Near-Ground Remote Sensing Technology for Field Crop Plant Height Measurement: Research Status and Prospects (Postprint)

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Date: 2023-02-17T00:00:00+00:00

Abstract

Plant height serves as a key indicator for dynamically assessing crop health and overall growth status, and is widely utilized for estimating crop biological yield and final grain yield. Traditional manual measurement approaches suffer from limitations including small scale, low efficiency, and time-intensive operations. Over the past decade, near-ground remote sensing technology has advanced rapidly in agriculture, enabling the high-precision, high-frequency, and high-efficiency acquisition of crop plant height. This paper first reviews the publication status of domestic and international research on plant height retrieval via remote sensing methods; subsequently, it introduces and evaluates the fundamental principles, advantages, and limitations of various platforms and sensors for plant height acquisition, with particular emphasis on the height measurement workflows and key technologies associated with LiDAR and visible light camera sensors; based on this foundation, it summarizes research progress in the application of plant height to crop biomass estimation, lodging monitoring, yield prediction, and breeding assistance; finally, it discusses and analyzes existing challenges in near-ground remote sensing for plant height acquisition, and presents future prospects from four perspectives: measurement platforms and sensors, bare soil detection and interpolation algorithms, plant height application research, and differences between agronomic and remote sensing-based height measurement, thereby providing references for future research and methodological applications in near-ground remote sensing plant height measurement.

Full Text

Preamble

Research Status and Prospect on Height Estimation of Field Crop Using Near-Field Remote Sensing Technology

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Abstract: Plant height is a key indicator for dynamically assessing crop health and overall growth status, widely used to estimate biological yield and final grain yield. Traditional manual measurement methods suffer from limited scale, low efficiency, and time-consuming procedures. Over the past decade, near-field remote sensing technology has developed rapidly in agriculture, enabling high-precision, high-frequency, and high-efficiency collection of crop height data. This paper first reviews publication trends of research on plant height acquisition using remote sensing methods. Second, it introduces and evaluates the basic principles, advantages, and limitations of different platforms and sensors for obtaining plant height, with emphasis on the height measurement processes and key technologies involved in LiDAR and visible-light camera sensors. Based on this foundation, the paper summarizes research progress in applying plant height data to crop biomass estimation, lodging monitoring, yield prediction, and breeding assistance. Finally, it discusses existing problems and challenges in near-field remote sensing for plant height acquisition, and provides future prospects from four perspectives: measurement platforms and sensors, bare soil detection and interpolation algorithms, plant height application research, and differences between agronomic and remote sensing height measurement. This work can provide references for future research and methodological applications in near-field remote sensing-based height measurement.

Keywords: plant height; near-field remote sensing; crop; unmanned aerial vehicle; visible-light camera; LiDAR

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1 Introduction

Plant height is a crucial growth indicator in crops, and appropriate plant height is fundamental for achieving stable and high yields. During the first Green Revolution, semi-dwarf wheat and rice varieties were developed that reduced plant height while improving lodging resistance and yield potential [?, ?]. However, excessively short plant height can also pose yield reduction risks [?], highlighting the importance of studying the genetic mechanisms of plant height and developing targeted breeding programs for crop improvement. Additionally, plant height is closely related to crop biomass and yield [?, ?], and monitoring height changes can determine crop health and growth status, providing valuable guidance for crop production management activities such as fertilization, weed control, and harvest.

In agronomy, plant height is typically measured manually using rulers, including three methods: natural height, physiological height, and leaf-collar height [?]. The most common approach measures the vertical distance from ground level to the top of the main stem in its natural state. Due to environmental, genotypic, and management factors, crop morphology varies significantly. For example, in upright crops like wheat, upper leaves may droop [?], requiring researchers to either extend the leaves or select erect plants to measure the vertical distance from base to top as physiological height. Leaf-collar height, measuring the distance from ground to the uppermost leaf collar, is also widely used. However, manual measurement requires extensive field surveys, suffers from low efficiency, and is subject to subjective errors. Sampling-based height data cannot represent entire field conditions.

The development of remote sensing technology provides a new solution for crop height measurement research and applications. This paper aims to comprehensively review crop height extraction studies based on remote sensing methods, summarize height acquisition methods and their limitations across different sensor types and platforms, consolidate research progress in applying plant height to phenotypic trait extraction, lodging monitoring, yield estimation, and breeding, and discuss future development trends and challenges of near-field remote sensing technology in crop height acquisition.

