Advances in UAV Remote Sensing for Forage Crop Growth Monitoring: A Postprint

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Abstract

Dynamic monitoring and quantitative estimation of forage crop growth are of great significance for large-scale forage production. UAV remote sensing, characterized by high resolution, strong flexibility, and low cost, has developed rapidly in the field of forage crop growth monitoring in recent years, with continuously expanding application scenarios. To grasp the domestic and international application status of UAVs in forage monitoring and identify key development directions, this paper first briefly describes the basic research methods of UAV remote sensing in forage crop monitoring from three aspects: data acquisition, data processing, and key technologies for forage crop growth monitoring. Secondly, it elaborates on the application status of UAV remote sensing for forage crop growth monitoring according to sensor types from five aspects: visible light, multispectral, hyperspectral, thermal infrared, and LiDAR remote sensing. Finally, it prospects future development directions by addressing key technical issues that remain unresolved in research and applications, and proposes that integrating spatiotemporal scale data of forage crops and multi-source remote sensing data, further expanding data acquisition means, and developing intelligent comprehensive data analysis platforms are the keys to application innovation in the future forage crop monitoring field.

Full Text

Advances in Forage Crop Growth Monitoring by UAV Remote Sensing

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Abstract: Dynamic monitoring and quantitative estimation of forage crop growth are crucial for large-scale forage production. UAV remote sensing offers high resolution, strong flexibility, and low cost, and has developed rapidly in forage crop monitoring in recent years with expanding application scenarios. To understand the current status of UAV applications in forage monitoring and identify key development directions, this paper first outlines the fundamental research methods of UAV remote sensing in forage crop monitoring from three aspects: data acquisition, data processing, and key monitoring technologies. Second, it reviews the application status of UAV remote sensing for forage crop growth monitoring according to sensor types, including visible light, multispectral, hyperspectral, thermal infrared, and LiDAR remote sensing. Finally, future development directions are proposed based on unresolved key technical issues in research applications. The integration of spatiotemporal data and multi-source remote sensing data for forage crops, further expansion of data acquisition methods, and development of intelligent comprehensive data analysis platforms are identified as critical innovations for future forage crop monitoring.

Keywords: UAV; remote sensing; forage crop; growth monitoring; sensor; biomass

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2 UAV Remote Sensing Monitoring Methods for Forage Crops

Traditional methods for obtaining field crop growth status indicators rely primarily on manual field sampling, which is time-consuming, labor-intensive, poorly timely, destructive, and inefficient. Satellite remote sensing can quickly, nondestructively, and extensively acquire crop information, achieving a transformation from point-based to area-based monitoring, but suffers from low spatiotemporal resolution and susceptibility to cloud cover [1]. UAV remote sensing for crop monitoring offers advantages including lower cost, high mobility, simple operation, high spatiotemporal resolution, and repeatability. In recent years, with continuous improvements in UAV platforms and sensor hardware, UAV remote sensing has been widely applied in crop pest identification [2], growth monitoring [3], yield estimation [4], and lodging detection [5], providing new means for crop growth monitoring.

The forage industry is an important component of modern agriculture and a key focus for optimizing agricultural structure. As China' s crop planting structure continues to adjust, a coordinated development pattern of "grain, cash, and forage crops" is gradually taking shape [6]. Since the 13th Five-Year Plan, China has implemented policies such as the "Grassland Ecological Protection Subsidy and Reward," "Grain to Forage," and "Revitalizing Dairy Industry with Alfalfa Development Action," leading to vigorous development of forage crops. In 2020, China' s major forage crops included silage corn, oat forage, Italian ryegrass, and alfalfa, with a cultivated area of nearly 5.4 million hectares and dry weight production of approximately 71.6 million tons, representing an increase of 24 million tons compared to 2015 [7].

Real-time monitoring of forage crop growth provides essential information for producers to improve field management. UAV remote sensing applications in forage crop monitoring are expanding, and to systematically understand the current status, analyze industry progress, and identify challenges, this paper focuses on data acquisition, processing, and key monitoring technologies. It reviews fundamental research methods, summarizes three key technologies—canopy structure information extraction, spectral reconstruction and optimization, and forage biomass estimation—analyzes recent development trends, and reviews domestic and international research progress from five sensor perspectives. Finally, it proposes future development directions to address unresolved technical challenges.

