Food and Scientific Reports

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Volume 7, Issue 1 January, 2026

ISSN 2582-5437
foodandscientificreports.com

Food and Scientific Reports
e-ISSN 2582-5437
foodandscientificreports.com

Popular Article

Integrating High-Throughput Plant Phenomics and Artificial Intelligence for Precision Agriculture

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OPEN ACCESS

Cite this article:

Tripathi, A. and Ranjan, R. (2026). Integrating High-Throughput Plant Phenomics and Artificial Intelligence for Precision Agriculture. *Food and Scientific Reports*, 7(1): 25-30.

Submitted: 2 January 2026
Accepted: 25 January 2026

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Abstract

The human population projected to reach 9.7 billion by 2050, addressing the escalating food demand necessitates a substantial increase in crop production amidst challenges posed by climate change. Agriculture faces significant hurdles in adapting to shifting climate patterns induced by rising greenhouse gas emissions, particularly affecting farmers in low-income countries. Sustainable intensification through modern cultivation techniques and resilient crop varieties emerges as a crucial strategy to enhance yields while minimizing environmental impact. The evolution from traditional agricultural practices to Agriculture 4.0 integrates cutting-edge technologies like AI, robotics and precision agriculture, revolutionizing field management and supply chain optimization. Ground-based and aerial-based platforms offer distinct advantages and challenges, underscoring the need for adaptive strategies in agricultural phenotyping. In this era of digital agriculture, high-throughput phenotyping emerges as a critical tool in ensuring food security and sustainability amid a changing climate and growing global population.

Keywords: Population, Climate change, Precision agriculture and phenotyping.

Introduction

The human population is expected to reach 9.7 billion by 2050, thus meeting food demand for the growing population will require an increase in crop production between 25% and 70% above the current levels by 2050. Agriculture faces its greatest challenge in adapting to the changing climate induced by rising greenhouse gas emissions, leading to extreme temperatures and adverse weather patterns. The impact of global warming varies across geographical regions, demanding tailored solutions for different agricultural ecosystems worldwide. Farmers in low-income countries are particularly vulnerable due to limited resources and less efficient farming practices. Achieving higher crop yields while minimizing environmental impact requires sustainable intensification through the adoption of modern cultivation techniques and crop management practices. Central to this endeavor is the development of resilient crop varieties suited to diverse environmental conditions and the implementation of automated monitoring systems for assessing plant health. Both objectives necessitate the use of high-throughput field-phenotyping tools. Throughout the evolution of agriculture from its early stages to Agriculture 4.0, advancements have consistently addressed the limitations of agricultural systems.

Agriculture 2.0 introduced mechanical equipment for irrigation, seeding, and harvesting, enhancing efficiency and effectiveness (Abbasi et al.,2022). Precision Agriculture (PA) techniques such as GPS, Satellite Images and Unmanned Aerial Vehicle-based analysis revolutionized field management, enabling intelligent decision-making to maximize production and optimize resource consumption (Bendig et al.,2015). Agriculture 4.0 is paving the way for data-driven agriculture, integrating cutting-edge technologies like Computer Vision, Machine Learning, Deep Learning, IoT and Blockchain. Combining these with traditional agricultural practices facilitates efficient control and management of fields, resource optimization, enhanced output, market-linked production, and modernized supply chains. In this digital and data-centric era, modelling and analyzing plant traits throughout their life cycle are pivotal tasks (Hati et al.,2021, Raman et al., 2024).

High-throughput phenotyping in precision agriculture enhances management practices while minimizing resource usage (Sankaran et al.,2015). Recent advancements in plant phenotyping and precision agriculture, including AI, smart sensors and robotics, offer non-invasive methods for assessing complex plant traits, measuring physiological parameters, diagnosing diseases and predicting yield across different scales (Araus et al.,2018). Comprehensive plant phenotyping considers dynamic interactions between phenotypes and the environment, benefiting farmers and breeders in identifying parameters and selecting desirable genotypes for informed agricultural decisions (Tattaris et al.,2016).

By evaluating complex plant traits such as growth, resistance, physiology and ecology, high-yielding and stress-tolerant crop varieties can adapt to future climate conditions, resist pests and diseases and meet the increasing global demand for food, feed, fiber and chemicals in the coming century.

High-Throughput Field Phenotyping (HTFP) Technique:

High-throughput phenotyping employs diverse imaging platforms whose suitability depends on the operational environment-laboratory, growth chamber, greenhouse, or field. In controlled environments (e.g., greenhouses), imaging is performed either by moving sensors to plants or by transporting plants to fixed imaging stations (conveyor/benchtop systems). These platforms enable precise, repeatable and automated measurement of traits (geometric, structural, color, textural) with minimal environmental interference, but are costly and limited in throughput (Madec et al., 2017 & Yang et al., 2020).

