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Review Article

A review of unmanned aerial vehicle based remote sensing and machine learning for cotton crop growth monitoring

Nueraili Aierken [a,b], Bo Yang [a], Yongke Li [b], Pingan Jiang [b], Gang Pan [a], Shijian Li [a,*]

[a] *College of Computer Science and Technology, Zhejiang University, Zheda Road No.38, 310007 Hangzhou, China*
[b] *College of Computer and Information Engineering, Xinjiang Agriculture University, Nongda donglu No.311, 830052 Urumqi, China*

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ABSTRACT

Cotton is one of the world's most economically significant crops. Evaluating and monitoring cotton crop growth play vital roles in precision agriculture. Unmanned aerial vehicle (UAV) based remote sensing, when integrated with machine learning technologies, exhibits considerable promise for crop growth management. Despite these technologies' substantial impact on cotton production, there exists a scarcity of consolidated information regarding various methods used. This paper offers a comprehensive review and analysis focused on methods for monitoring and evaluating cotton growth using UAV-based imagery combined with machine learning techniques. We synthesize the existing research from the past decade within this context, particularly discussing data acquisition strategies, preprocessing methods necessary for handling UAV-acquired images effectively, and a range of machine learning models applied. This investigation offers a comprehensive outlook that could guide future research efforts towards more efficient and sustainable agricultural practices in cotton production, leveraging state-of-the-art technology.

1. Introduction

Precision agriculture requires the acquisition of precise and timely data regarding soil and plant conditions, followed by the implementation of targeted interventions to enhance agricultural productivity while also safeguarding the environment. Evaluating and monitoring crop growth is a crucial aspect of precision agriculture, particularly in cotton production (Haboudane et al., 2002; Li and Chen, 2011). Crop growth, which refers to the growth condition and trend of crops, is often assessed using phenotypic indicators such as plant height, leaf area index, leaf nitrogen accumulation, biomass, and soil moisture (Liu et al., 2018). The rapid and comprehensive acquisition of information from cotton fields is critical for effective crop and water management, as well as for accurate pesticide applications (Maes and Steppe, 2019). Moreover, gaining in-depth insight into cotton plant growth and development can help stakeholders to make informed agricultural decisions, which are essential for producers aiming to cultivate high-yielding and high-quality crops. Therefore, research on different growth stages of cotton has significant theoretical and practical value for enhancing cotton productivity.

Remote sensing (RS) technology, capable of gathering data from different platforms, is a valuable tool for precision management in cotton production. RS technology has been adopted by numerous countries and international organizations due to its ability to provide timely, dynamic, and largescale monitoring. It has become an essential component of precision agriculture, facilitating the optimization of crop production and management (Ma et al., 2022). Unmanned aerial vehicles (UAVs) have increasingly been employed to acquire remote sensing data for crop growth monitoring, capitalizing on their ability to capture high-resolution images quickly and repeatedly at low cost (Radoglou-Grammatikis et al., 2020; Hafeez et al., 2023), particularly at regional, farm and field levels.

Machine learning (ML) is a branch of artificial intelligence (AI) that focuses on developing algorithms and statistical models. It involves using data to identify patterns and make decisions with minimal human intervention. ML approaches are flexible and find their applications in numerous fields, including agriculture (Rodriguez-Sanchez et al., 2022; Xia et al., 2019; Xu et al., 2021). Although the application of ML in agriculture is still in its early stages, it is already demonstrating significant potential. In recent years, numerous studies have utilized high-resolution images taken from UAVs and ML techniques for various purposes, including stand counting (Oh et al., 2020; Lin and Guo, 2021),

* Corresponding author.
E-mail address: shijianli@zju.edu.cn (S. Li).

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disease detection (Thomasson et al., 2018; Xavier et al., 2019; Wang et al., 2020b; Wang et al., 2020 e), weed management (Sapkota et al., 2020; Genze et al., 2022) and yield estimation (Feng et al., 2020c; Xu et al., 2021; Li et al., 2022a; Rodriguez-Sanchez et al., 2022) in cotton production. Xia et al. (2019) utilized support vector machine (SVM) and maximum likelihood classification methods to identify cotton plants from UAV-captured RGB images, the germination rate was then calculated from the count of cotton plants versus sown seeds. Convolutional neural networks (CNNs) are being used for yield estimation and disease classification from images across various plants. Several CNN and traditional ML approaches have been compared to identify lesions on cotton leaves (Caldeira et al., 2021). The proposed CNN approaches leverage deep learning for screening cotton leaves, which can aid in monitoring cotton health and making informed management decisions. Moreover, deep learning techniques are increasingly applied to extract hierarchical features from UAV images in the agriculture sector (Bah et al., 2018; Wang et al., 2022). Feng et al. (2020a) evaluated cotton emergence using UAV imagery and a pre-trained deep learning model, resnet18, and developed a method for near real-time image processing.

Several existing reviews primarily focus on the application of UAVs in cotton production. Huang et al. (2016) assessed low-altitude remote sensing systems developed to detect crop stress caused by various factors, showcased their applications, and discussed the use of UAVs for crop sensing. Velusamy et al. (2022) emphasized the importance of UAVs in precision agriculture by comparing different types and their technical specifications, while also examining their contributions to precision pest management. Plant counting is a fundamental task during the early stages of cotton growth. Pathak et al. (2022) investigated the evolution of plant stand counting methods in row crops, identified research gaps, and provided suggestions for future work. Herr et al. (2023) discussed the use of unmanned ariel system (UAS) technology for phenotyping four staple crops, addressing four topics per crop and highlighting the efficiency gains in trait measurement and breeding.

Based on the author's findings, there is a notable gap in the literature: no existing review focuses on methods for monitoring and evaluating cotton growth using UAV-based imagery and machine learning, despite their substantial impact on cotton production. This review study aims to address that gap by providing a comprehensive overview of the topic. It will conduct a systematic literature review using two of the most widely used academic databases to identify relevant articles published within the past decade. Rather than comparing methods or endorsing a single optimal approach, this study offers a broad perspective on the

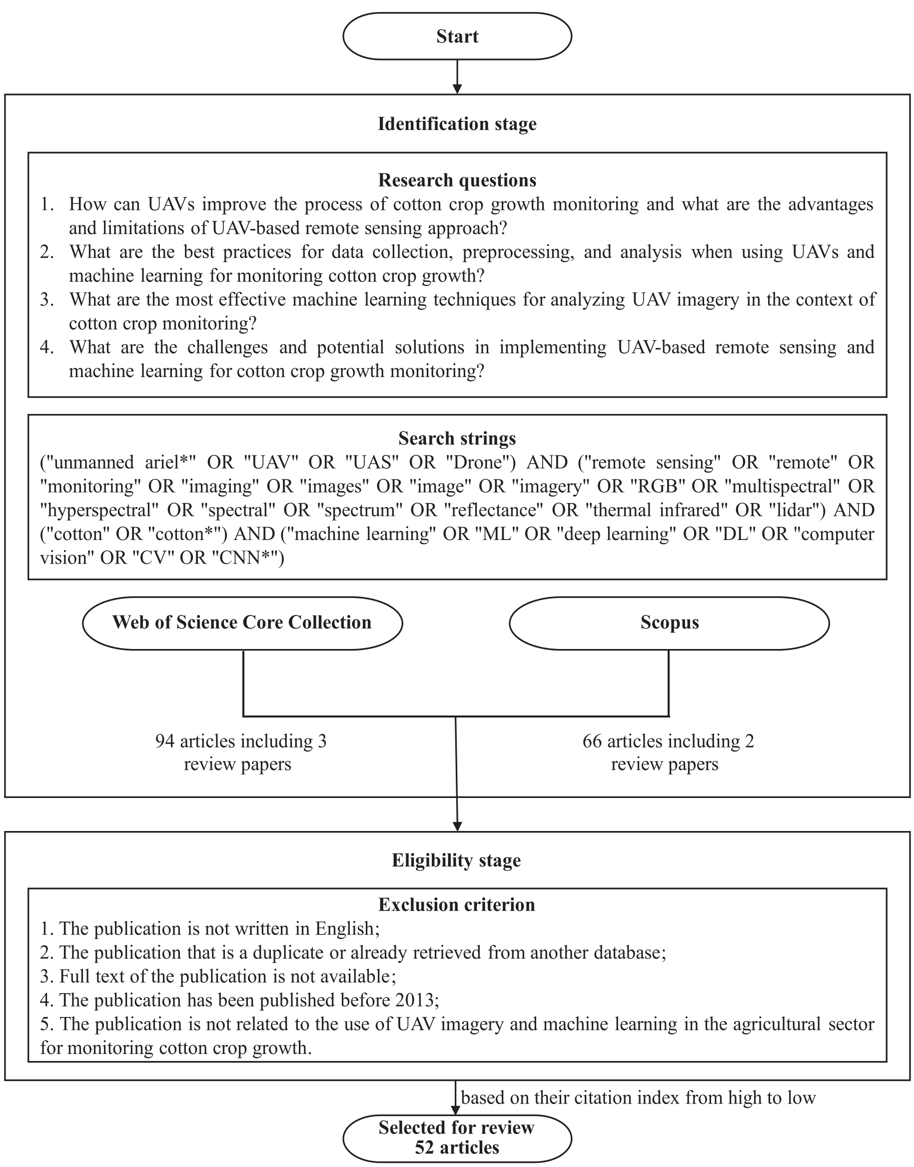

Fig. 1. Process of selecting the pre-reviewed articles.

capabilities of UAV-based remote sensing and machine learning technologies for monitoring cotton crops. Additionally, it directs readers toward more detailed reviews or articles as necessary.

The remainder of this paper is structured into three sections. The first section describes the methodology and materials used in the literature review. The second section presents the results of the literature search while discussing the research questions, including the use of UAVs for monitoring cotton crop growth, data acquisition and preprocessing, and the machine learning approaches applied to UAV-collected data. The final section offers the conclusions. This work seeks to provide researchers with a comprehensive understanding of the current state of the art by systematically reviewing the subject, synthesizing information on the methods, identifying research gaps, and offering valuable insights to stakeholders.

2. Review methodology

This section outlines the methodology employed for the systematic literature review and presents the outcomes of the literature search. The bibliographic analysis follows a two-step process. The first step involves defining research questions and collecting related works, as well as evaluating and selecting articles for the review, as illustrated in Fig. 1. This process includes identifying research questions, selecting databases, and determining keywords, followed by establishing eligibility based on five criteria. The second step entails a detailed analysis and discussions of these works, during which we aim to provide answers to the research questions defined in the first step.

In the identification stage, we conducted a literature search on cotton growth monitoring using UAV-based remote sensing and machine learning techniques via two major databases: Web of Science Core Collection and Scopus. We accessed the databases through an institutional subscription, focusing on articles published between 2013 and December 2023, a decade representing significant research in this area. The results, shown in Fig. 2, indicate a recent increase in publications on this topic.