2.1 Data Acquisition

The quality of UAV-acquired data directly affects orthophoto quality and largely determines crop growth monitoring outcomes. Selecting appropriate UAV platforms and sensors based on specific monitoring indicators, and rationally setting flight parameters according to operational requirements, are fundamental to UAV remote sensing data acquisition.

2.1.1 Flight Platforms UAV remote sensing systems typically consist of a UAV platform, sensors, and a ground station system [2]. UAV platforms can be categorized by configuration into multi-rotor, fixed-wing, and vertical take-off and landing (VTOL) fixed-wing aircraft, while single-rotor, flapping-wing, and airship platforms have limited applications in crop monitoring [8]. The operational scenarios, advantages, and limitations of these three mainstream UAV types are summarized in . Multi-rotor UAVs offer high flexibility and applicability with balanced payload capacity and flight duration, making them the most widely used platform for remote sensing. Fixed-wing UAVs such as the SenseFly eBee are commonly used [9,10], while multi-rotor UAVs like DJI' s Phantom series are popular [11,12]. For applications requiring larger payloads, DJI' s M600 series hexacopter [13,14], S1000 octocopter [15,16], and Scheveningen' s AT8 octocopter [17,18] are frequently employed.

2.1.2 Sensors Sensors are the core equipment for UAV remote sensing. Commonly used sensors include visible light cameras, multispectral cameras, hyperspectral cameras, thermal infrared cameras, and LiDAR [19]. compares the application scope, advantages, and limitations of each sensor type. Visible light sensors are most widely used in forage monitoring due to their high resolution, low cost, and simple data processing, with common models including Sony $ $6000 [20] and Canon S110 [10]. Representative multispectral sensors include MicaSense' s RedEdge series [21] and Parrot' s Sequoia [22], which differ in band number and wavelength. Hyperspectral, thermal infrared, and LiDAR sensors have fewer applications in forage monitoring. Common hyperspectral models include the push-broom Headwall Nano-Hyperspec [23] and frame-based Cubert FireflEYE 185 [24]. Thermal infrared sensors typically use OPTRIS PI series [25], while LiDAR applications often employ GreenValley' s RIEGL VUX-1 [26].

2.1.3 Flight Parameters To ensure high-quality data acquisition, flight altitude, speed, overlap, and capture interval must be properly set. For small-scale monitoring, flight altitude is typically below 100 m [27,28], while large-scale operations use altitudes above 100 m [29,30]. Image stitching quality improves with increasing overlap at the same resolution [31], with forward and side overlaps generally not less than 75%, though this can be reduced for time-critical applications like disaster surveys [32]. Higher flight speeds and shorter capture intervals reduce operation time, but excessive speed may cause image blur. Therefore, flight parameters must be rationally configured based on operational requirements, environment, and sensor characteristics. For forage monitoring, flight altitude is generally set within 120 m for small-scale studies, though some applications use 191 m [33] or 850 m [34] for larger-scale model validation.

2.2 Data Processing

UAV sensors acquire massive amounts of remote sensing data with higher spatial resolution than satellite data, providing comprehensive support for crop monitoring. However, this high resolution also poses challenges for data processing, with massive data handling and multi-source data registration being key concerns.

2.2.1 Data Preprocessing Visible light, multispectral, hyperspectral, and thermal infrared sensors require radiometric correction, image stitching, geometric correction, and georeferencing [35]. Radiometric correction converts pixel values to radiance, reducing effects of solar angle, cloud shadows, camera gain, and exposure [2]. Sensors like MicaSense RedEdge and Cubert FireflEYE 185 can be calibrated using manufacturer-provided panels, while thermal sensors like DJI' s Zenmuse XT series use radiometric software with meteorological parameters. Empirical linear methods based on ground reflectance measurements [36] and pseudo-invariant feature methods [37] are also common. Image stitching uses geographic coordinates for feature matching, while geometric correction addresses distortions from flight attitude changes [38]. These processes typically use commercial software like PhotoScan and Pix4D Mapper for automated processing [39]. Georeferencing employs high-precision GNSS receivers to measure ground control points for implementation in Pix4D Mapper, ArcGIS, or QGIS.

