasting, nutrient diagnosis, and stress detection. With multi-source fusion and machine learning, UAV systems are transitioning from passive observation to intelligent analysis and decision support, forming a vital bridge between field sensing and farm management.

Third, at the regional scale, phenotyping will continue its shift from "remote-sensing-based identification" to "operational perception." International examples—

continental-scale in-season crop mapping in the USA, multi-crop multi-stage phenology estimation in Germany, and near-real-time monitoring via CubeSat, Harmonized Landsat and Sentinel (HLS), and Internet-of-Things integration—demonstrate that satellite phenotyping is moving from offline analysis toward near-real-time products that meet the timeliness demands of agricultural management. The key will be coordinated development of high spatio-temporal-resolution satellite observations, multi-source fusion algorithms, and standardized phenotypic indicators, yielding regional-scale products that are cross-regionally reusable, dynamically updated within the growing season, and directly actionable for decision-making.

Fourth, a new research paradigm that combines multi-scale collaboration with process constraints is needed. Image classification alone cannot satisfy precision agriculture's requirements for interpretability, robustness, and transferability. Deep fusion of satellite remote sensing, UAV observations, ground sensing, and crop-growth models will move the field from "crop visualization" to "crop mechanistic understanding." Under complex cropping systems, future work must improve the accuracy of phenological-parameter and state-variable retrieval, strengthen the integration of phenology perception, environmental-stress characterization, process-model constraints, and artificial-intelligence spatio-temporal modelling, and ultimately deliver a multi-scale phenotyping framework that simultaneously provides regional coverage, fine-scale detail, and mechanistic insight—better supporting precision-input optimization, agricultural risk early warning, and sustainable production.

Acknowledgments

We thank all authors who contributed to this special issue.

Author contributions

Xuping FENG conceived and edited the draft of the manuscript. Zhenhai LI and Kun WANG performed the literature review and co-wrote the draft. All authors reviewed and approved the final manuscript.

Compliance with ethics guidelines

Xuping FENG, Zhenhai LI, and Kun WANG declare that they have no conflicts of interest.

This editorial does not contain any studies with human or animal subjects performed by any of the authors.

Declaration on the use of generative AI tools

During the preparation of this work, the authors used Grok in order to improve language and readability, and to check for grammatical errors. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Introducing Guest Editors-in-Chief

Xuping FENG, Ph.D.
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Dr. FENG specializes in plant phenomics and digital agriculture. Her research leverages multi-level remote-sensing technologies to monitor crop health, predict yields, and optimize agricultural practices. She has published extensively in leading journals including *Nature Plants*, *ISPRS Journal of Photogrammetry and Remote Sensing*, and *Plant Communications*. Her work has been recognized with the Gold Award in the Food and Agriculture Organization of the United Nations (FAO) Global Agri-Innovation Competition and the First Prize in the Zhejiang Provincial Science and Technology Progress Award.

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Dr. LI has 15 years of research experience in agricultural remote sensing and crop-growth modelling. He has led or participated in six National Natural Science Foundation of China (NSFC) grants, three UK–China Newton Agri-Tech projects and two China–ESA Dragon 4/5/6 programmes. He has published extensively in *Remote Sensing of Environment*, *European Journal of Agronomy and Computers*, and *Electronics in Agriculture*.

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Dr. WANG's research advances precision agriculture by coupling mechanistic crop-growth models with high-throughput phenotyping platforms. As principal investigator, she has secured funding for more than ten national-level projects, including grants from the National Key R&D Program of China and the National Natural Science Foundation of China (NSFC). She has authored more than 20 SCI-indexed publications in top-tier journals such as the *Agricultural and Forest Meteorology* and *Chemical Engineering Journal*.