During the eligibility stage, the initial 160 articles were assessed against exclusion criteria, leading to the removal of 78 papers, while four review articles were analyzed in the introduction. The remaining papers were examined for their analysis methods, categorized into four groups: machine learning approaches, remote sensing analytics, statistical modeling, and time-series analysis. These methods are crucial for extracting insights from raw data and are often used together to enhance understanding of crop growth conditions. Table 1 summarizes these methods and their corresponding publication counts.

In our assessment, we counted publications that solely used machine learning or combined it with other methods under machine learning approaches, acknowledging that this may overlook some less prominent areas. However, we believe this approach provides valuable insights. After applying criterion five and reflecting on the research questions, we selected 52 articles for detailed review and analysis. Detailed reference

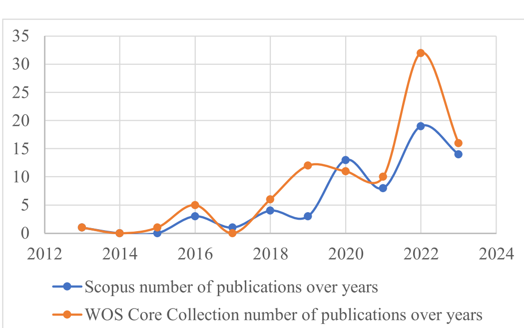

Fig. 2. Literature search result showing the number of peer-reviewed articles published from the year 2013 to December 2023 after identification stage.

Table 1
The scope of the analysis methods and number of publications.

Analysis methods	Scope	Number of Publications
Machine learning approaches	Conventional ML-based supervised or unsupervised learning, and DL-based methods. The method will be discussed in section 3.2 in detail.	52
Remote sensing analytics	Vegetation indices analysis utilizes indices like Normalized Difference Vegetation Index (NDVI) to assess plant health from UAV imagery, while change detection compares remote sensing data over time to detect changes in crop conditions.	18
Statistical modeling	Correlation and regression analysis identify relationships between different data variables and crop growth outcomes, while multivariate analysis examines multiple variables simultaneously to understand the complex interactions affecting crops.	7
Time-series analysis	Focuses on examining data collected at multiple time points to identify trends and patterns in cotton crop growth over time, employing methods such as trend analysis and seasonal decomposition.	1

information for these articles can be found in Table A1 in the Appendix A. The columns of the table correspond (from left to right) to the 'Reference', 'Citations', 'Growth parameters', 'Analysis methods', 'ML algorithms', 'Farm jobs', 'Journal or Conference'.

3. Analysis and discussions

Cotton is a vital raw material in both the textile and industrial sectors, playing a critical role in supporting a country's economic development. Monitoring cotton crop growth is essential for optimizing yields and managing resources. Furthermore, it provides accurate, real-time data that aids agricultural producers in implementing precision management practices. Monitoring cotton growth shares similarities with other crops in monitoring methods, importance, influencing factors, and data utilization. However, the unique characteristics of cotton cultivation, its growth cycle, and plant distribution render its monitoring methods and data applications distinctive.

Recent technological advancements have facilitated a transition from manual cotton picking to mechanical harvesting in various regions worldwide, transforming cultivation practices through machinery integration (Feng et al., 2017). Mechanized cotton sowing, as illustrated in Fig. 3, results in distinct plant distribution patterns that differ notably from those of other agricultural crops. The developmental phases for cotton can be divided into five main growth stages: germination and emergence, seedling establishment, vegetative growth, reproductive growth, and maturation (Xun et al., 2021; CottonInfo, 2023; Ritchie et al., 2007). The growth cycle exhibits significant differences compared to other crops, necessitating varied agricultural operations at different growth stages. For instance, farmers must assess residual films before planting and evaluate cotton plant populations shortly after planting to make replanting decisions in response to adverse conditions. The operations throughout the entire growth cycle can be categorized into soil management, water management, and crop management, with the latter being the primary focus of this study. Furthermore, various platforms such as ground-based vehicles, satellites, manned aircraft, and UAVs are used for data acquisition, with our particular interest being in UAVs. The collected data, such as UAV imagery of the surveyed cotton fields, are preprocessed for use in further analysis methods, including efficient machine learning model training. Additionally, the growth parameters of cotton further distinguish it from other crops, influencing its monitoring methods and data applications.

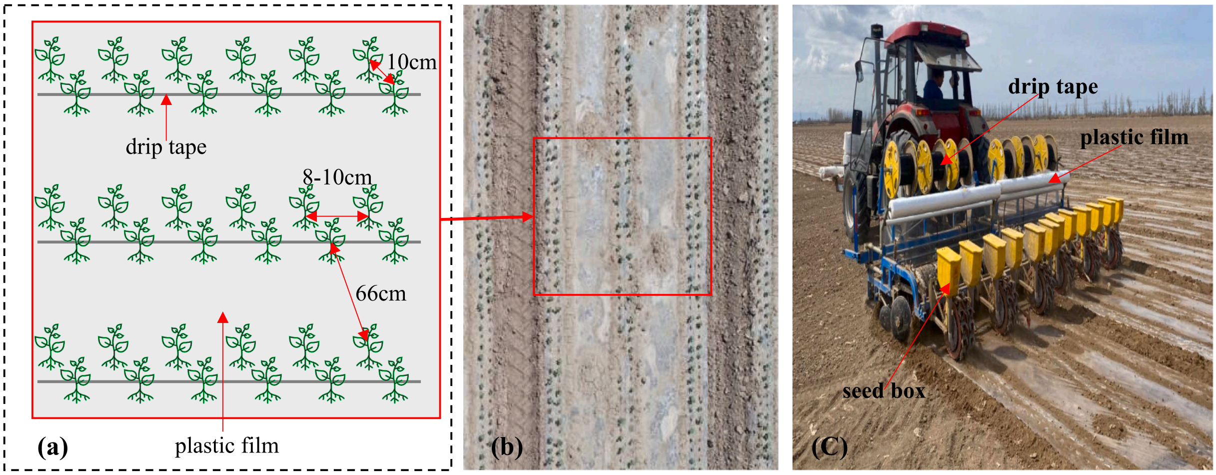

Fig. 3. The mechanized cotton cultivation in Xinjiang, China. (a) The planting adopts a 'double-row pattern,' with a total row spacing of 76 cm, consisting of six rows under one plastic film. The external row spacing is 66 cm, the internal row spacing is 10 cm, and the plant distance is 8–10 cm. (b) UAV image taken at 10 m altitude 16 days after planting. (c) Mechanized precision planting, accompanied by the simultaneous mulching of plastic film and drip irrigation tape.

Fig. 4 provides an overview of monitoring cotton crop growth. The subsequent subsections will provide a detailed discussion of each process depicted in the chart. It is important to recognize that, although many procedures and practices may overlap among various crops, the distinct agronomic characteristics of cotton—such as its growth cycle, water requirements, pest vulnerabilities, and yield optimization—demand focused attention in data collection, processing, and modeling efforts. Customizing approaches to meet these specific needs ensures effective monitoring and improvement of cotton production practices.

3.1. UAV-based remote sensing for cotton crop growth monitoring

Remote sensing applications in agriculture rely on the interaction of electromagnetic radiation with soil, water, and plant material, typically measuring reflected radiation (Mulla, 2013). Essentially, remote sensing refers to the non-invasive measurement of radiation that is either reflected or emitted from agricultural landscapes. Each material in an agricultural field exhibits a unique spectral response, which is contingent upon the characteristics of the imagery used and the sensor's structural and operational traits, such as spatial, radiometric, and spectral resolution (Alves Varella et al., 2015). Additionally, differences in crop leaf colors, textures, shapes, and attachment can be discerned based on the energy reflected, absorbed, or transmitted. Healthy crops generally exhibit higher reflection in the near-infrared region and at least one reflection in the visible region, while infected plants display the opposite pattern (Roman and Ursu, 2016; Wan et al., 2022).

Our review of the literature reveals that UAV-based remote sensing technology has become an important tool in cotton production management, with various applications developed in the field, including crop identification, soil moisture estimation, soil fertility, irrigation management, disease and pest detection, weed management, and yield prediction estimation. In these applications, high-resolution images obtained from UAV platforms serve as critical input data. Table 2 presents a comprehensive comparative analysis of the service quality delivered by different RS platforms utilized in precision agriculture. The resolutions of different remote sensing platforms vary, as do their associated costs. As the spatial scale increases, coverage expands, efficiency improves, and speed increases; however, this comes at the cost of a relative decrease in resolution and accuracy. Reducing costs while enhancing the quality of output imaging are essential tasks in data acquisition.

While many crops can be monitored using the same remote sensing platforms, UAVs are better suited for data collection tasks compared to other platforms, such as ground-based vehicles, satellites, and manned aircraft. They offer several advantages, including the ability to conduct on-demand visits without damaging crops, provide high spatial and temporal resolution (Radoglou-Grammatikis et al., 2020; Boursianis et al., 2022), manage a more controllable data acquisition process, collect data under cloudy conditions, and exhibit cost-effectiveness (Pathak et al., 2022). However, UAVs face certain limitations that restrict their broader application, including limited power sources and payload capacity (Rejeb et al., 2022). Furthermore, they require substantial computational resources and mosaic techniques to be utilized effectively.

3.1.1. Data acquisition

The data acquisition process begins with selecting the study area for data collection and gathering information about planting, such as the cotton variety, planting date, and planter configurations. Meteorological elements, including temperature, humidity, wind speed, wind direction, visibility, and rainfall, are also critical to collect. The duration that a cotton plant spends in each growth stage is consistent and determined by plant genetics and environmental factors, such as temperature (Ritchie et al., 2007). Additionally, flight parameters and camera settings, configured according to the intended data collection requirements, are important considerations. Collecting ground truth data is a vital aspect of data acquisition. When gathering field survey data, sampling mode and scale are also important factors. Some sampled data contribute to the establishment of efficient models, while others are used for validation. The parameters for ground truth data vary across applications and depend on specific objectives. During the data acquisition process, ground control points (GCPs) may also be needed to ensure that measurements captured by UAVs or other tools accurately align.