2 Global Research Trends in Remote Sensing-Based Height Measurement

To understand research progress in remote sensing-based height measurement and summarize mainstream sensors, platforms, and key observation targets, we searched the Web of Science and ScienceDirect platforms for academic papers published globally from 2010 to 2019. The search keywords were: "canopy or crop or plant or vegetation or wheat or maize or corn or rice or barley or soybean or sorghum or rapeseed" and "height or lodging or biomass or yield or lai" .

The results are shown in Figure 1. Figure 1(a) shows the number of articles using four main methods: UAV platform with visible-light camera, LiDAR (Light Detection and Ranging), synthetic aperture radar, and ultrasonic sensors, plus other methods. The overall trend shows increasing publication numbers. Due to rapid development of low-altitude remote sensing and computer vision methods, UAV platforms with visible-light cameras have become the most common approach for crop height acquisition, followed by LiDAR. Figure 1(b) indicates that most crop height studies focus on staple food crops such as wheat, maize, and rice. Moreover, crop height measurement primarily relies on near-field remote sensing platforms including ground-based and UAV systems (Figure 1(c)), which are more suitable for crops with short stature and dense planting structures.

3 Research Progress in Near-Field Remote Sensing for Height Measurement

Near-field remote sensing height measurement technologies can be divided into active and passive remote sensing based on sensor operation principles. Active remote sensing sensors emit electromagnetic or acoustic signals and receive reflected signals from targets, making them less affected by lighting conditions and capable of day-and-night operation. Passive remote sensing sensors directly receive and record electromagnetic waves reflected from natural radiation sources or emitted by targets themselves. These sensors typically have lower cost but are more susceptible to lighting conditions and lack penetration capability.

3.1 Active Remote Sensing and Its Characteristics

LiDAR accurately locates laser spots on objects by recording the Time of Flight (ToF) of laser pulses. Due to its strong penetration capability, multiple echo reflections from pulses can simultaneously record canopy and soil point cloud information, from which object height can be derived through classification and filtering. In the 1990s, LiDAR systems mounted on helicopters or fixed-wing aircraft developed rapidly for forest resource inventory and topographic mapping. In recent years, lightweight LiDAR development has enabled UAV-based crop height measurement as a research hotspot.

4 Applications of Near-Field Remote Sensing Height Measurement in Agriculture

Plant height data obtained non-destructively and with high precision through remote sensing are commonly used as model variables for crop physiological and biochemical parameter inversion, lodging identification, yield prediction, and breeding applications (Table 1).

4.1 Biomass Estimation

Current research primarily uses plant height or spectral indices combined with canopy coverage to estimate above-ground biomass through various modeling approaches including linear regression [?, ?], exponential regression [?, ?, ?], partial least squares regression [?], random forest [?, ?], and support vector machines [?]. Additionally, constructing crop volume models by accumulating plant height over specified areas can achieve accurate biomass predictions [?, ?]. Compared with spectral indices, morphological indicators are less affected by lighting conditions, and spectral indices tend to saturate during late growth stages [?], making biomass calculations based on plant height more accurate and stable.

4.2 Lodging Monitoring

Lodging refers to permanent displacement of crop upright parts [?], and lodging resistance is an important genetic trait and breeding selection criterion [?]. Lodging area and severity can be determined by extracting spectral features, texture information, or height changes before and after lodging [?, ?]. Singh et al. [?] subtracted post-lodging DSM from pre-lodging DSM to obtain differential DSM and extracted mean elevation values for each plot, showing correlation coefficients between 0.77 and 0.93 with manually scored lodging incidence, severity, and lodging index. Su et al. [?] used gray-level co-occurrence matrices to extract texture features from visible images before and after maize lodging, and also obtained lodging area through DSM differencing, with estimation errors of 10.00% and 0.85% respectively. These results demonstrate that plant height measurements are more accurate than texture indices for determining lodging degree and area.

4.3 Yield Prediction

Plant height is also an important indicator for yield prediction. Li et al. [?] used UAV-mounted visible-light and multispectral sensors to extract plant height and various vegetation indices for wheat yield prediction, finding that plant height at the grain-filling stage ranked first in importance scores for both Lasso and random forest models. Generally, yield estimation models using plant height achieve higher accuracy when approaching harvest time [?, ?].