LiDAR data preprocessing differs fundamentally, extracting 3D information about vegetation structure and position. It involves point cloud denoising, ground point classification, and normalization. Noise points from sensor limitations and environmental interference must first be removed, followed by filtering to separate ground and non-ground points, and normalization to eliminate terrain effects on elevation. Software like LiDAR360 [26] and TerraScan [40] can perform complete LiDAR data preprocessing.

2.2.2 Growth Monitoring Model Construction UAV remote sensing is widely used to monitor leaf area index, chlorophyll content, plant height, and biomass based on relationships between crop characteristics and canopy spectral reflectance. Models fall into two categories: empirical statistical models and canopy radiative transfer models.

Empirical statistical models use sensitive band reflectance or spectral indices to build linear or nonlinear relationships with crop growth indicators. Common methods include correlation analysis, principal component analysis, and multiple regression. Machine learning algorithms like Support Vector Regression (SVR) [36], Random Forest (RF) [41], and Artificial Neural Networks (ANN) [42] are increasingly used for nonlinear fitting to improve inversion accuracy. These models are simple, computationally efficient, and suitable for rapid application, but are sensitive to crop type and environment, requiring extensive sample data and having limited universality.

Radiative transfer models are based on physical optics, using explicit physical relationships between canopy reflectance and growth indicators. They are less affected by crop type and environment, offering good generality, but require numerous input parameters and complex inversion processes constrained by the "curse of dimensionality" and "ill-posed inversion" problems [43]. Commonly used models include PROSAIL, GeoSail, and the Two-Layer Canopy Reflectance Model (ACRM), with PROSAIL being most widely applied [44].

2.3 Key Technologies for Forage Crop Growth Monitoring

Extracting and interpreting remote sensing data for forage crop growth is critical for widespread UAV application. Key technologies include canopy structure information extraction, spectral reconstruction and optimization, and forage biomass estimation.

2.3.1 Canopy Structure Information Extraction Canopy structure includes plant height, canopy volume, and leaf area, reflecting crop growth status. For forage crops, the canopy is both the carrier for photosynthesis and transpiration and an indicator of dry matter accumulation [45,46]. Efficient, large-scale extraction of canopy structural features and their spatiotemporal patterns is essential. LiDAR-based methods have been successfully applied to phenotype switchgrass [47] and natural grasslands [40]. Structure-from-Motion (SfM) methods are also common, extracting feature points from highly overlapping images and generating point clouds through triangulation to create canopy structure models. Studies have confirmed SfM' s effectiveness for extracting canopy structure information from mixed grasslands of red clover-alfalfa [48], guinea grass [49], ryegrass-red clover [50], and ryegrass-pearl millet [12].

2.3.2 Spectral Reconstruction and Optimization UAV remote sensing generates massive data volumes, particularly for hyperspectral data, which complicates transmission, analysis, storage, and model application. To balance model accuracy and data volume, spectral data are typically reconstructed and optimized. Correlation analysis is widely used to identify relationships between remote sensing data and key indicators. Gao et al. [13] used correlation coefficients to select remote sensing variables sensitive to natural grassland nutrition indicators, finding MERIS Terrestrial Chlorophyll Index (MTCI) most correlated with crude protein content. Lussem et al. [11] used Pearson correlation to select vegetation indices for biomass modeling, identifying Normalized Green-Red Difference Index (NGRDI) as most correlated with dry biomass. For hyperspectral data, Kang et al. [51] proposed a feature-parameterized spectral reconstruction method that significantly reduced data volume while maintaining comparable accuracy for grassland biomass estimation. Feng et al. [52] extracted narrowband spectral indices and used recursive feature elimination to rank their importance.