As UAV and sensor technology advances, UAVs equipped with various imaging sensors have emerged as an effective tool for obtaining timely and precise information about agricultural fields. The applications discussed in the reviewed literature encompass five specific types of sensors: visible light (RGB), multispectral, hyperspectral, thermal infrared, and LiDAR. These sensors capture crop features by recording light across specific wavelengths of the electromagnetic spectrum, corresponding to distinct wavebands (Fig. 5). A multispectral camera, for instance, utilizes green, red, red-edge (RE), and near-infrared (NIR) wavebands to capture images that reveal both visible traits and hidden aspects of crops. The data from each spectral band are processed to extract different crop features, such as using the NIR channel for plant health assessment and the red or green channel for chlorophyll concentration analysis. By applying algorithms to combine these channels,

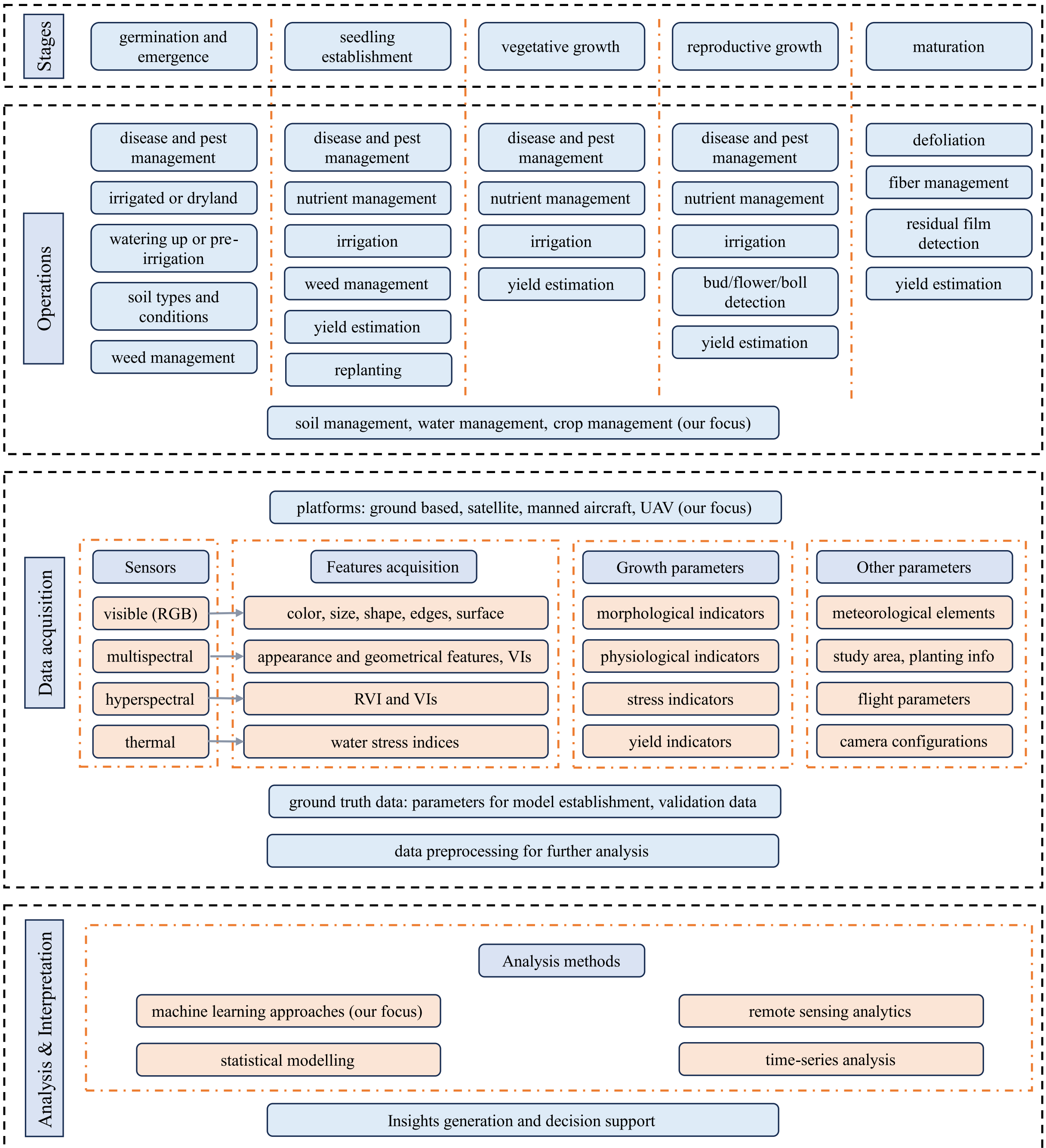

Fig. 4. Overview of cotton crop growth monitoring.

various vegetation indices can be calculated, providing quantitative measures of plant health, vigor, and biomass. From the processed images and these indices, specific features related to cotton crop growth—including leaf area index (LAI), canopy cover, plant count, biomass, water stress, and nutrient status—can be extracted. Capturing these features at different growth stages enables farmers and researchers to monitor changes and make informed decisions regarding irrigation, fertilization, and disease control (Zhang et al., 2021). Additionally, integrating camera sensor data with other sources, such as meteorological data or soil moisture readings, offers a more comprehensive understanding of cotton crop conditions.

- **Visible light (RGB):** high-definition digital cameras (RGB) are commonly employed for general imaging purposes. While cost-effective and capable of delivering high spatial resolution, these cameras exhibit comparatively limited spectral resolution. They can provide valuable information regarding the physical condition of cotton crops, including their height, density, stand count, canopy size and color, as well as boll and fiber.
- **Multispectral:** multispectral cameras capture data from the visible light spectrum extending into the near-infrared band. Healthy plants display an absorption trough in the red-light region, leading to a sudden increase in reflectance around the 0.76 μm wavelength (Fig. 5), and present high reflectance in the near-infrared area. Multispectral images can provide insights into cotton plant health, crop vigor, and nutrient status.
- **Hyperspectral:** hyperspectral imagers typically encompass a significantly broader range of wavelengths, comprising hundreds of bands, each confined within a narrow bandwidth of 5–20 nm. These hyperspectral images can provide more detailed information about

Table 2
QOS comparison of RS platforms used in precision agriculture (Istiak et al., 2023; Velusamy et al., 2022).

Quality of Services	Types of Remote Sensing Platforms			
	UAV	Satellite	Manned Aircraft	Ground Based
Flexibility	high	low	low	low
Adaptability	high	low	low	low
Cost	low	high	high	low
Time Consumption	low	low	low	high
Risk	low	average	high	low
Accuracy	high	low	high	moderate
Deployment	easy	difficult	complex	moderate
Feasibility	yes	no	no	yes
Availability	yes	no	yes	no
Operability	easy	complex	complex	easy
Data Acquisition	yes	yes	yes	yes
Decision Making	yes	no	no	yes
Action Perform	yes	no	no	yes

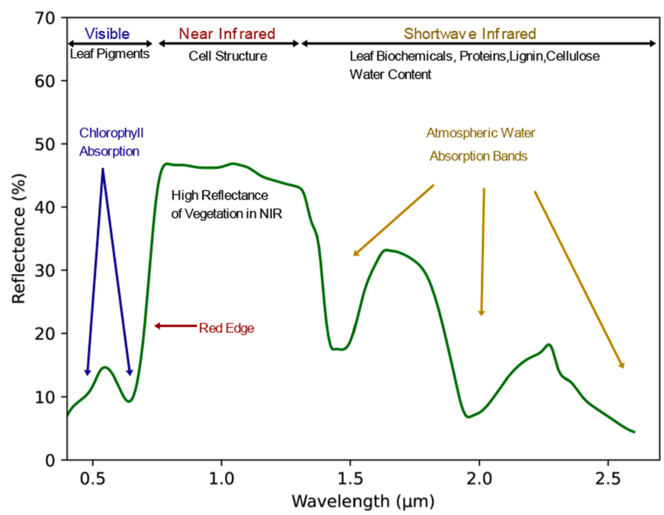

Fig. 5. The spectral reflectance curve of vegetation. The major absorption and reflectance features are indicated.

cotton crops, including plant health, soil properties, and their respective nutrient statuses.

- **Thermal infrared:** thermal infrared cameras, which are typically low-resolution and utilize a single band in the 7–12 μm range for most remote sensing applications, can accurately measure the temperature of cotton canopies and soil. This capability is valuable for detecting water stress as well as diseases and pests.
- **LiDAR:** it is an active type of sensor that employs light in the form of a pulsed laser to measure distances. LiDAR systems can provide detailed 3D information about cotton crops, including their topography, structure, and additional data on vegetation features. Despite their high resolution and strong resistance to interference, LiDAR systems are expensive and require extensive data processing.

Cotton monitoring often emphasizes capturing data on specific growth stages relevant to particular operations, such as boll detection at the reproductive growth stage and fiber detection at the maturation stage for yield estimation. Appropriate sensors should be selected to capture the features of cotton crops based on their intended use. Additionally, the spatial distribution of cotton fields, including row spacing and plant density, may influence how monitoring is conducted and what specific data is collected. These factors can differ from the distribution methods used for crops such as grains or vegetables. Liu et al. (2018) classified the key parameters of crop growth into four categories: morphological index, physiological and biochemical index, stress index, and yield index. These parameters can be analyzed using images captured by the UAV-mounted camera. Table 3 summarizes the cotton crop features studied in the reviewed literature.

In most studies, a single sensor is used to capture field information, which often proves insufficient for characterizing target areas. Integrating data from various sensor types can mitigate the limitations of single-source data and provide comprehensive information about the targets (Maimaitijiang et al., 2017; Karmakar et al., 2024). Stein et al. (2016) proposed that data fusion represents promising area of remote sensing data analysis. This concept suggests that by combining sensors that capture different types of information, the accuracy of estimations can be enhanced, particularly when the information is complementary; each sensor can contribute to addressing a portion of the target variability. Feng et al. (2020b) combined UAV-based RGB, multispectral, and infrared thermal cameras to capture images of a cotton field at two growth stages. These images were processed to generate orthomosaic images and a digital surface model. Eight image features were extracted, and models were developed to assess the accuracy of each image feature for yield estimation.

UAVs can produce vast quantities of data, presenting significant challenges in effective management. Since the accuracy of the final models highly depends on the quality of the collected data, the data acquisition process must be well-organized. Our study indicates that no specific articles have focused on this topic; therefore, there is a pressing need for synthesized data acquisition methods.

3.1.2. Data preprocessing

In this subsection, we discuss the preprocessing methods used to analyze UAV-acquired images. UAV imagery may display irregular patterns, inconsistent grayscale values, and significant geometric distortions. These issues often arise from changes in the UAV's flight trajectory and orientation, as well as optical aberrations from camera lenses (Feng et al., 2020a). Consequently, preprocessing is essential to meet the requirements of the intended application. This process involves a series of pixel-level manipulations applied to the UAV imagery, including image distortion correction, calibration, and georeferencing. The entire process encompasses steps such as geometric and radiometric calibrations, image enhancement, registration, and fusion.

Fig. 6 depicts the overall data preprocessing pipeline. Digital processing techniques are used on UAV imagery for initial preparation and subsequent analysis, as well as for producing final geospatial products such as Digital Surface Model (DSM), Digital Terrain Model (DTM), Digital Elevation Model (DEM), and Orthomosaic. The main techniques applied in the analysis process are detailed in Table 4, which also outlines the objectives, principles, and the types of approaches associated with each technique. It is important to note that the precision and effort required may vary depending on the sensor type. Preprocessing, especially for thermal and hyperspectral data, necessitates expertise in remote sensing (Maes and Steppe, 2019). The specific preprocessing operations and approaches should be determined based on the sensor

Table 3
Cotton crop features acquired from UAVs.