4.4 Breeding Assistance

Plant height is a quantitative trait controlled by multiple genes [?] that is easily affected by environment, genotype, and their interactions. Studying height variation characteristics can improve understanding of crop growth genetic mechanisms [?, ?, ?]. Hassan et al. [?] performed genome-wide and Quantitative Trait Locus (QTL) mapping for plant height traits, finding that genomic values predicted from UAV-estimated wheat height correlated with actual values between 0.47 and 0.53, showing similar genomic prediction capability compared with ground measurements. Increasingly, studies are using remote sensing to obtain crop height for breeding [?], demonstrating that remote sensing can acquire high-frequency, high-precision, repeatable continuous canopy height distribution data that are important for crop breeding [?].

In summary, empirical statistical regression methods are predominantly used in agricultural applications of near-field remote sensing height measurement due to low technical barriers, few inversion parameters, and simple yet effective implementation (Table 1). However, these models require extensive measured data for inversion and lack clear physical meaning. Some applications use machine learning models based on plant height traits to optimize crop growth parameter inversion, but separate models are generally needed to adapt to different crop varieties, growth stages, and environments. Yu et al. [?] attempted to couple sugarcane plant height traits with hydrological models to construct a new data assimilation system that improved yield estimation accuracy for gramineous crops. Assimilating plant height data into crop models can improve trait inversion accuracy and enable spatiotemporal model expansion. Therefore, future research should integrate plant height into crop models to improve growth parameter inversion accuracy and address the weak universality and poor stability of empirical and traditional machine learning models.

5 Discussion and Outlook

5.1 Balancing Height Measurement Accuracy and Cost

UAV platforms with visible-light cameras can optimize height measurement accuracy using various spatial auxiliary data including DTM, DSM, Ground Control Points (GCP), and ground-measured plant height data. Different fields such as scientific research and agricultural production make trade-offs between these data types to meet accuracy and cost requirements. Xie et al. [?] systematically evaluated the height measurement accuracy and cost of UAV visible-light cameras under various spatial auxiliary data combinations. Building upon their discussion, this study uses coefficient of determination (R^2) and root mean square error (RMSE) as accuracy metrics, and labor, time, and operational costs as cost metrics to evaluate height measurement results under different combinations of DTM, GCP, plant height measurements, and canopy density (Table 2).

Category 1, which collects both DTM and GCP data, achieves high-precision plant height measurement when combined with DSM. Adding ground-measured data to build linear regression models can effectively reduce absolute height error. Using complete spatial auxiliary data increases data collection costs but is necessary for precise plant height extraction. For example, gene mapping of plant height traits has important theoretical and application value for crop breeding [?], requiring breeders to collect complete spatial auxiliary data to achieve high-precision estimation of plant height changes throughout the entire growth period [?].

DTM data are typically collected before crop emergence or after harvest to avoid soil occlusion by crops. However, when crop canopies are sparse, bare soil elevation can be extracted from DSM as the base, reducing data collection costs while achieving accuracy similar to complete data conditions (see Section 3.3.2). When crop canopies are closed and terrain is undulating, accurate DTM construction through bare soil interpolation becomes difficult, making separate DTM data collection necessary.

GCP deployment is challenging to implement in rugged terrain, scattered areas, or fields with irrigation systems [?]. GCP spatial positions require Real-Time Kinematic (RTK) instruments, whose signal strength is susceptible to environmental influences such as high-voltage power lines, transformers, or terrain. From an agricultural production perspective, GCP deployment and position collection are difficult and costly. When GCP field deployment is impractical, extracting GCPs directly from images can help with multi-temporal data registration, though measurement accuracy is typically lower than with complete data.

Table 2 provides a dual-perspective evaluation from both accuracy requirements and data acquisition costs, offering references for developing crop height measurement schemes in scientific research and practical agriculture to reasonably select spatial auxiliary data while ensuring accuracy.

5.2 Fine Height Measurement with UAV Remote Sensing Platforms

Low-altitude UAV passive remote sensing constructs three-dimensional models through imaging to obtain field crop height. For crops with upright and narrow leaves such as maize, rice, and wheat, especially at the ear or leaf tip, height information extraction is difficult and prone to underestimation. Liu et al. [?] used Mavic Pro2 to collect images and construct canopy 3D point clouds for direct height measurement at 5 m flight altitude, but still could not recover complete ear structures.