2.3.3 Forage Biomass Estimation Biomass is a critical monitoring indicator for forage crops. Timely and accurate assessment via UAV remote sensing ensures rational forage resource utilization and informs ranch construction decisions. Numerous studies have investigated biomass estimation, such as Miao et al. [53] who combined UAV hyperspectral data with ground measurements using machine learning to model alpine grassland biomass. Viljanen et al. [54] used visible and hyperspectral cameras to build biomass models for timothy-meadow fescue mixtures. Wang et al. [16] integrated GPS trajectory data of livestock herds with grassland biomass to assess natural grassland utilization intensity. UAV-based biomass estimation enables determination of reasonable stocking rates, protecting natural grasslands while maximizing production [55] and achieving sustainable grassland ecosystem management.

3 Research Status of UAV Remote Sensing in Forage Crop Monitoring

3.1 Research Trends

To understand research trends in UAV remote sensing for forage crop monitoring, relevant publications were retrieved from the Web of Science Core Collection using the search terms: (UAV or UAS or unmanned aerial vehicle) AND (grassland or herbage or forage) AND (height or lodging or biomass or yield or LAI or nitrogen or water stress or evapotranspiration or phenotyping or quality or vegetation parameters or feed values or drought tolerance or diseases or chlorophyll). The results are shown in [Figure 1: see original paper].

Publication numbers from 2012-2021 show an overall trend from zero to rapid growth. Fewer than 30 papers were published between 2012-2017. Since 2018, increasing numbers of studies have employed machine learning [41] and SfM [56] techniques, expanding monitoring indicators to nitrogen concentration [9], quality [57], and leaf area index [58], demonstrating that rapid development of computer information and remote sensing technologies has unlocked the application potential of UAV remote sensing in forage monitoring.

[Figure 2: see original paper] shows publication numbers by major countries during 2012-2021. China started later in this field, with no relevant papers before 2015. However, with the implementation of the "Revitalizing Dairy Industry with Alfalfa Development Action" (2012) and "Grain to Forage" (2015) policies, China' s forage industry entered a period of vigorous development. Regions like the Hexi Corridor in Gansu, Hetao Irrigation Area in Ningxia, and Mu Us Sandy Area have become major alfalfa production zones due to favorable dry climate conditions [59]. With expanding forage production areas, Chinese researchers have increased investment, publishing 38 papers during 2016-2021, ranking first globally. The United States has a long history of forage production, with forage crops planted on approximately 24.7 million hectares (14% of farmland) [60], often in rotation with corn, soybean, and wheat. U.S. research is well-established, with 34 papers published since 2013. Other countries including Germany, Australia, and the UK have also published research in recent years, indicating global progress in this field, though overall it remains a relatively niche research area based on publication numbers.

3.2 Current Research Status

This section reviews recent research applications from five sensor perspectives: visible light, multispectral, hyperspectral, thermal infrared, and LiDAR.

3.2.1 Visible Light Remote Sensing Visible light sensors offer high resolution, simple processing, and low cost, making them most widely used for forage crop coverage and biomass monitoring. Studies by Liu et al. [61] and Zhao et al. [42] confirmed the feasibility of Excess Green Index (EXG) for estimating forage crop vegetation coverage. Yu et al. [62] used supervised classification with vegetation index histograms to evaluate six visible light indices, finding Normalized Green-Red Difference Index (NGRDI) effective. Fu et al. [63] reported that Vegetative Index (VEG) and EXG estimated grassland coverage with over 93% accuracy.

Directly constructing linear or nonlinear models between sensitive vegetation indices and biomass is a common approach. Zhang et al. [34] used NGRDI to build a biomass regression model for subalpine meadows, while Shi et al. [64] used Red Green Blue Vegetation Index (RGBVI) for grazing grasslands on the Tibetan Plateau, both achieving good results. Recent studies show that Digital Surface Model (DSM) features containing absolute height information provide important references for biomass estimation, compensating for limited spectral bands in visible light imagery and improving prediction accuracy [11,48-50]. Castro et al. [65] used AlexNet deep learning to predict biomass of different guinea grass genotypes, achieving a correlation coefficient of 0.88. Minch et al. [66] investigated effects of flight altitude (50 m) and camera angle (75°) on alfalfa biomass modeling, finding optimal accuracy at these settings. DiMaggio et al. [67] compared models at 30, 40, and 50 m altitudes, obtaining R^2 values of 0.65, 0.63, and 0.63, respectively, indicating non-significant altitude effects.