	Cotton crop features
Vegetation	morphological indicators: plant height (PH), canopy cover (CC), canopy size and color, stand count, growth stage, defoliation rate physiological and biochemical indicators: leaf area index (LAI), crop coefficient, chromophyll, nutritive element content, different vegetation indices (VIs) stress indicators: leaf water potential (LWP), stomatal conductance, disease, pest, vigor of the crop, canopy temperature yield indicators: net assimilation rate (NAR), boll, cotton fiber index (CFI), biomass
Soil	biomass, moisture content, temperature, electrical conductivity (EC), residual film

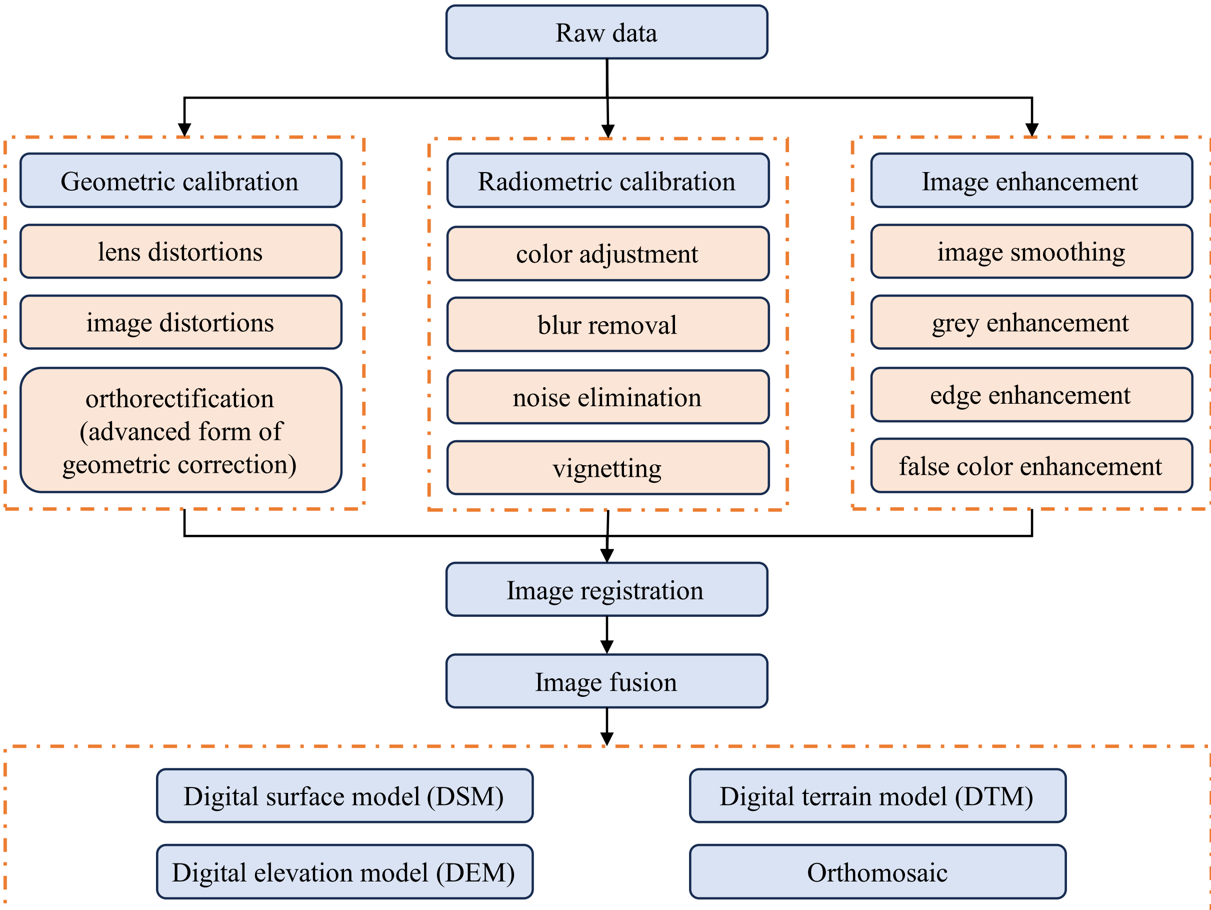

Fig. 6. Overall data preprocessing pipeline.

type and the objectives of the application.

Reviewed studies commonly utilize commercial software such as Agisoft PhotoScan and Pix4D for the processing of UAV images. However, generating orthomosaic images is a time-intensive and complex task that can delay decision-making at the field level. The traditional processing of UAV imagery typically requires significant overlap, both front and side (approximately 75 %), to produce orthomosaic images of agricultural fields (Tsouros et al., 2019)., This requirement leads to inefficient data collection due to an increased number of flight passes and slower speeds. Such inefficiencies are particularly pronounced when collecting low-altitude UAV data necessary for achieving high resolution during the early stages of cotton growth (Feng et al., 2020a). Issues such as artifacts and distortions can compromise the accuracy of subsequent analyses, and additional software — including Matlab, ArcGIS, and QGIS — for post-processing can further complicate and prolong the duration of data processing. The process often demands significant computational resources, which vary based on field size, image quantity, and resolution (Feng et al., 2020a).

Wang et al. (2018) implemented a real-time sensing and management platform for crop production. This system supports the spatial analysis and management of crop growth parameters using multi-rotor UAVs. Feng et al. (2020a) developed a preprocessing workflow to identify and geospatially align the crop rows within each separate image frame before further processing the data. Tsouros et al. (2020) introduced a fully open-source framework to support the processing of data acquired from UAVs, aiming to reduce costs. Wang et al. (2021) developed an open-source software tool, EasyIDP, to simplify intermediate data processing in agricultural applications, offering features such as ROI cropping and reverse calculation on UAV images. These functionalities effectively reduce the workload, particularly regarding data annotation for machine learning. Feng et al. (2023a) focused on creating a real-time image processing pipeline for UAV images to enhance positional accuracy. The pipeline was applied to generate emergence maps for cotton and corn on a field scale and provided a low-cost near real-time tool for mapping emergence parameters.

Nevertheless, a research gap remains regarding the scalability and adaptability of these systems across diverse agricultural environments. Comprehensive research is needed to enhance the accuracy and efficiency of these data preprocessing systems while ensuring they are cost-effective, capable of real-time processing, and applicable in real-world agricultural scenarios at a larger scale.

3.2. Machine learning approaches based on UAV imagery for cotton crop growth monitoring

As highlighted by Jordan and Mitchell (2015), machine learning enables systems to autonomously identify and learn from data patterns, adapting over time without requiring predefined rules or programming. This advancement is facilitated by efficient algorithmic designs that optimize computational resources while accurately processing vast datasets. Conventional machine-learning methods required extensive engineering and expertise to convert raw natural data into usable feature representations for pattern detection and classification (LeCun et al., 2015). Deep learning is an advanced machine learning technique that enables computers to automatically extract, analyze, and comprehend valuable information from raw data (Chauhan and Singh, 2018).

Machine learning algorithms excel at managing large datasets to construct models specifically tailored for various agricultural operations. This capability is crucial for identifying patterns that may not be immediately apparent to human analysts or traditional computational

Table 4
Main techniques for preprocessing of UAV imagery. Adapted from (Alves Varella et al., 2015)

Technique	Purpose	Principle	Approaches
Geometric calibration	Mitigate the effects of geometric distortions arising from imagery processing and assign coordinates to the pixels of an image corresponding to their actual geographic locations in space	Mathematical operations such as rotation and translation, performed by means of polynomials involving the coordinates of the image and control points whose real coordinates are known beforehand	Rectification, orthorectification, record
Radiometric calibration	Convert the digital numbers (gray levels) of image pixels to physical data regarding spectral radiance and reflectance; mitigate the effect of the atmosphere in the spectral response of the targets	Application of mathematical relationships between spectral reflectance/radiance and gray levels from a 'gross' image; application of mathematical functions for correction or mitigation of atmospheric effects for the spectral response of targets on the surface	Radiometric calibration; atmospheric correction, cloud filtering, etc.
Image enhancement	Enhance the visual effect and clarity of images and amplify the distinction between different object features	Specific features are highlighted, and others suppressed according to the image's intended application; adjust the transformation coefficients within a specific transformation domain and then applying an inverse transformation to return to the original spatial domain.	Image smoothing (noise reduction, edge preservation, filtering—mean, median, gaussian filters,); gray scale transform (linear, segmented linear, nonlinear gray transform); histogram equalization; spatial and frequency domain enhancement
Image registration	Establish the transformation model relationships between features to achieve spatial matching of images; geometrically aligns one image to another	Identify key features in images that can be used for matching and find corresponding features between images; determine the mathematical model that will map one image onto another and apply the transformation model to align the images	Characteristics, gray information and transform domain-based image registration algorithms
Image fusion	Merge the registered images based on a certain transformation model into a seamless stitched image; preserve all relevant information from the source images while minimizing the introduction of artifacts	Use transformation models to convert the registered images into a suitable form and then apply the fusion algorithms to combine the transformed images, the choice of algorithm depends on the application; apply the inverse transformation to bring the fused image back into the domain	averaging, principal component analysis (PCA), pyramid-based methods, wavelet transforms, and artificial intelligence techniques

methods. For example, models utilizing high-resolution UAV imagery have effectively identified pest infestations, significantly reducing crop loss (Huang et al., 2018) and facilitating precise field management practices that contribute to optimized replanting decisions (Feng et al., 2020a). Features of the cotton crop, as specified in Table 3, can be effectively extracted from UAV imagery using efficient machine learning models.

During our survey process, we observed that machine learning approaches derived from literature predominantly fall into two categories as illustrated in Fig. 7; conventional machine learning (ML)-based methods and deep learning (DL)-based methods. Conventional ML-based methods typically employ traditional supervised or unsupervised algorithms using structural features and in situ data for application development. In contrast, DL-based approaches utilize complex neural networks to process raw (or preprocessed) imagery along with other forms of data. These algorithms find extensive applications throughout all growth stages of cotton addressing various areas. Notably, yield estimation receives substantial attention, reflecting farmers' growing demand for informed decision-making processes aimed at maximizing crop yield; this focus is closely followed by intensive efforts on disease and pest detection, as these significantly impact cotton production. The germination rate, another important agronomic factor for field management during the early stages, has been studied by several researchers. Furthermore, weed management, canopy cover estimation, nitrogen content assessment, and residual film identification have also been examined, yielding noteworthy findings. For an exhaustive insight into each application's functionality, including the datasets utilized, the algorithms implemented, and their peak performances, please refer to Table A2 within Appendix A.