Deriving crop elevation from visible-light images is an indirect height measurement method, whereas LiDAR provides direct measurement through point cloud data, typically achieving higher accuracy than visible-light methods [?, ?]. Currently, some lightweight LiDAR systems have been mounted on UAVs for preliminary crop height measurement studies (Table 3), with weights below 4 kg and measurement accuracies of 0.5–5 cm. However, Table 3 shows that good measurement accuracy is only achieved at low altitudes (below 20 m), with R^2 values below 0.8 for most other crop height measurement results. Moreover, these LiDAR systems have not solved the high-cost problem, which is a major factor limiting the development of UAV-LiDAR systems in agriculture.

In October 2020, DJI released the "Zenmuse L1" system integrating the low-cost, lightweight Livox LiDAR AVIA. Hu et al. [?] evaluated the same brand' s MID 40 for forest resource inventory, obtaining point cloud densities greater than 464 pts/m^2 at 100 m flight altitude for accurate calculation of tree height, canopy cover, and gap fraction. AVIA has a larger Field of View (FOV) and higher point cloud data rate than MID 40, improving data collection efficiency and density, though no studies have yet applied it to field crop phenotyping. The high cost of LiDAR systems and insufficient performance in point cloud density and ranging accuracy for precise field crop phenotyping remain urgent problems in remote sensing-based height measurement.

5.3 Differences Between Remote Sensing and Agronomic Height Measurement

Crop morphology changes due to cultivation practices, environment, and variety. Agronomic plant height measurement typically excludes awns in gramineous crops and tendrils in leguminous crops [?]. However, remote sensing height measurement generally captures the vertical distance from ground to the top of all plant structures under natural field conditions, resulting in differences from agronomic measurements. For clarity, we use "natural plant height" and "plant length" to represent heights measured by remote sensing and agronomy, respectively (Figure 5). For example, cultivation practices affect wheat plant architecture, which can be classified as "upright" or "drooping" based on flag leaf morphology [?]. Remote sensing methods can underestimate the true plant length of "drooping"types, while natural plant height can assist lodging area identification but cannot provide true plant length after lodging. Similarly, remote sensing includes awns in height calculation, which may affect yield estimation applications.

Remote sensing height measurement requires targeted measurement schemes based on agricultural application needs. When natural plant height differs from true plant length, multi-sensor collaboration can be attempted. For example, using visible-light cameras to obtain texture images for identifying plant main structures, then using LiDAR for skeleton extraction, with segmented height measurement for bent parts. Multi-camera oblique photogrammetry can obtain rich texture information [?, ?], and establishing 3D crop models may provide solutions for measuring plant length in inclined states.

5.4 Future Research Directions

Over the past decade, near-field remote sensing technology has been widely applied in field crop height measurement research, enabling synchronous monitoring of large areas and acquisition of high-precision, repeatable crop height data. Considering remaining challenges, future research should focus on four main aspects:

1. **Platforms and Sensors**: As UAVs are the primary platform for crop height acquisition, payload capacity and endurance need improvement, while height measurement sensors should develop toward lightweight, low-cost designs for efficient large-area observation.

2. **Bare Soil Detection and Interpolation**: Passive sensors cannot penetrate crop canopies, requiring either a separate flight mission to collect bare ground elevation or DTM extraction from DSM through soil interpolation. The former increases data collection costs, while the latter performs poorly with limited bare soil. Therefore, bare soil detection algorithms and interpolation methods need improvement to enable accurate bare soil interpolation with small sample sizes and precise detection in complex field environments, thereby improving data collection efficiency and measurement accuracy.

3. **Plant Height Application Research**: Plant height has broad agricultural applications. On one hand, it can be used to estimate various crop growth parameters, but current inversion methods primarily rely on empirical statistics and traditional machine learning, requiring exploration of universal models for different crops, growth stages, and environments.

On the other hand, strengthening integration between remote sensing and genetic breeding research can provide high-throughput plant height data for studying height genetic mechanisms, breaking through data acquisition bottlenecks and advancing field crop breeding for improved grain yield and quality.

4. **Agronomic vs. Remote Sensing Differences**: There are differences between remote sensing and agronomic height measurement methods. Research on crop height extraction methods should be conducted based on crop structural characteristics and scientific questions to meet research and practical application needs.

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Note: Figure translations are in progress. See original paper for figures.