

Review Article

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Recent advances in plant imaging technology: a concise review

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Abstract

Imaging technologies have become indispensable tools in modern plant phenotyping, transforming visual information into measurable traits essential for analyzing morphology, physiology, biochemistry, and micro- to nanoscale structures. This concise review summarizes recent advances by dividing plant imaging into two major categories: (1) physiological and biochemical, which includes hyperspectral, multispectral, and fluorescence hyperspectral imaging, as well as terahertz imaging, surface-enhanced Raman scattering, and carbon dot-based techniques; and (2) structural and morphological, encompassing RGB, thermal, light detection and ranging (LiDAR), confocal microscopy, and optical coherence tomography. Together, these modalities deliver insights from the canopy to the molecular level, enabling precise monitoring of plant stress, disease, and developmental traits. By integrating these multimodal imaging techniques with artificial intelligence, the review highlights key developments, current challenges, and future perspectives in plant measurement and analysis.

Keywords

artificial intelligence, molecular-scale imaging, phenotyping, spectral imaging, structural imaging

Introduction

The combined impacts of population growth and climate change necessitate a 100–110% increase in global crop yields by 2050 (Tilman et al. 2011), underscoring the urgent need to improve agricultural efficiency and sustainability. To meet this challenge amid climate stresses, such as heat and drought, agricultural research is shifting from traditional, destructive methods to advanced plant imaging technologies that are indispensable tools for modern phenotyping. These technologies quantify essential plant traits across morphology, physiology, and biochemistry, ranging from the macro- to the nanoscale. This review categorizes recent imaging progress into two analytical domains: (1) physiological and biochemical trait assessment, which includes multispectral, fluorescence, hyperspectral, and nanomaterial-based approaches (terahertz, SERS, and Carbon dots); and (2) structural and morphological monitoring, which includes RGB, thermal imaging, unmanned aerial vehicle (UAV) drones, light detection and ranging (LiDAR), confocal microscopy, and optical coherence tomography. In addition to these domains, this review addresses the integration of artificial intelligence with multimodal

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strategies, challenges in data standardization, and future directions for unified data-driven phenotyping platforms.

Physiological and biochemical plant imaging

These approaches enable non-destructive monitoring of key metabolites and their responses to environmental factors, including drought, heat, nutrient status, and photosynthetic dynamics. These techniques are essential for investigating plant functions at the macro-, micro-, and nanoscale levels. This section is divided into two parts: (i) Spectral imaging and (ii) molecular-scale biosensing. These techniques are essential for investigating plant functions at the macro-, micro-, and nanoscale levels.

Spectral imaging technologies

Spectroscopic technologies analyze how light interacts with plant tissues through reflectance, absorbance, and transmittance, revealing key biochemical components, such as chlorophyll, phenylpropanoids, proteins, and water. Infrared (IR), near-infrared (NIR), and Raman spectroscopies detect functional groups (e.g., N-H, O-H, and C-H), offering detailed chemical insights, but limited spatial resolution. To address this issue, spectral imaging technologies combine spectral and spatial information for a comprehensive plant analysis. Hyperspectral imaging (HSI) captures hundreds of contiguous bands to form a hypercube, enabling precise profiling of nutrients and stress-related metabolites such as phenolics and flavonoids (Jayapal et al. 2022). Multispectral imaging (MSI) records fewer bands (3-15) and is widely used to compute vegetation indices such as normalized difference vegetation index (NDVI) to assess plant health (Vuletić et al. 2023). Fluorescence hyperspectral imaging integrates fluorescence and hyperspectral data to monitor changes in chlorophyll fluorescence, thereby providing insights into photosynthetic efficiency (Faqeerzada et al. 2022). Collectively, these high-throughput technologies deliver multidimensional data that are essential for assessing plant physiological responses to drought and heat stress. By monitoring variations in key metabolites such as chlorophyll and phenolics, as well as imaging-derived indicators related to water-use efficiency, these approaches provide valuable insights into plant resilience under variable climate conditions (Beegum et al. 2024; Roy et al. 2023).

Molecular-scale biosensing

Spectral imaging provides valuable spatial and spectral insights; however, its sensitivity and spatial resolution can fall short of micro- and nanoscale measurements. These constraints can be overcome using molecular-scale biosensing technologies that enable highly sensitive molecular characterization. Surface-enhanced Raman scattering (SERS) amplifies Raman signals using gold or silver nanostructures to precisely map pesticides, pathogens, and metabolites (Fleischmann et al. 1974; Huang et al. 2025; Ma et al. 2015). Terahertz (THz) imaging exploits the radiation between infrared and microwave frequencies, providing a noninvasive assessment of plant water status and crop yield estimation (Federici et al. 2009; Zang et al. 2019). Carbon dots (CDs) are nanoscale fluorescent materials that support nutrient tracking and chemical detection with high biocompatibility (Bhattacharya et al. 2024; Liu et al. 2020; Maholiya et al. 2023). Together, these methods provide high-resolution molecular-level insights that are crucial for precision agriculture.