3.2.1. *Conventional ML-based methods*

The most commonly used conventional ML models implemented in the selected studies include support vector machines (SVMs), random forests (RFs), K-means clustering, boosting algorithms, and artificial neural networks (ANNs). Fig. 8 (Feng et al., 2020a) illustrates the general pipeline of machine learning approaches for cotton crop growth monitoring. After completing data collection and preprocessing, discussed in previous subsections, conventional machine learning models typically involve extracting features using various feature engineering strategies. This process transforms raw data into a set of attributes that can effectively represent underlying patterns within datasets. Subsequently, the dataset will be split into two or three parts for training, testing and evaluating the model. Finally, model training, validation and deployment are performed; once satisfactory results are achieved on unseen data, the outcomes from these models are analyzed to generate valuable insights that support decision-making processes for relevant stakeholders.

Several researchers specifically addressed yield estimation as a regression task, which is one of the typical a common application of supervised learning tasks. They used classification or clustering algorithms to extract features of cotton crop before developing a regression model to predict yield. Maja et al. (2016) explored the use of RGB imagery and K-means clustering to generate four distinct clusters, allowing researchers to differentiate cotton bolls from other objects within the images. Furthermore, a linear regression (LR) model was developed based on the relationship between yield and computed cotton boll pixels, yielding a prediction error of less than 10 % at the validation site. To address misclassification resulting from highly reflective areas and large clusters, the researchers imposed a fixed cluster size constraint, which, while effective, may limit utility in densely planted fields where bolls naturally group closely. Zou et al. (2018) employed decision tree classification to analyze small densely planted cotton fields, achieving a 97.2 % accuracy rate by manually labeling pixels and using gray values from the RGB color space for model training. The study introduced the Cotton Unit Coverage (CUC) index from this data, correlating it with cotton yield at an estimation accuracy of 89.13 %. However, further

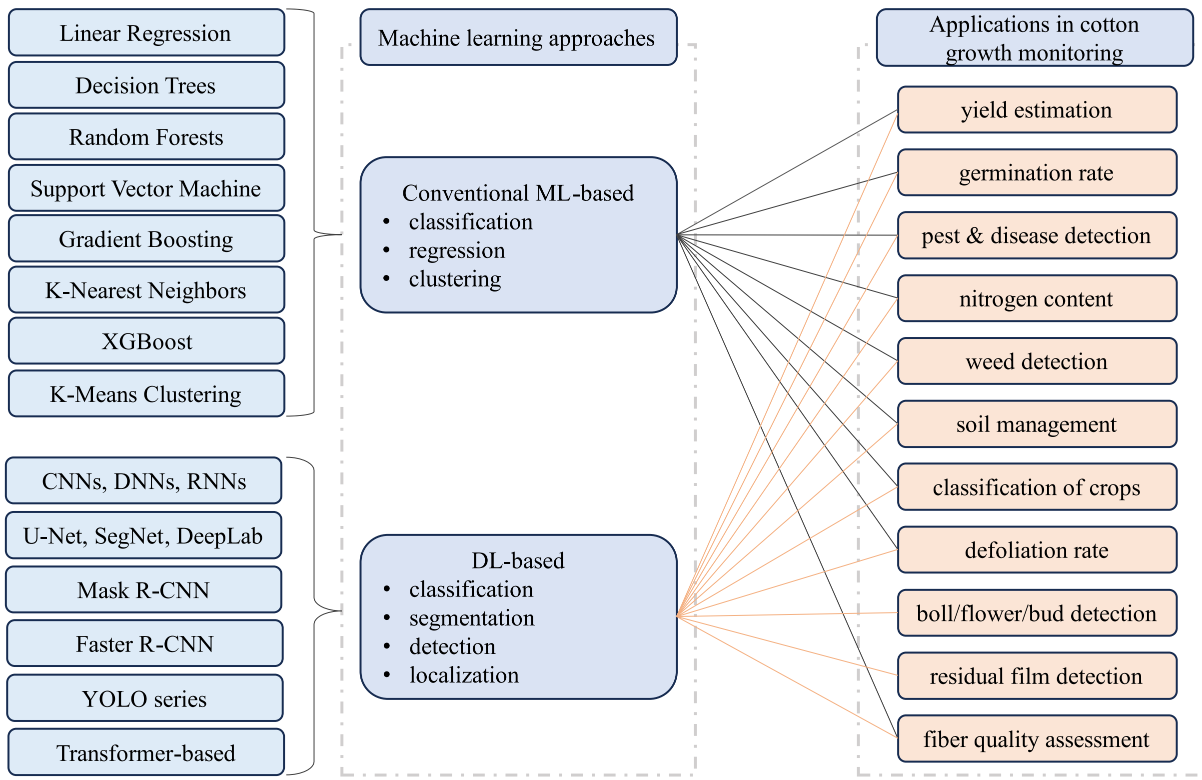

Fig. 7. Taxonomy of machine learning approaches using UAV imagery for monitoring cotton crop growth based on the reviewed literature. For detailed information, please refer to Table A2 in Appendix A.

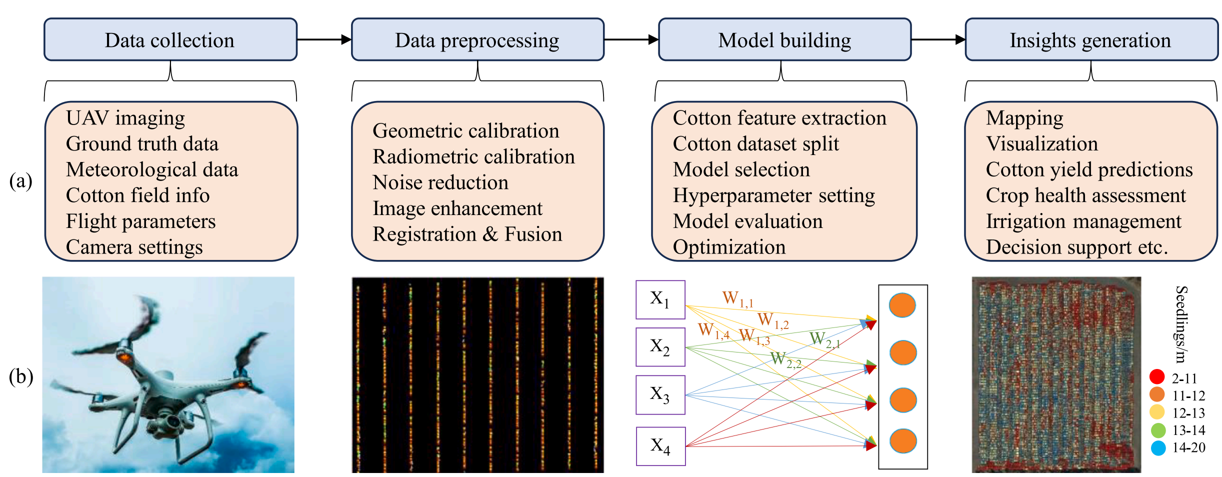

Fig. 8. The general pipeline of machine learning approaches for cotton crop growth monitoring.

exploration of different yield indicators across various planting patterns and cotton varieties is necessary. Ashapure et al. (2020a) utilized RGB and multispectral sensors to capture images, subsequently developing an artificial neural network (ANN) based model. This model integrated various crop features for yield prediction, encompassing five multi-temporal features and three non-temporal attributes, in addition to irrigation status as a qualitative feature. The ANN model outperformed support vector regression (SVR) and random forest regression (RFR), achieving high accuracy with a best-case R^2 value of 0.89. Redundant features were eliminated via correlation analysis, identifying key predictors such as canopy volume, the excessive greenness index (ExG), boll count and volume, along with irrigation status. Furthermore, the study demonstrated that reliable yield predictions could be made as early as 70 days post-planting. Shi et al. (2022) applied traditional image processing techniques to extract cotton bolls from the cotton field background in multispectral and thermal images. Five conventional ML-based methods were implemented to evaluate the relationship between cotton boll pixels and field survey datasets. The RF method exhibited the best yield estimation performance; however, its results were not satisfactory compared to those of other studies, with an average $R^2 = 0.77$. Rodriguez-Sanchez et al. (2022) and Bawa et al. (2023) both utilized SVM to classify cotton yield indicators from RGB images. Shrestha et al. (2023) developed a custom ANN model and compared its performance with that of standard ANN and RF models. The customized ANN model outperformed the other two, potentially due to its consideration of different growth stages independently rather than as a single entity. However, to assess the robustness of this model, more diverse spatio-temporal datasets are needed for validation.

Conventional machine learning methods offer several advantages for cotton crop monitoring, such as predictive analysis capabilities, automated monitoring, scalability, and the ability to recognize complex patterns. However, these methods also present challenges including dependency on high-quality data and the risk of overfitting to the training dataset without careful design and validation. Furthermore, implementing these models effectively requires significant computational and agricultural expertise, and they can be sensitive to temporal changes in the growth phases of crops if such changes are not considered during modeling.

3.2.2. DL-based methods

Advanced machine learning methodologies predominantly leverage artificial neural networks, which typically require extensive datasets for effective training and accurate representation of complex data patterns. These sophisticated models, such as deep learning algorithms, have been instrumental in achieving breakthroughs across numerous fields including image recognition, natural language processing, and autonomous vehicles, due to their ability to model high-level abstractions in data. Deep learning, a specialized branch of machine learning employing multi-layered ANNs, demonstrates superior proficiency in processing large datasets and often surpasses conventional machine learning techniques (LeCun et al., 2015).

Among DL-based models, CNNs have significantly advanced scene understanding due to their precise feature representation capabilities. Models such as U-net (Ronneberger et al., 2015), ResNet (He et al., 2016), DenseNet (Huang et al., 2017a; Huang et al., 2017b), YOLO (Redmon et al., 2016) series, along with various customized CNNs, have achieved considerable success in cotton crop monitoring using UAV imagery. As illustrated in Fig. 8, the third phase of the workflow involves designing a deep learning model tailored to the specific requirements of agricultural application, following initial data collection and preprocessing. This step includes selecting an appropriate architecture and compiling the model by defining critical parameters that guide its learning process, such as optimizer function, loss function, and performance monitoring metrics. The compiled model then undergoes a training phase followed by testing and validation to evaluate its effectiveness. Based on the outcomes of this evaluation, iterative optimization may be performed prior to final deployment or inference if necessary.

