# OPTICAL REMOTE SENSING IN PRECISION FIELD PLANT BREEDING. A REVIEW

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***Abstract:*** *Remote sensing in precision plant breeding involves using advanced technologies, such as drones, satellites, and sensors, to collect detailed data on plant traits and environmental conditions. These tools capture information on crop health, growth, stress responses, and other vital parameters through non-destructive methods like multispectral and hyperspectral imaging. This data helps plant breeders make informed decisions on selecting and developing crops with desirable traits, improving breeding efficiency, and accelerating the development of resilient, high-yield varieties tailored to specific environments. The equipment and characteristics of remote sensing used to date, as well as directions for the future development of these studies.*

# ОПТИЧНИ ДИСТАНЦИОННИ МЕТОДИ ЗА НАБЛЮДЕНИЕ ЗА ПОЛЕВА ПРЕЦИЗНА РАСТИТЕЛНА СЕЛЕКЦИЯ. ОБЗОР

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***Ключови думи:*** *Фенотипиране, Феномни признаци, Фенотипни признаци*

***Резюме:*** *Дистанционните методи за наблюдение на Земята в прецизното растително селектиране включва използването на съвременни технологии, като дронове, сателити и сензори, за събиране на подробни данни за растителните характеристики и условията на околната среда. Тези инструменти улавят информация за здравето на културите, растежа, реакциите на стрес и други важни параметри чрез дистанционни методи като мултиспектрални и хиперспектрални изображения. Тези данни помагат на селекционерите да вземат информирани решения при избора и разработването на култури с желани характеристики, като подобряват ефективността на селекцията и ускоряват създаването на устойчиви, високодобивни сортове, пригодени за конкретни условия. Разгледани са оборудването и характеристиките на дистанционното наблюдение, които са използвани до сега, както и насоките за бъдещото развитие на тези изследвания.*

## Introduction

Humanity faces an unparalleled challenge to meet the coming decades' growing food demands, population growth, rising per capita consumption, shifting climate conditions, limited arable land, and increasing pressure on water and resources. To boost crop productivity, one key strategy is enhancing crop genetics for greater efficiency and resilience [1].

Plant phenotypic traits are the observable characteristics of an organism, such as its appearance, behaviour, or physiology. They directly result from the interaction between an organism's genetic makeup (genotype) and its environment. [2]. The selection of cultivars is increasingly dependent on yield-related indicators, chosen either directly or through marker-assisted selection once the quantitative trait loci (QTLs) responsible for the trait's variability have been identified [3]. While genotyping technologies have advanced rapidly, phenotyping technologies have lagged [1, 3, 4]. Plant phenotyping is a transdisciplinary field of research that employs non-invasive imaging and sensor-based time-series data, frequently integrated with high-throughput measurements, to study plant anatomy, physiology, and biochemistry [4]. Phenomic traits are a subset of phenotypic traits measured using high-throughput technologies, often quantitative and automated. They emphasise the systematic and large-scale measurement of phenotypes.

In recent decades, plant phenotyping has rapidly evolved, creating numerous opportunities to address agriculture's increasing and diverse demands. However, research in remote sensing for plant phenotyping is primarily concentrated within the EU, with countries like Germany, France, and the United Kingdom leading the way [5]. In Bulgaria, this field remains relatively new and is still in early development [6–8]. The progress in phenotyping must continue in tandem with the integration of innovative technologies, data standardisation [9–11], and multidisciplinary research efforts [2, 5, 9].

In field crops, grain yield is the most critical phenotypic trait for breeders, as it serves as a comprehensive indicator that reflects the combined influence of key characteristics and genes, making it biologically and economically significant. Beyond yield, there is a range of secondary traits that, while theoretical in some instances, have been demonstrated to contribute to overall crop performance in several cases [12].

To accurately capture these traits, remote sensing phenotyping has developed techniques that offer a top-of-canopy perspective, enabling accurate assessments of visible plant organs known as aboveground traits. However, this approach has clear limitations when assessing roots, lower leaves, or fruits obscured from the sensor's view.