In field conditions, platforms are ground-based (tower/pole, mobile vehicles, gantry, cable-suspended) or aerial-based (UAVs, manned aircraft, satellites) (Babar et al., 2006, Geipel et al., 2014 & Pauli et al., 2016). Ground systems offer high spatial resolution and deployment flexibility but are slower and environmentally sensitive, while aerial platforms provide rapid, large-area coverage with constraints on payload and spatial resolution due to altitude and speed.

Commonly Used Imaging Techniques for High-Throughput Plant Phenotyping:

1. **Visible Light Imaging:** Visible light (RGB) sensors operate in the 400-700 nm range and record reflected red, green and blue signals. Due to their low cost, simplicity and wide availability, RGB imaging is extensively used in high-throughput phenotyping. High-resolution RGB images enable assessment of plant biomass, growth rate, root architecture, germination, yield, disease incidence and abiotic stress responses. However, field applications are constrained by low color contrast between foliage and background and variations in illumination, which can affect automated image analysis.
2. **Thermal Imaging**: Thermal infrared imaging visualizes the spatial distribution of surface temperature by converting emitted infrared radiation into thermal images. Thermal sensors operate in the 3-5 μm or 7-14 μm range, recording temperature values at the pixel level. This technique is effective for assessing plant physiological status under biotic and abiotic stresses, including canopy/leaf temperature, transpiration, stomatal conductance and plant water status. Under water deficit, stomatal closure reduces transpiration and cooling, leading to elevated leaf temperature. Consequently, thermal imaging is a valuable tool for irrigation scheduling and water management in precision agriculture.
3. **Hyperspectral Imaging**: Hyperspectral imaging records both spectral (λ) and spatial (x, y) information at each pixel, forming a 3D hypercube across the 250-2500 nm range (UV, VIS, NIR, SWIR). It provides rich information for extracting diverse phenotypic, physiological and biochemical traits, including nutrient status, disease detection, fruit

maturity/ripening, plant growth and yield estimation. However, its widespread use is constrained by the large data volume and the complexity of storage and analysis.

4. **Fluorescence Imaging:** The light energy absorbed by chlorophyll can be used for photosynthesis, dissipated as heat, or re-emitted. Fluorescence is the light emitted when the plant absorbs radiation of shorter wavelengths, mainly via the chlorophyll complex and is very small are time-consuming and are not suitable when a large number of samples are under consideration. In addition, due to the larger size and heavy weight of the equipment it is not usable on aerial imaging platforms.

Comparison of Imaging Techniques for High-Throughput Plant Phenotyping:

Imaging technique	Phenotyping Traits	Advantages	Limitations	Potential Application
Visible Light Imaging	Shape, color, size, biomass, pigment content, disease and pest, stress responses, nutrient stress & vegetation indices	Cheap, easy operation and maintenance, provide color information, high resolution, fast data acquisition	Limited to three spectral bands (RGB), affected by light, only provide relative measurement	Growth monitoring, plant stress detection, fruit maturity and ripening estimation, yield prediction, 3D modelling, robotic harvesting.
Thermal Imaging	Leaf greenness, leaf chlorophyll content, leaf/canopy temperature, disease and pest, phenology, photosynthetic status	Wide measurement range, background interference can be removed	Requires sensor calibration and atmospheric correction, through-time comparisons are difficult due to variations in ambient conditions.	Plant stress detection, irrigation scheduling
Hyperspectral Imaging	Leaf/canopy water status, leaf greenness, disease and pest, photosynthetic rate, metabolites	High spectral resolution, background interference can be removed	Expensive, low spatial resolution, too large image data challenging for storage and analysis, affected by ambient light condition	Growth monitoring, biotic and abiotic stress detection, biomass estimation, metabolite prediction
Fluorescence Imaging	Chlorophyll content, canopy coverage, disease and pest, photosynthetic status	Sensitive to fluorescence and water stress	Limited in field application, difficult to measure at the canopy scale due to the small signal-to-noise ratio	Growth monitoring, early detection of biotic and abiotic stress
Multispectral Imaging	Canopy coverage and volume, chlorophyll content, plant diseases & pests, water content	Easy in image processing; mature technology	Limited to several spectral bands, effects of camera geometrics, illumination condition, and sun angle on the data signal	Growth monitoring, biotic and abiotic stress detection
LiDAR	Plant height, canopy volume, shoot biomass	Provide three-dimensional shape	Expensive, sensitive to the small difference in path length, specific illumination required for some laser scanning instruments,	Growth monitoring, structure capture

Phenotyping For Precision Agriculture

The concept of precision agriculture emerged in the late 1970s with the development of the Global Positioning System (GPS), which enabled accurate spatial referencing of field locations. It is an integrated, technology-driven approach that uses high-resolution spatial and temporal data to maximize crop productivity while minimizing inputs (Chawade et al., 2019). Key factors optimized under precision agriculture include fertilizer, pesticide and herbicide application, irrigation, disease and weed management and plant density (Narvaez et al., 2017).