We synthesized existing research on DL-based approaches in cotton crop monitoring using UAV imagery into three groups: classification, segmentation and detection. In recent years, significant advancements have been made in image classification through deep CNNs with numerous enhancements proposed to their architectures via layer augmentation. This task involves assigning an image or its segments to predefined categories. Applications range from classifying cotton flowers to distinguishing between healthy plants and those affected by diseases or pests (Xu et al., 2018; Huang et al., 2018; Petti and Li, 2022). Segmentation involves dividing an image into regions corresponding to different objects or features within the scene. For example, it is used to separate individual plants, cotton bolls, residual plastic films, and weeds within a field from its background (Narvaria et al., 2021; Sudarshan Rao et al., 2021; Li et al., 2022a; Zhai et al., 2022; Qiu et al., 2022; Raptis et al., 2023). Object detection is the process of identifying specific objects within images and typically involves two key components: object localization and classification. Object detection models can be classified into two categories. The first category comprises two-stage detectors, which initially generate a set of region proposals, that are subsequently subjected to classification. While these models offer high accuracy, they are characterized by slower processing speed. The second category consists of one-stage detectors, which perform object localization and classification simultaneously in a single step. This approach significantly increases detection speed but may result in reduced accuracy, especially for small or rare objects. Two-stage object detection architectures, such as Faster R-CNN (Ren et al., 2017) and Mask R-CNN (He et al., 2017), along with one-stage object detection architectures like CenterNet (Duan et al., 2019) and the YOLO series, are utilized for diverse tasks in cotton production. These tasks include counting cotton stands to estimate germination rates, differentiating weeds from crops, detecting bolls for yield estimation, identifying residual plastic films, and disease detection.

Oh et al. (2020) utilized the YOLOv3 model to count cotton seedlings in RGB field images, achieving an R^2 value ranging from 0.96 to 0.97 for plant densities of 0–14 plants per linear meter. However, additional photogrammetry procedures were required to localize the cotton seedlings accurately. Lin and Guo (2021) evaluated the application of MobileNet and CenterNet models for counting cotton plants at the seedling stage, finding that both models demonstrated improved performance when trained on a dataset of 900 images. Counting cotton seedlings presents challenges due to soil dominance in images, sensitivity to lighting conditions, and difficulties in color differentiation caused by the small plant size. Feng et al. (2023b) utilized multispectral images acquired by an UAV at different times points to construct models for detecting and counting cotton seedlings. They trained the YOLOv5, YOLOv7, and CenterNet algorithms on these multispectral images collected at six different times during the cotton seedling establishment phase. Among these methods, YOLOv7 outperformed the others, achieving approximately 97 % in both precision and recall. Yadav et al. (2022) employed YOLOv5 to detect volunteer cotton plants in a corn field. In addition, they applied the same methodology to detect plastic contaminants in cotton fields, potentially accelerating mitigation efforts (Yadav et al., 2023). Sapkota et al. (2022) investigated the performance of Mask R-CNN model for weed detection and segmentation, also evaluating its output for biomass estimation. Lu et al. (2023) proposed an optimization method for YOLOv8 aimed at enhancing the detection of small objects in UAV images. This modified version, named YOLOv8-UAV, was assessed on several datasets, including a cotton boll dataset, and achieved a precision of 87.6 % and a recall of 78.8 %.

Deep networks encounter several challenges such as exploding (or vanishing) gradients and degradation in the training process. The degradation problem occurs when accuracy decreases as the depth of the network increases. Another challenge is internal covariate shift, which refers to changes in the distribution of input data to a layer during training. Researchers have proposed various optimization techniques, including skip connections, transfer learning, initialization strategies, batch normalization and layer-wise training, to effectively address these challenges. Additionally, while some state-of-the-art models require significant computational resources, advancements in GPUs and distributed computing have helped to address the high computational demands of agricultural applications.

Given the complexity and diversity of cotton fields across different regions, the scalability of developed models is crucial for real-world applications. Generalized models that employ transfer learning can be adapted to new conditions; however, they must be undergo rigorous validation in varied environments and crop species to ensure their scalability and robustness. Additionally, interdisciplinary collaboration is critical to the effective monitoring of cotton crop growth.

3.2.3. Time series data analysis

Time series data, which consists of continuous information collected over various time periods, enables researchers to capture dynamic changes across multiple fields, including agriculture. Analyzing this data provides insights into trends and patterns by revealing information inherent in the dataset (Jin et al., 2024). Cotton's sensitivity to seasonal variations throughout its growth cycle necessitates the use of trend analysis, which examines time series data to identify consistent patterns in growth stages. At the same time, seasonal adjustment accounts for these variations, allowing for a clearer understanding of underlying growth trends. For example, cotton yield was estimated using NDVI time series (Gao et al. 2012) and EVI time series (Liu et al., 2016a). Yield prediction models using time series data demonstrate greater accuracy and precision than those utilizing single period data (Lambert et al. 2018).

In recent years, there has been a growing interest in the application of machine learning techniques for time series analysis. Compared to traditional statistical methods, these approaches provide greater flexibility, scalability, and accuracy by effectively capturing complex patterns and enabling real-time predictions (Maharaj et al., 2019; Lim and Zohren, 2021). A mixed model that combines ARIMA (autoregressive integrated moving average) and SVM has been shown to outperform single-model approaches by effectively managing linear aspects of time series data with ARIMA while addressing nonlinear components with SVM (Wen et al. 2019). Deep learning techniques excel at capturing the temporal dependencies inherent in time series data, making them an attractive choice for analysis. Xu et al. (2021) developed a model that integrates the pixel percentage of cotton boll opening, extracted using U-Net from UAV images, with remote sensing time series indices to predict cotton yield, achieving an R2 value of 0.853. The same authors assessed cotton fiber quality using time series remote sensing data, applying pixel-level fusion of time series RGB and multispectral images to enhance the model's accuracy. Their findings suggest that using a neural network algorithm with time series data can improve the precision of estimating cotton fiber quality by implementing a more accurate spectral index (Xu et al., 2023).

The application of deep learning techniques to time series analysis has yielded valuable insights for seasonal cotton monitoring; however, challenges persist. Recurrent neural networks (RNNs), particularly long short-term memory networks (LSTMs), have demonstrated considerable success in analyzing time series data across various fields, excelling in managing missing data and capturing both short- and long-term trends (Che et al., 2018; Hewamalage et al., 2021). Furthermore, transformers have proven effective in modeling long-range dependencies (Wen et al., 2023). Therefore, it is recommended to incorporate these advanced techniques into seasonal cotton monitoring. Additionally, integrating external time series data, such as soil moisture, irrigation schedules, and climatic information, can enhance the comprehensive understanding of cotton growth.

3.3. Prospects for future research

In cotton farming practices, UAV-based remote sensing not only provides critical data throughout all stages of crop growth but also enhances the spatiotemporal resolution capabilities inherent to traditional remote sensing techniques. This technological advancement improves efficiency in traditionally labor-intensive tasks while providing technical support for the accurate acquisition of multidimensional information. Based on the analytical techniques discussed above, actionable insights are generated, thereby facilitating precision management and informed decision-making in cotton production. Building on the findings of this review, we identify several key areas that warrant further exploration by researchers.

- **Lack of large-scale datasets:** The majority of research findings are derived from specially designed datasets obtained from certain field instances (as illustrated in Table A2), which makes the generalization of applied methodologies and models across practical applications challenging. The development of image datasets and spectral datasets for various growth stages of cotton remains in its initial stages. Therefore, although some existing studies may achieve high recognition rates during individual experiments, many results still lack generalizability and applicability. Future efforts should concentrate on creating publicly accessible datasets and benchmarks to facilitate standardized training and evaluation of models.
- **Integration among various procedures:** The prevalent software currently employed for UAV image preprocessing primarily relies on commercial solutions, which requires substantial technical skills among researchers and presents challenges in meeting real-time processing demands. Therefore, more extensive exploration is required to enhance integration among various procedures—such as flight planning, image preprocessing, agricultural analysis, and prescription map generation—to streamline workflows in cotton crop monitoring.
- **Model transferability across environments:** Ensuring effective transferability of models across diverse environments, regions, and crop varieties is critical. Future studies should focus on developing models that can generalize across these aspects while minimizing the need for retraining.
- **Edge Deployment and Real-Time Processing:** Deploying models on edge devices for real-time processing can facilitate their application in real-world scenarios. However, the challenge lies in deploying lightweight models that can function optimally within the limited resources of edge devices (Mittal, 2024).
- **Promoting societal adoption and technology dissemination:** Fostering societal acceptance and widespread application of UAV and machine learning technologies in cotton farming is essential. This necessitates improving system usability, lowering costs, and encouraging broader adoption of these technologies among both researchers and farmers.

4. Conclusions

In this article, we presented a comprehensive review of the use of UAVs and machine learning in monitoring cotton crop growth. Despite the significant impact of these technologies on cotton production, a noticeable gap exists in consolidated information on the subject. This paper aims to address this gap by performing a systematic literature review conducted across the Web of Science Core Collection and Scopus databases. We have explored the methodologies and materials that underpin current research in the field, presented the findings from our extensive literature search, and discussed key research questions. Our analysis has highlighted the advancements in UAV technology for data acquisition, the complexities of data preprocessing, and the efficient machine learning techniques applied to UAV-collected data.

The study does not aim to compare methods or recommend a single best approach; rather, it provides a broad overview of the capabilities offered by UAV-based remote sensing and machine learning technologies for monitoring cotton crops. The insights gained from this review suggest significant potential for these technologies to transform cotton growth monitoring by providing solutions that are more precise, efficient, and cost-effective than traditional methods. Nonetheless, the review also highlights several areas requiring further research, including the development of well-organized data acquisition and management strategies, the creation of cost-effective systems for real-time preprocessing, and the enhancement of machine learning model scalability and accuracy across diverse agricultural environments. Addressing these challenges is essential for stakeholders to fully leverage the benefits of UAV and machine learning technologies, thus paving the way for smarter and more sustainable agricultural practices.

CRediT authorship contribution statement

Nueraili Aierken: Writing – original draft, Visualization, Investigation, Formal analysis, Data curation, Conceptualization. **Bo Yang:** Investigation, Writing – review & editing. **Yongke Li:** Validation, Funding acquisition. **Pingan Jiang:** Formal analysis, Funding acquisition, Writing – review & editing. **Gang Pan:** Resources, Project administration. **Shijian Li:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
Summary of existing survey works on the topic. The number of citations retrieved from WOS Core Collection or Scopus as of December 2023.