Aboveground phenomic traits include plant development and biophysical and biochemical properties, photosynthetic efficiency in utilising solar energy during the primary growth phase, plant phenology, plant stress evaluation, and yield and quality assessment.

Selecting root phenomic traits for crop improvement is more challenging than aboveground traits because roots cannot be directly observed through remote sensing technologies. However, using remote sensing, root traits can still be characterized by analyzing how root processes influence crop productivity under specific field conditions. Moreover, targeted physiological approaches can help identify proxy traits that serve as indicators of root function, aiding in the selection and improvement of root-related traits [13].

Phenotyping efforts are often focused on specific critical stages of plant development, but there is growing anticipation that field phenotyping will evolve toward continuous, whole-season monitoring. This approach would enable the identification of critical time windows in crop growth and provide a deeper understanding of interactions between genetics, environment, and management practices (G×E×M) [13].

This review explores current efforts, offers insights, and highlights potential research directions for utilising optical remote sensing in field-based plant phenotyping. The focus is on vital phenotyping tasks, particularly those related to plant stress and growth.

This review mainly concentrates on studies that meet the following criteria: (1) published in peer-reviewed or open-reviewed journals and conferences; (2) published within the past seven years (2018 to 2024); and (3) focused on the application of optical remote sensing for field plant phenotyping. The literature was sourced primarily from Google Scholar, using keyword combinations such as "phenotyping plant review" for the search.

## Aboveground phenotypic traits

Unmanned aerial vehicles (UAVs) are among the most widely used tools in field phenotyping due to their relatively low cost and ability to capture high-resolution images with fine temporal and spatial detail. UAVs equipped with RGB, multispectral, or hyperspectral cameras have been utilised to capture a wide range of phenotypic traits, including geometry-related (canopy height, LAI, biomass, plant density); physiological (chlorophyll and other pigments); stress detection (weed, water, disease); and nutrition status [14,15].

Numerous studies have explored the application of imaging sensors and artificial intelligence (AI) in detecting plant stress [16–19]. AI refers to systems that mimic human intelligence, allowing machines to engage in tasks such as reasoning, learning, perception, and decision-making [20]. AI encompasses various subfields, including machine learning (ML), deep learning (DL), natural language processing, and computer vision. Although AI has only recently been applied to plant stress detection, its adoption has accelerated rapidly since 2019. However, much of the research focuses on biotic stress, as it is easier to detect due to the visible symptoms, such as necrotic and chlorotic lesions caused by disease. This emphasis is likely due to the widespread use of RGB sensors, particularly suited to capturing these visual cues. Deep learning is currently the most popular AI methods, followed by machine learning algorithms like support vector machines (SVM), artificial neural networks (ANN), and random forests.

Hyperspectral data with nonparametric models is mainly used in plant stress phenotyping [18], such as disease severity assessment [6]. A notable development is the custom-supervised 3D

Convolutional Neural Network architecture, designed to directly process spatial and spectral information within hypercubes using 3D convolutional operations. This neural network was recently applied in research to detect plant diseases from hyperspectral images, demonstrating its potential in plant phenotyping [21].

The rapid advancement of smartphones with high-resolution RGB cameras and powerful computing capabilities has created highly versatile applications. Building on this progress, the development of next-generation portable or wearable phenotyping tools has the potential to be a disruptive technology, dramatically transforming and accelerating the phenotyping process [9].

High-resolution optical satellite imagery has also been employed for field phenotyping, offering valuable data on crop traits at both spatial and temporal scales [22]. However, the high cost of such imagery remains a significant barrier to its widespread, practical application.

**Root system phenotyping**

Roots are vital organs responsible for regulating water and nutrient uptake in crops, playing a pivotal role in drought tolerance and significantly influencing both yield and quality. However, since roots function below ground, direct observation is challenging. While significant progress has been made in controlled root phenotyping studies [9]Translating these findings to real-world field conditions remains uncertain.

In the field, direct root evaluation, or in-situ root phenotyping, is not feasible with traditional optical remote sensing techniques [13,23,24]. Nonetheless, indirect indicators, or proxies, offer a valuable alternative. Canopy temperature (CT), for example, can serve as a reliable proxy for assessing root capacity under hot and dry conditions [25]. Cooler canopy temperatures suggest a more extensive, more efficient root system, as greater root mass allows for better water uptake, enabling crops to maintain cooler canopies under drought and heat stress [24].