These studies demonstrate successful application of high-resolution visible light imagery through regression analysis, machine learning, and SfM methods for vegetation coverage, plant height, and biomass estimation. However, visible light sensors lack red-edge and near-infrared bands, challenging research on nutritional value estimation [57], lodging detection [10], and nitrogen monitoring [68]. Nevertheless, their lower cost compared to multispectral and hyperspectral sensors provides good economic viability for widespread UAV remote sensing adoption.

3.2.2 Multispectral Remote Sensing Unlike visible light sensors with only R, G, B bands, multispectral cameras include red-edge and near-infrared bands that better capture spectral reflectance characteristics throughout crop growth stages. Vegetation indices based on these bands enable accurate biomass estimation and nutritional monitoring. Commonly used indices include Normalized Difference Vegetation Index (NDVI) [69], Green Normalized Difference Vegetation Index (GNDVI), and Normalized Difference Red-Edge Index (NDRE) [70].

In breeding phenotyping, Cazenave et al. [71] used NDVI and coverage to calculate alfalfa hay quality and evaluate productivity across varieties. Biswas et al. [72] analyzed correlations between NDVI, NDRE, GNDVI, and Green-Red Ratio Vegetation Index (GRVI) with alfalfa biomass, improving breeding trial efficiency. In nitrogen monitoring, Wang et al. [9] built models for nitrogen concentration, uptake, biomass, and Nitrogen Nutrition Index (NNI) in fescue-ryegrass mixtures. López-Calderón et al. [33] used RF algorithms to construct nitrogen content models for silage corn based on five multispectral indices.

Numerous studies confirm multispectral indices can predict forage yield [15,16,73]. Théau et al. [74] noted that combining spectral indices with canopy structure information can avoid saturation in high-yield areas. Researchers have improved predictions for ryegrass [22,75,76], white clover-ryegrass mixtures [77], and alfalfa [21] by incorporating canopy structure data. Compared to visible light remote sensing, multispectral near-infrared bands provide more support for crop information retrieval and offer greater flexibility in data processing and model construction. While current research mainly focuses on simple band combinations without fully reflecting continuous absorption processes, multispectral remote sensing offers substantial comprehensive application value as a mature and suitable monitoring approach.

3.2.3 Hyperspectral Remote Sensing Hyperspectral sensors provide richer spectral information than multispectral sensors, sensitively capturing spectral reflectance changes caused by normal or stressed vegetation growth [78]. Näsi et al. [41] compared visible light and hyperspectral imagery for grassland biomass and nitrogen estimation, confirming hyperspectral superiority for nitrogen content. Feng et al. [52] built an alfalfa yield prediction model using UAV hyperspectral vegetation indices with RF, SVR, and K-nearest neighbors, showing ensemble models outperformed base algorithms with optimal R^2 of 0.87. Feng et al. [23] first applied Multi-Task Learning (MTL) using Long Short-Term Memory (LSTM) and ANN to estimate alfalfa quality, demonstrating MTL superiority over other models. Wijesingha et al. [24] found SVR achieved highest accuracy for crude protein models while Cubist regression performed best for acid detergent fiber.

These results demonstrate hyperspectral remote sensing' s high feasibility for nitrogen, yield, and nutritional value monitoring. However, fewer hyperspectral studies exist compared to visible light and multispectral research. Future studies should leverage hyperspectral characteristics of high spectral resolution and information content to further improve monitoring effectiveness for different crops.

3.2.4 Thermal Infrared Remote Sensing Thermal infrared remote sensing (0.76-1000 m) performs well for canopy temperature, soil moisture, and evapotranspiration. Zhang et al. [79] demonstrated UAV thermal infrared technology can quickly and accurately obtain surface temperature data for alpine meadow drought monitoring. Hassan-Esfahani et al. [80] combined UAV thermal imagery with ground sampling to accurately estimate soil moisture distribution in alfalfa and oat fields ($R^2 = 0.77$). Evapotranspiration models based on surface energy balance are important for obtaining canopy evapotranspiration, with UAV thermal data being more suitable than satellite data for small and medium field monitoring [25,81].