Structural and morphological plant imaging

Biochemical imaging provides valuable physiological information but offers limited insight into structural traits such as plant height, crown diameter, and architecture. To address this gap, structural and morphological imaging methods are essential and broadly divided into two main categories: (i) two-dimensional (2D) imaging technologies and (ii) three-dimensional (3D) imaging technologies, from the macroscale to the microscale.

2D plant imaging technologies

Two-dimensional imaging has long been central to plant phenotyping because of its simplicity, accessibility, and cost-effectiveness. Among these, RGB imaging is the most widely used and employs digital cameras to capture red, green, and blue light, enabling detection of phenotypic differences between healthy and stressed plants (Pérez-Bueno et al. 2016). This high-resolution method enables real-time monitoring of growth and developmental traits; however, its accuracy declines in dense canopies due to leaf overlap and occlusion, thereby hindering organ-level segmentation. Thermal imaging complements RGB by measuring the canopy surface temperature, offering insights into plant water status, heat stress, and disease symptoms. Stressed plants often display distinct thermal signatures compared to healthy controls, although thermal imaging is limited by its low spatial resolution and sensitivity to ambient environmental conditions (Pérez-Bueno et al. 2016). UAV platforms have further enhanced field-scale phenotyping by integrating RGB and thermal sensors for the large-area monitoring of canopy temperature, chlorosis, pest distribution, and irrigation efficiency (Toscano et al. 2024). Collectively, these 2D imaging technologies underpin the development of scalable high-throughput phenotyping systems.

3D imaging technologies: from the macroscale to the microscale

Although 2D imaging techniques offer rapid and efficient measurements, they are limited in their ability to capture complex plant architectures due to self-occlusion and overlapping leaves. 3D imaging addresses these challenges by enabling detailed analysis of plant morphology, including volume, density, leaf arrangement, and stem organization. LiDAR is a prominent 3D technique that uses pulsed lasers to generate dense point clouds and provides precise measurements of plant height, canopy volume, leaf area, and stem spacing. Its effectiveness has been demonstrated by large-scale phenotyping in sorghum (Patel et al. 2023). For tissue-level characterization, confocal microscopy offers high-resolution 3D visualization of cells and tissues, revealing plant-microbe interactions and developmental processes (Nelson et al. 2024; Harline and Roeder 2023). Optical coherence tomography (OCT) provides nondestructive cross-sectional imaging at micrometer resolution, enabling internal tissue observation and disease monitoring (Fujimoto et al. 2000; Sasi and Chauvet 2025). Collectively, these macroscale and microscale 3D methods provide hierarchical morphological insights that are vital for comprehensive plant phenotyping.

Role of artificial intelligence (AI) integration in plant imaging

AI has revolutionized plant imaging by processing massive datasets across diverse modalities, including RGB, thermal, hyperspectral, multispectral, fluorescence, 3D imaging, SERS, THz, and CDs. AI enhances data interpretation, robust feature extraction, and precise classification of plant health indicators, including stress, disease, and biochemical traits. Machine learning excels at estimating chlorophyll levels, detecting pesticide residues, and tracking biochemical changes (Bhattacharya et al. 2024; Faqeerzada et al. 2022; Jayapal et al. 2022). Deep learning analyzes complex 3D and high-dimensional data for accurate segmentation and morphological insights (Jin et al. 2025; Patel et al. 2023). Multimodal data integration via AI enables scalable high-throughput phenotyping systems that are essential for precision agriculture (Yang et al. 2025). AI-driven fusion improves trait analysis, minimizes human error, and supports reliable decision making. Fig. 1 shows a schematic representation of these advanced plant-imaging techniques across all four domains.