**Data standardisation, uncertainty analysis and propagation**

Phenotyping technologies generate large volumes of diverse data from remote sensing, imaging, and sensor-based platforms. Standardisation ensures that this data can be effectively compared, shared, and utilised across studies and platforms [26].

Standardising phenomic data involves establishing common protocols and formats for data collection, processing, and reporting. This allows for consistency across experiments and makes data more reusable in larger multi-omics and multi-site research efforts. It includes standardising units of measurement, trait definitions, data storage formats, and metadata documentation. Without these standards, it becomes difficult to integrate phenotypic data into larger datasets for comparative studies, limiting the potential of high-throughput phenotyping technologies.

Uncertainty analysis in phenotyping quantifies potential errors or variations in data collection and interpretation. Variability can arise due to differences in environmental conditions, measurement technologies, or biological factors. By identifying and understanding these uncertainties, researchers can improve the reliability and accuracy of their phenotypic assessments. This analysis is fundamental when correlating phenotypes with genotypes, where even minor inaccuracies can lead to incorrect conclusions about genetic traits.

Propagation of uncertainty refers to how uncertainties in individual measurements or variables can affect the overall outcome of phenotypic analysis. As phenotypic data moves through various stages—from collection to analysis and finally to decision-making in breeding programs—errors can compound, leading to significant deviations from true values. Effective uncertainty propagation analysis helps researchers model how these errors accumulate and can provide insights into which variables are most prone to uncertainty. Addressing these issues early in the data processing pipeline helps ensure the accuracy of downstream analyses, such as genomic prediction and trait selection.

**Multidisciplinary research**

Remote sensing has become a key technology in phenotyping, especially for extracting traits related to genomic data. The integration of remote sensing techniques with genomic prediction models has the potential to revolutionise plant breeding and crop improvement strategies. However, a multidisciplinary approach is still necessary [2,5] to fully realise its benefits, requiring collaboration across fields such as genetics, agronomy, data science, and engineering.

In Bulgaria, this collaborative effort began with the launch of the “National Research Programme-Smart Crop Production” funded by the Bulgarian Ministry of Education and Science, approved by the Decision of the Ministry Council №866/26.11.2020 г. At a European level, the Cost Action PANGEOS CA22136 (www.pangeos.eu, last visited 17.10.2024) aims to convene leading experts in remote sensing technologies, young researchers and innovators, government, nonprofits, and other stakeholders from European and neighbouring counties to establish best practices and calibration protocols, improve the scalability and repeatability of each technology and application across European environmental conditions, and explore new innovative advancements beyond the state-of-the-art in field phenotyping with focus on sensor synergies for biophysical trait retrievals.

## Conclusion

Plant phenotyping efforts are focused on discovering new complex traits, identifying heritable diversity through high-throughput selection, and producing reusable data sets. While technological advancements are progressing quickly, further contributions from academia and industry are required to develop robust methodologies, advance technologies, establish protocols, and integrate data more effectively.

Although much of the focus remains on aboveground traits, noninvasive field phenotyping is evolving into a reliable, accessible tool that helps scientists and breeders analyse crop characteristics and improve traits in diverse and dynamic field environments.

Root phenotyping advances rapidly, deepening our understanding of essential traits in controlled environments. Notable progress has also been made in extending root phenotyping to field conditions, mainly by integrating root structure-function models and alternative remote sensing techniques beyond optical methods. For instance, thermal remote sensing has shown promise and can be seamlessly incorporated into field experiments, offering valuable insights into root function and its impact on crop performance.

Standardised data collection and analysis methods and a robust understanding of uncertainty and its propagation are key to ensuring that phenotyping remains a reliable and valuable tool in advancing plant breeding.

A multidisciplinary effort remains essential for advancing phenotyping and linking it to genotyping. Bridging the gap between the two requires collaboration across multiple disciplines, including genetics, agronomy, data science, engineering, and bioinformatics.

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