Current thermal infrared sensors have relatively low resolution, prompting researchers to fuse thermal with multispectral and visible light data to improve monitoring. Chandel et al. [82] used Crop Water Stress Index (CWSI) from thermal sensors and vegetation indices from multispectral sensors to characterize alfalfa vigor and yield. Looftens et al. [17] used visible light indices and canopy temperature to assess drought tolerance in fescue and ryegrass, showing stepwise regression models could accurately estimate visual scores. De Swaef et al. [18] similarly found high correlation between vegetation indices and expert visual scores, with CWSI from thermal remote sensing applicable for analyzing physiological differences among ryegrass varieties.

These studies confirm thermal infrared sensor feasibility in forage monitoring, though low resolution and complex environmental conditions pose challenges. Future research should focus on developing more applicable thermal sensors for accurate, economical, and practical applications.

3.2.5 LiDAR Remote Sensing LiDAR differs from optical imaging by actively emitting laser pulses to obtain spatial data, offering high point density, spatial resolution, and low-altitude detection performance. Hao et al. [83] combined LiDAR data with elevation points to construct DSM for grasslands in Xilinhot, obtaining canopy height models through spatial matching. Wang et al. [84] investigated discrete-return LiDAR for modeling canopy height and coverage in Hulunber grasslands, finding mean canopy height was the best biomass predictor (RMSE = 81.89 g/m^2). LiDAR has stronger anti-interference capability than optical sensors, though improper flight parameters can cause point cloud information loss. Zhang et al. [40] confirmed flight altitude significantly affects coverage estimation, while Zhao et al. [26] recommended reduced flight speed and terrain-following modes to ensure data quality.

LiDAR offers higher measurement precision [85] but involves complex data processing and high costs, resulting in limited application in forage monitoring. Future research should focus on developing low-cost sensors and supporting algorithm models.

4 Challenges and Prospects

4.1 Challenges

Despite recent progress, UAV remote sensing for forage crop monitoring faces significant challenges in model accuracy, universality, and processing timeliness:

(1) Most current achievements are based on single-time or temporally close image sequences, without considering differences in canopy morphology across growth stages, making it difficult to reflect full growth cycle trends. Additionally, remote sensing images differ among forage species, regions, and years for perennial crops, preventing broad application of existing models.

(2) Current UAV platforms are mostly small UAVs with visible light or multispectral sensors. Most studies limit data fusion to airborne sensors without establishing connections with ground or satellite remote sensing data, resulting in single data acquisition methods that constrain model improvement and scale expansion.

(3) Current UAV data processing software is fragmented and lacks systematic integration, requiring different software environments for image stitching, preprocessing, and prescription map generation, which demands high operator expertise. Moreover, increasing forage planting areas and image resolution produce massive data volumes that cannot be transmitted to ground stations in real time, limiting timely feedback on crop growth status.

4.2 Prospects

To address these challenges, future research on model construction, data fusion, and system development should focus on:

(1) **Temporal scaling:** Build multi-temporal growth monitoring models based on characteristics of different growth stages and years for forage crops, gradually transitioning from single-stage to multi-temporal models. **Spatial scaling:** Conduct monitoring around representative regions to increase sample data and improve model applicability.

(2) **Sensor integration:** Expand use of hyperspectral, thermal infrared, and LiDAR sensors in forage monitoring, accelerate multi-sensor fusion technology development, establish multi-source UAV remote sensing databases, and conduct integrated monitoring combining satellite data, historical yield, soil conductivity, and other data.

(3) **Intelligent systems:** Develop intelligent, user-friendly, full-process UAV remote sensing data analysis systems. Simplify operations and processing steps, introduce intelligent interactions (voice, image, text) to improve usability [86], and employ 5G networks and edge computing to solve data transmission and real-time processing issues [87] for timely, accurate monitoring of forage crop growth.

In conclusion, UAV remote sensing research for forage crop monitoring remains in its early stages with significant gaps to practical application. However, with rapid development of computer information technology, sensor technology, GIS, and communication technology, UAV remote sensing and its applications in forage monitoring will mature and truly serve agricultural production.

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