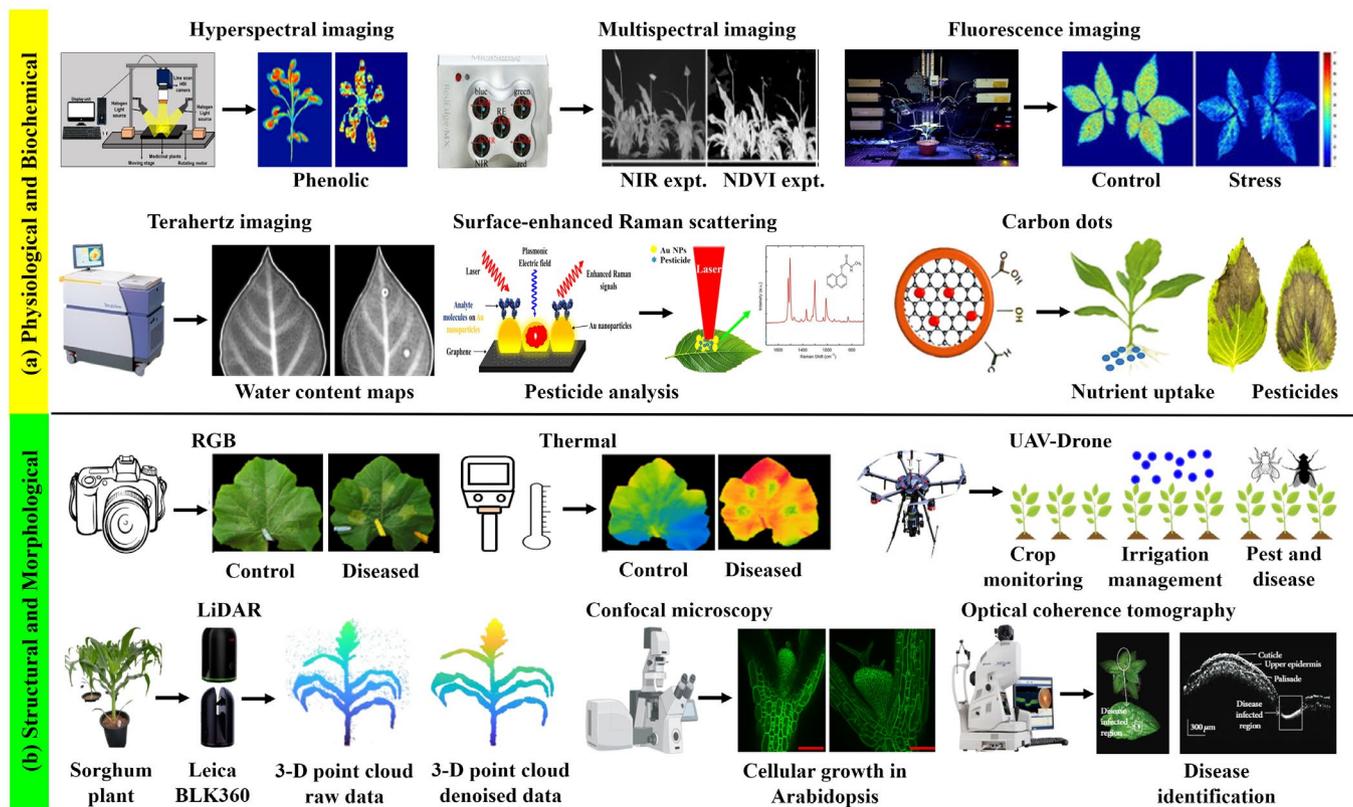


Fig. 1. Imaging and sensing modalities for plant phenotyping using (a) physiological/biochemical methods and (b) structural/morphological methods. Images adapted from literature cited in the text. NIR, near-infrared; NDVI, normalized difference vegetation index; SERS, surface-enhanced Raman scattering; RGB, red-green-blue; UAV, unmanned aerial vehicle; LiDAR, light detection and ranging; 3-D, three-dimensional; OCT, optical coherence tomography.

Discussion and future perspectives

The imaging techniques discussed, spectral, structural, molecular, and AI-driven, collectively enable comprehensive plant phenotyping, capturing biochemical traits, morphological features, cellular-level details, and effective multimodal data fusion. Despite these strengths, key challenges remain in achieving real-time measurements, data standardization, and scalable field deployment. Future investigations should aim to unify the complementary modalities within AI-enhanced multiscale platforms. Continued progress in standardization, hardware optimization, and multimodal data fusion is essential to enable real-time and resilient phenotyping systems in precision agriculture.

Conclusions

This review provides an overview of current plant imaging approaches and grouping technologies into physiological, biochemical, and structural/morphological domains. Although spectral imaging (HSI, MSI, and fluorescence) captures vital chemical signatures, it is limited by high costs and the need for intensive data processing. Biosensing modalities (SERS, THz, and CDs) offer nanoscale sensitivity for stress detection, but struggle with reproducibility. Furthermore, although 2D systems are prone to environmental interference and occlusion, 3D techniques (LiDAR, confocal, and OCT) provide superior structural resolution at the expense of portability and acquisition speed. Together, these tools form a robust phenotyping foundation, providing the data-driven insights necessary for precision agriculture.

Author contribution

Methodology: Joshi R, Faqeerzada MA, Kim T; Investigation: Joshi R, Faqeerzada MA, Kim T; Supervision: Cho BK; Writing – original draft: Joshi R, Faqeerzada MA, Cho BK; Writing – review and editing: Joshi R, Faqeerzada MA, Kim T, Cho BK.

Disclosure statement

The authors have no conflict of interest.

Ethical approval

Not applicable.

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Data availability statement

Not applicable.

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