	Reference	Citations	Sensor types	Growth parameters	Analysis Methods	ML algorithms	Farm jobs	Journal or Conference
1	(Xu et al., 2018)	63	RGB	yield indicators	machine learning	CNN	bloom detection	Frontiers in Plant Science
2	(Ashapure et al., 2020a)	51	RGB, multispectral	morphological, physiological, yield indicators	machine learning	SVM, RF, ANN	yield estimation	ISPRS Journal of Photogrammetry and Remote Sensing
3	(Feng et al., 2020a)	38	RGB	morphological indicators	machine learning	Resnet18	germination rate	Computers and Electronics in Agriculture
4	(Wang et al., 2020b)	38	multispectral	soil parameters	machine learning, remote sensing	KMSVM, KMSEG	disease detection	Remote Sensing
5	(Ashapure et al., 2019)	37	RGB, multispectral	morphological, physiological indicators	machine learning, time-series analysis, remote sensing	K-means	canopy cover estimation	Remote Sensing
6	(Oh et al., 2020)	36	RGB	morphological indicators	machine learning	YOLOv3	germination rate	Remote Sensing
7	(Xu et al., 2021c)	32	RGB, multispectral	physiological, yield indicators	machine learning, time-series analysis, remote sensing	U-Net	yield estimation	International Journal of Applied Earth Observations and Geoinformation
8	(Mattupalli et al., 2018)	21	RGB	soil parameters	machine learning, remote sensing statistical modelling	Maximum likelihood	disease detection	Remote Sensing
9	(Lin and Guo, 2021)	20	RGB	morphological indicators	machine learning	MobileNet, CenterNet	germination rate	Remote Sensing
10	(Feng et al., 2020b)	19	hyperspectral	morphological indicators	machine learning, remote sensing	AdaBoost	germination rate	Remote Sensing
11	(Huang et al., 2018)	17	multispectral	morphological indicators	machine learning	SVM, CNNs	pest detection	Remote Sensing Letters
12	(Wang et al., 2020a)	17	multispectral	soil parameters	machine learning, remote sensing	SVM, K-means, KMSVM, KMSEG	disease detection	Remote Sensing
13	(Marang et al., 2021)	17	multispectral, hyperspectral	physiological indicators	machine learning, remote sensing	DBH clustering, RF	nitrogen content	Remote Sensing
14	(Sapkota et al., 2020b)	9	RGB	morphological indicators	machine learning, remote sensing	RF	weed management	AgriEngineering
15	(Xia et al., 2019)	9	RGB	morphological indicators	machine learning	SVM	germination rate	Applied Sciences-basel
16	(Wang et al., 2020c)	9	multispectral	soil parameters	machine learning, remote sensing	Maximum likelihood	disease detection	Journal of Applied Remote Sensing
17	(Maja et al., 2016)	8	RGB	morphological indicators	machine learning	K-means clustering	yield estimation	Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping
18	(Shi et al., 2022)	7	multispectral, thermal	yield indicators	machine learning	LR, SVR, CART, RF, KNN	yield estimation	Drones
19	(Yin et al., 2022)	7	Hyperspectral	morphological, physiological indicators	machine learning, remote sensing, statistical modelling	SVR	nitrogen content	Remote Sensing
20	(Kou et al., 2022)	6	RGB	morphological, physiological indicators	machine learning, remote sensing	LR, SVM, CNN	nitrogen content	Sustainability

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Table A1 (*continued*)

	Reference	Citations	Sensor types	Growth parameters	Analysis Methods	ML algorithms	Farm jobs	Journal or Conference
21	(Qi et al., 2022)	6	multispectral	stress indicators	machine learning, remote sensing	XGBoost, CNN	soil management	Land Degradation & Development
22	(F. Li et al., 2022b)	6	RGB	yield indicators	machine learning, statistical modelling	CD-SegNet	yield estimation	Plant Methods
23	(Davidson et al., 2022)	5	RGB, multispectral	physiological indicators	machine learning, remote sensing	cGAN, LR	crop management	Computers and Electronics in Agriculture
24	(Rodriguez-Sanchez et al., 2022b)	5	RGB	morphological, yield indicators	machine learning, remote sensing	SVM	yield estimation	Frontiers in Plant Science
25	(Yadav et al., 2019)	5	RGB, multispectral	morphological, physiological indicators	machine learning, remote sensing, statistical modelling	Several supervised classifications	crop detection	Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping, C
26	(Raptis et al., 2023)	4	RGB	morphological, physiological indicators	machine learning, remote sensing	CNNs	crop management	Journal of Intelligent & Robotic Systems
27	(Kumar Yadav et al., 2023)	4	RGB	morphological indicators	machine learning	YOLOv3	crop detection	Computers and Electronics in Agriculture
28	(Sapkota et al., 2022)	4	RGB	morphological, yield indicators	machine learning	CNNs	crop management	Scientific Reports
29	(Yan et al., 2022)	4	multispectral, LiDAR	physiological indicators	machine learning, remote sensing	RF, SVR, ANN	crop management	Remote Sensing
30	(Petti and Li, 2022)	4	RGB	morphological indicators	machine learning	DenseNet	bloom detection	Computers and Electronics in Agriculture
31	(Senyurek et al., 2022)	4	multispectral	soil parameters	machine learning, remote sensing, statistical modelling	RF	soil moisture content	IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing
32	(Chen et al., 2022)	3	RGB	morphological, physiological indicators	machine learning, remote sensing, statistical modelling	CNNs	defoliation rate	Remote Sensing
33	(Bawa et al., 2023)	3	RGB	morphological, yield indicators	machine learning, statistical modelling	SVM	yield estimation	Smart Agricultural Technology
34	(Sudarshan Rao et al., 2021)	3	multispectral	morphological, physiological indicators	machine learning	U-Net, SegNet, PSPNet	crop classification	Computer Vision and Image Processing
35	(Narvaria et al., 2021)	3	multispectral	morphological, physiological indicators	machine learning, remote sensing	U-Net	crop classification	2021 IEEE International India Geoscience and Remote Sensing Symposium (InGARSS)
36	(Zhao PEI et al., 2023)	2	multispectral	morphological, physiological indicators	machine learning, remote sensing, statistical modelling	SVM, BPNN, XGB	nitrogen content	Journal of Integrative Agriculture
37	(Zou et al., 2018)	2	RGB	morphological, yield indicators	machine learning, statistical modelling	DT	yield estimation	American Society of Agricultural and Biological Engineers
38	(Feng et al., 2024)	1	multispectral	morphological, yield indicators	machine learning	YOLOv5, YOLOv7, CenterNet	germination rate	Remote Sensing
39	(Zhai et al., 2022)	1	RGB	–	machine learning	U-Net, SegNet, FCN	residual film detection	Frontiers in Plant Science
40	(Yadav et al., 2022)	1	RGB	morphological indicators	machine learning	YOLOv5	crop detection	Artificial Intelligence in Agriculture
41	(Thomasson et al., 2018b)	1	multispectral	soil parameters	machine learning, remote sensing	SVM	disease detection	Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping
42	(Suryawanshi and Khurjekar, 2021)	1	RGB	physiological, stress indicators	machine learning	CNNs	disease detection	2021 International Conference on Computing, Communication and Green Engineering (CCGE)

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Table A1 (*continued*)

	Reference	Citations	Sensor types	Growth parameters	Analysis Methods	ML algorithms	Farm jobs	Journal or Conference
43	(Xu et al., 2023)	0	RGB, multispectral	morphological, yield indicators	machine learning, time-series analysis	CNN	fiber quality estimation	Remote Sensing
44	(Ashapure et al., 2020b)	0	RGB, multispectral	morphological, physiological indicators	machine learning, remote sensing	SVM, ANN	crop management	2020 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)
45	(A. Feng et al., 2023b)	0	multispectral	soil parameters	machine learning, remote sensing, statistical modelling	CNNs	yield estimation	Precision Agriculture
46	(Yadav et al., 2023)	0	RGB	–	machine learning, statistical modelling	YOLOv5	residual film detection	Agriculture
47	(Jiang et al., 2023)	0	multispectral	physiological, stress indicators	machine learning, remote sensing, statistical modelling	XGBoost, GWO, SVR	pest prediction	IEEE Access
48	(Lu et al., 2023)	0	RGB	yield indicators	machine learning	Yolov8	boll detection	IEEE Access
49	(Qiu et al., 2022)	0	RGB	–	machine learning, statistical modelling	LinkNet, FCN, DeepLabv3	residual film detection	Frontiers in Plant Science
50	(Y. Li et al., 2022)	0	multispectral	morphological, physiological indicators	machine learning, remote sensing	AdaBoost, DT	topping time	Discrete Dynamics in Nature and Society
51	(Ma et al., 2023)	0	RGB	morphological, physiological, yield indicators	machine learning	MSR, KRR, ELM, PSO–ELM	Defoliation& boll-opening rate	European Journal of Agronomy
52	(Shrestha et al., 2023)	0	multispectral	yield indicators	machine learning	ANNs, RF	yield estimation	Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping

Table A2
Detailed information of reviewed literature.

	Reference	Functionality	Dataset					Models/ Algorithms	Best output
			stages	**Field area (acres)**	**Flight height (m)**	**GSD (mm)**	**Input data**		
1	(Xu et al., 2018)	detect and count cotton flowers	reproductive growth	0.57	15	2.61	RGB images	Customized CNN	precision = 0.9, recall = 0.91
2	(Ashapure et al., 2020a)	yield estimation	whole stages	1.6	RGB:13 ~ 40, Multi:35 ~ 50	4.92 ~ 14.6, 20.9 ~ 27.1	RGB & multispectral images, in situ data	ANN, SVR, RFR	ANN: R^2=0.898, MSE = 0.0025
3	(Feng et al., 2020a)	evaluate stand count and canopy size	seedling establishment	12.65	10	2.7	RGB images, in situ data	Resnet18	stand count: R^2 = 0.95, MAPE = 4.3 %, canopy size: R^2 = 0.93, MAPE = 4.5 %
4	(Wang et al., 2020b)	classification of cotton root rot disease	after harvest	143.6	120	76.4	multispectral images	KMSVM, KMSEG	KMSEG: accuracy = 88.39 %, Kappa coefficient = 0.7198, error of commission = 16.13 %, error of omission = 11.44 %
5	(Ashapure et al., 2019)	canopy cover estimation	first four stages (two years)	0.22	RGB:20,35, Multi:25,47	5 ~ 7.2, 8.1 ~ 16.5	RGB & multispectral images	K-means clustering	2017: R^2 = 0.98, 2018: R^2 = 0.97
6	(Oh et al., 2020)	cotton plant count	germination and emergence	0.22	10	2.5	RGB images	YOLOv3	mAP = 88 %, F1 Score = 0.85, R^2 = 0.97, RMSE = 0.56
7	(Xu et al., 2021)	yield estimation	maturation	15.16	RGB:100, Multi:100	27.4, 52.9	RGB & multispectral images, in situ data	Linear regression, BP neural network	BP: R^2 = 0.854, MSE = 0.96

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Table A2 (*continued*)