Advanced nano sensor-equipped sowing and spraying machinery, along with high-throughput field phenotyping, supports site-specific crop management (Mukherjee et al., 2019). Satellite imagery integrated with weather data enables stress detection (biotic and abiotic), assessment of nutrient and water variability and yield prediction (Patrício et al., 2018). The effectiveness of satellite-based precision agriculture depends on revisit frequency, spatial resolution and spectral bands, as timely decisions are critical (Jones et al., 2007). Decision Support Systems (DSS) combining phenotypic and weather data facilitate early detection and rapid response, making precision agriculture a dynamic, data-driven management strategy. Utility of modern phenotyping tools in precision agriculture can be utilized for:

- **Optimizing Fertilization:** Soil nutrients are spatially heterogeneous, making uniform fertilizer application inefficient, uneconomical and environmentally risky. Optimized fertilization uses variable-rate nutrient application based on soil or crop status to reduce losses and improve efficiency. High-throughput plant phenotyping (HTPP) adopts a crop-centric approach, employing optical sensors to assess in-field nutrient status and guide site-specific fertilizer delivery (Lee et al.,2018). However, discriminating nutrient deficiencies from diseases at the phenotypic level remains challenging, this can be addressed by combining multiple vegetation indices and spectral wavelengths for more accurate diagnosis.

- **Detecting diseases and pests:** Manual field scouting for diseases is labour-intensive and time-consuming. Modern phenotyping tools enable automated early disease detection, functioning as a warning system that supports targeted interventions, reduces crop losses and lowers pesticide use (Li et al., 2022). Disease monitoring is a core component of Integrated Pest Management (IPM) and high-throughput phenotyping can enhance its field-level implementation. Although accurate disease identification remains challenging, advances in image processing, deep learning and machine learning on large datasets have significantly improved simultaneous detection of crops and pests.

- **Detecting Weeds:** Weeds can cause greater yield loss compared to pests and pathogens. At present, spraying of herbicides is commonly used method to combat yield loss. However, due course of time, resistance against herbicides have been fetched by several species of weeds because of excess use of them (Harker et al., 2013). It is inefficient also to spray in whole field with herbicides against a small affected patch of the field (Kumar et al., 2025). Scientists have achieved the higher accuracy in weed detection using modern phenotyping approaches.

- **Decision Support Systems (DSS):** The effectiveness of precision agriculture depends on rapid and accurate analysis of phenotypic data, especially for complex traits. High-quality sensors and platforms alone are insufficient success is fundamentally data-driven, relying on data quality, robust processing and integration of biometrics, statistics, genotype-phenotype relationships and genomic selection. Decision Support Systems (DSS) can combine phenotypic, weather, market and disease data to optimize yield and farm profitability, yet their adoption remains limited (Sarkar et al., 2021). Low uptake is linked to issues of usability, cost, reliability, relevance, trust and farmer-specific factors such as age, education and landholding size (Rose et al., 2016). Examples such as mobile, phenotyping-based applications using deep learning for nutrient stress and disease detection-effective data collection, classification and translation into actionable decisions remain key research challenges.

- **Affordable approaches:** Adoption of modern phenotyping tools requires high initial investment, particularly for testing networks and large-scale deployment. A major challenge is developing affordable, reliable phenotyping technologies that perform consistently across diverse Agro-ecological regions, especially in low- and middle-income countries where labour is relatively inexpensive. For field-based applications, proximal phenotyping using field-deployable vehicles equipped with robust sensors is often more practical and effective than other high-throughput phenotyping approaches.

Conclusion:

Crop improvement is central to enhancing productivity and ensuring global food security. Emerging technologies such as UAVs, advanced sensors, AI and robotics are transforming plant phenotyping and precision agriculture by enabling data-driven, real-time crop monitoring and improved field management. Integrated approaches, rather than single technologies, are essential to address the combined challenges of population growth, climate change, pests, diseases and resource limitations. The key challenge lies in developing affordable, robust, rapid and automated phenotyping methods that effectively feed into Decision Support Systems (DSS) under variable field conditions. Future agriculture will increasingly rely on unmanned, intelligent farming systems, integrating robotics, AI and DSS for monitoring, disease control, and harvesting.

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