	Reference	Functionality	Dataset					Models/ Algorithms	Best output
			stages	**Field area (acres)**	**Flight height (m)**	**GSD (mm)**	**Input data**		
8	(Mattupalli et al., 2018)	classification of cotton root rot disease	last four stages (two years)	61.28	120	18 ~ 64	RGB images	Maximum likelihood classification	Accuracy = 90 ~ 96 %
9	(Lin and Guo, 2021)	cotton plant count	seedling establishment	0.29	20	3.3	RGB images	MobileNet, CenterNet	CenterNet: R^2 = 0.96, MAPE = 0.11 %
10	(Feng et al., 2020b)	Evaluate stand count and uniformity	seedling establishment	12.65	50	Spatial: 7.9 Spectral:2–5 nm	Hyperspectral images, in situ data	AdaBoost combined with DT	Accuracy = 84.1 %, density: MAPE = 9.0 %, uniformity: MAPE = 9.1 %
11	(Huang et al., 2018)	Detection of spider mite-infested cotton	vegetative growth	1.48	60	27	multispectral images, in situ data	SVM, transferred AlexNet	transferred AlexNet: Accuracy = 95.4 %
12	(Wang et al., 2020a)	classification of cotton root rot disease	reproductive growth	143.6	120	76.4	multispectral images, in situ data	SVM, PBP K-means, KMSVM, KMSVG	PBP K-means: accuracy = 92.1 %, Kappa coefficient = 0.786, error of commission = 15.16 %, error of omission = 15.9 %
13	(Marang et al., 2021)	Retrieve cotton nitrogen status	vegetative growth	0.56	50	Spatial: 52 Spectral:5–10 nm	Hyperspectral images, in situ data	Density-based and hierarchical clustering, RF	Green (B3 543–578 nm): R^2 = 0.852, RMSE = 0.187
14	(Sapkota et al., 2020)	Evaluate weed density level	seedling establishment	1.48	15	8	RGB images	Random Forest	Accuracy = 89.16 %, Kappa coefficient = 0.84
15	(Xia et al., 2019)	Monitor cotton budding rate	reproductive growth	0.61	15	5.2	RGB images	SVM, Maximum likelihood	SVM: Accuracy = 96.65 %, Kappa coefficient = 0.94
16	(Wang et al., 2020c)	classification of cotton root rot disease	reproductive growth	83.3	120	36.7, 76.4	multispectral images, in situ data	Maximum likelihood	–
17	(Maja et al., 2016)	yield estimation	maturation	0.41	25, 30, 40	33.7	RGB images, in situ data	K-means clustering, Linear regression	LR: error < 10 %
18	(Shi et al., 2022)	yield estimation	maturation	0.034	Multi: 50, Thermal: 50	21.6, 135.6	multispectral images, in situ data	LR, SVR, CART, RF, KNN	RF: R^2 = 0.77, rRMSE = 0.075
19	(Yin et al., 2022)	Monitor leaf nitrogen content	vegetative growth	0.5	60, 80, 100	Spatial: 60 Spectral:2.2 nm	Hyperspectral images, in situ data	MLR, SVR, PCR	MLR: R^2 = 0.96, RMSE = 1.12, MAE = 1.57
20	(Kou et al., 2022)	Estimation of leaf nitrogen content	reproductive growth	0.56	20	50	RGB images, in situ data	LR, SVM, CNNs	two-dimensional CNN regression: R^2 = 0.8, RMSE = 1.67
21	(Qi et al., 2022)	Soil salinity inversion	vegetative growth	2.77	–	50	multispectral images, in situ data	RF, XGBoost, CNN	CNN: R^2 = 0.85
22	(F. Li et al., 2022a)	yield estimation	maturation	94.1	5	1.5	RGB images, in situ data	CD-SegNet, SegNet, RF	CD-SegNet: mIoU = 77.13 %, Recall = 84.71 %, Percision = 90.82 %, F1-score = 87.93 %
23	(Davidson et al., 2022)	Prediction of vegetation indices	Several stages	–	30 ~ 90	3.3 ~ 25.8, 20 ~ 82.5	RGB & multispectral images, in situ data	a conditional GAN called Pix2Pix	SSIM = 0.9958, PSNR = 0.9720, MSE = 0.9689
24	(Rodriguez-Sanchez et al., 2022)	yield estimation	reproductive growth	0.59	15	2.6	RGB images, in situ data	SVM	R^2 = 0.93, RMSE = 0.07, MAPE = 0.137
25	(Yadav et al., 2019)	detection of volunteer cotton in grain fields	seedling establishment	1.33	120, 60	82, 21.5	RGB & multispectral images, in situ data	Parallelepiped, Maximum Likelihood, Mahalanobis distance classification	Mahalanobis: Accuracy = 91.75 %, Kappa coefficient = 0.87
26	(Raptis et al., 2023)	Weed detection	vegetative growth	–	–	–	RGB images	DeepLabv3+	mIoU = 70.29 %
27	(Kumar Yadav et al., 2023)	detection of volunteer cotton in corn fields	seedling establishment	0.25	18.3	5	RGB images	YOLOv3	Accuracy > 0.8, F1 Score = 0.785, R^2 = 0.97, RMSE = 0.56

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Table A2 (*continued*)

	Reference	Functionality	Dataset				Input data	Models/ Algorithms	Best output
			stages	**Field area (acres)**	**Flight height (m)**	**GSD (mm)**			
28	(Sapkota et al., 2022)	Weed detection and biomass estimation	germination and emergence	–	4.9	0.0274	RGB images	Mask R-CNN	mAP(mask): 0.80, mAP(box): 0.83
29	(Yan et al., 2022)	Estimation of leaf area index	Last three stages	–	70	50	LiDAR & multispectral images, in situ data	RFR, SVR, ANN	RFR: $R^2 = 0.95$, RMSE = 0.332
30	(Petti and Li, 2022)	count cotton flowers	reproductive growth	–	10,15,32	2.3 ~ 2.7	RGB images	LeNet, AlexNet, VGG-16, DenseNet	DenseNet: MAE = 2.43, AUC = 0.87
31	(Senyurek et al., 2022)	Estimation of soil moisture	After harvest	5.71	15	–	multispectral images, in situ data	Random Forest	RMSE = 0.013
32	(Chen et al., 2022)	Evaluation of defoliation rate	maturation	13.1	100	27.6	RGB & multispectral images	MLR, neural network	neural network: $R^2 = 0.945$, RMSE = 0.006
33	(Bawa et al., 2023)	counting open cotton bolls and estimating lint yield	maturation	–	RGB:30, Multi:15	7.5, 10.7	RGB & multispectral images, in situ data	SVM	accuracy > 95 %, precision > 0.96, recall > 0.93
34	(Sudarshan Rao et al., 2021)	Crop classification	maturation	–	–	–	Thermal & multispectral images	U-Net, SegNet, PSPNet	U-Net: Accuracy = 97 %
35	(Narvaria et al., 2021)	Crop classification	maturation	–	–	–	RGB & multispectral images	U-Net	Accuracy = 83.35 %
36	(Zhao PEI et al., 2023)	diagnosis of nitrogen nutrition	vegetative growth	1.24	30	14	multispectral images, in situ data	SVM, BPNN, XGB	XGB: R^2= 0.83, RMSE = 1.08, RE = 0.1971
37	(Zou et al., 2018)	yield estimation	reproductive growth	0.014	10	–	RGB images, in situ data	DT, LR	Cotton boll pixels classification, DT: Accuracy = 97.2 % Yield estimation, LR: Accuracy = 89.13 %
38	(Feng et al., 2024)	Detection and counting of seedlings	germination and emergence	–	10	–	multispectral images	YOLOv5, YOLOv7, CenterNet	YOLOv7: precision = 0.969, recall = 0.966, F1-score = 0.967 $R^2 = 0.94$, RMSE = 3.83, RRMSE = 0.027
39	(Zhai et al., 2022)	Evaluation of residual plastic film	Before planting		5,7,9	–	RGB images	Modified U-Net, SegNet, FCN	Modified U-Net: MIOU = 0.8753, $R^2 = 0.9849$, RMSE = 0.0563, MRE = 0.0533
40	(Yadav et al., 2022)	detection of volunteer cotton in corn fields	First three stages	18	18.3	5	RGB images	YOLOv5	Accuracy = 98 %, mAP = 96.3 %
41	(Thomasson et al., 2018)	detection of cotton root rot disease	vegetative growth	83.3	121.9	36.7,76.4	multispectral images, in situ data	SVM	–
42	(Suryawanshi and Khurjekar, 2021)	disease detection	vegetative growth	–	–	–	RGB images	CNN	Accuracy = 76 %
43	(Xu et al., 2023)	Estimation of fiber quality	maturation	15.07	RGB:100, Multi:100	27.4, 52.9	RGB & multispectral images, in situ data	LR, CNN	CNN: Average $R^2 = 0.7952$, Average MSE = 0.1094,
44	(Ashapure et al., 2020b)	Estimation of canopy parameters	vegetative growth	200	–	–	RGB & multispectral images, in situ data	A three-layer ANN, SVM	ANN: $R^2 > 0.9$
45	(Feng et al., 2023a)	yield estimation	vegetative growth	12.65	30, 50	15.6, 20	Soil data, weather data,	A gated recurrent unit (GRU) network	8.9 %< mean average error < 13.7 %
46	(Yadav et al., 2023)	Detection of plastic contaminant	vegetative growth	0.6	18.28	10	RGB images	YOLOv5	White bags: Accuracy = 92.35 %, mAP = 87.68 %, brown bags: Accuracy = 77.87 %, mAP = 87.68 %

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Table A2 (*continued*)

	Reference	Functionality	Dataset					Models/ Algorithms	Best output
			stages	**Field area (acres)**	**Flight height (m)**	**GSD (mm)**	**Input data**		
47	(Jiang et al., 2023)	Prediction of dynamics in cotton aphid	vegetative & reproductive growth	63	70	50	multispectral images, in situ data	XGBoost, GWO, SVR, ANOVA	XGBoost-GWO-SVR: $R^2 = 0.980$, MAE = 2.838
48	(Lu et al., 2023)	Detection and counting of plants	reproductive growth	–	–	–	RGB images	Yolov8	precision = 0.876, recall = 0.788, MAE = 3.3 RMSE = 5.93
49	(Qiu et al., 2022)	Prediction of residual plastic film	Before planting	–	5	–	RGB images	LinkNet, FCN, DeepLabv3	DeepLabv3: accuracy = 0.9971, precision = 0.8529, recall = 0.7938, F1-score = 0.7973 MIOU = 0.7462
50	(Y. Li et al., 2022)	Monitor topping time of cotton	vegetative growth	–	–	–	multispectral images	AdaBoost + decision tree	Cotton plant height: $R^2 = 0.93$, RMSEP = 0.23, Number of buds: $R^2 = 0.90$, RMSEP = 0.97
51	(Ma et al., 2023)	Monitor defoliation rate and boll-opening rate	maturation	0.26	–	–	RGB images, in situ data	MSR, KRR, ELM, RF-PSO–ELM	defoliation rate, RF-PSO–ELM: $R^2 = 0.59$, RMSE = 0.1937, rRMSE = 0.3454, defoliation rate, RF-PSO–ELM: $R^2 = 0.73$, RMSE = 0.1911, rRMSE = 0.4640
52	(Shrestha et al., 2023)	yield estimation	maturation	405	30	20	multispectral images, in situ data	ANN+, RF	ANN+: $R^2 = 0.90$, MAP = 0.1229,

Data availability

No data was used for the research described in the article.

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