Estimation Methods for Fractional Vegetation Cover Using UAV Remote Sensing

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Abstract: Fractional vegetation cover is an important parameter for evaluating ecological conditions and crop growth. This paper analyzes the technical workflow and principal methods for estimating fractional vegetation cover from unmanned aerial vehicle (UAV) RGB and multispectral imagery. The findings indicate that threshold segmentation and the two-endmember pixel model are straightforward to implement, whereas spectral unmixing and machine learning are better suited to complex backgrounds. However, estimation results are affected by illumination, shadows, phenology, endmember selection, and spatial scale. Future research should standardize the definition of fractional vegetation cover and its validation protocols, strengthen multitemporal and multisensor data fusion and cross-regional generalization, and establish a traceable uncertainty-assessment system.

Keywords: UAV remote sensing; fractional vegetation cover; spectral unmixing; machine learning; scale effects

Introduction

Fractional vegetation cover (FVC) represents the proportion of a unit land-surface area occupied by the vertical projection of vegetation. It is an important parameter for ecological-quality assessment, soil-erosion monitoring, desertification surveys, and crop-growth diagnosis. Conventional quadrat-based visual estimation, point-intercept methods, and ground photography can provide detailed information at individual sampling locations, but their survey efficiency is limited. Moreover, substantial scale differences exist between quadrat areas and satellite pixels. Satellite remote sensing provides extensive spatial coverage but may be constrained by cloud cover, revisit intervals, and spatial resolution, making it difficult to represent field boundaries and patches of sparse vegetation.

Unmanned aerial vehicles offer centimeter-level spatial resolution, operational flexibility, and repeatable observations on demand. They can carry RGB, multispectral, hyperspectral, and light detection and ranging (LiDAR) sensors, thereby providing a bridge between ground surveys and satellite observations. High spatial resolution, however, does not automatically ensure high accuracy. Leaf shadows, soil brightness, non-green vegetation, image mosaicking, and endmember selection can all affect the results. From the perspectives of theoretical foundations, estimation algorithms, error sources, and validation methods, this paper compares data from representative studies and develops a technical framework applicable to both croplands and natural vegetation.

1 Theoretical and Technical Foundations of Fractional Vegetation Cover Estimation

1.1 Conceptual Definition and Application Scales

FVC is generally expressed on a scale of 0–1 or 0%–100% and represents the proportion of an observed area covered by the vertical projection of the vegetation canopy. It differs from the leaf area index (LAI). FVC indicates whether the land surface is covered by the canopy, whereas LAI represents the total one-sided leaf area per unit ground area. Once the canopy is fully closed, FVC tends to become saturated, while LAI may continue to increase as additional foliage layers develop.

Studies should also distinguish among green fractional vegetation cover, non-green fractional vegetation cover, and total fractional vegetation cover. Algorithms based solely on the normalized difference vegetation index (NDVI) or green pixels primarily represent photosynthetically active vegetation; senescent grass, litter, and woody components may be classified as background.

Scale determines the meaning of the indicator. Individual-plant or quadrat scales are suitable for phenotyping and agronomic management, the field scale emphasizes stand uniformity, and the landscape scale is used to evaluate ecological patterns or validate satellite products. Different spatial resolutions may produce different estimates of vegetation cover in the same area because the proportions of within-pixel components, boundary lengths, and aggregation methods change. Studies should therefore report the support area of ground samples, the UAV ground sampling distance, and the final statistical unit.

1.2 UAV Platforms and Sensor Configurations

Multirotor UAVs can hover and fly at low speeds and are flexible to deploy, making them suitable for detailed measurements over small areas. Fixed-wing UAVs offer longer flight endurance and greater coverage efficiency and are more appropriate for large areas such as grasslands and forests.

RGB cameras are inexpensive and provide high spatial resolution. They can identify green canopies through color indices and image segmentation, but their digital numbers are affected by exposure, white balance, and illumination. Multispectral cameras generally include red, green, blue, near-infrared, and red-edge bands. They can be used to calculate indices such as NDVI and the normalized difference red-edge index (NDRE), while reflectance calibration improves comparability among observation dates. Hyperspectral sensors provide continuous bands and rich spectral information but have higher costs, heavier payloads, and greater processing complexity. LiDAR can characterize three-dimensional canopy and understory structures but requires specialized point-cloud classification.

Sensor selection should be determined by the intended objective. RGB imagery may be prioritized for rapid mapping of green cover in croplands. Calibrated multispectral imagery is more appropriate for quantitative comparisons across dates, sparse grasslands, or environments in which vegetation and soil have similar spectral characteristics. Point-cloud data can be integrated into studies of vertically stratified forest structure. Regardless of the selected configuration, researchers should record the lens, exposure mode, flight altitude, forward and side overlap, solar elevation angle, wind speed, and ground control points.

1.3 Data-Processing Workflow

A complete workflow comprises mission design, synchronized ground surveys, image-quality inspection, aerial triangulation, orthorectification, radiometric processing, vegetation-information extraction, FVC calculation, and accuracy validation. Exposure and white balance should be kept as constant as possible for RGB imagery. Multispectral images should be radiometrically calibrated using reflectance panels and incident-light sensors.

After image matching is used to generate a dense point cloud, digital surface model, and orthomosaic, the outputs should be inspected for ghosting, voids, striping, and misalignment along field boundaries.

For a binary classification result, FVC within the study unit can be expressed as

where is the number of pixels classified as vegetation and is the total number of valid pixels. If probabilistic classification or spectral unmixing is used, an area-weighted mean of pixel-level vegetation abundance can be calculated. Water bodies, roads, buildings, and invalid shadow areas should be masked in advance to prevent changes in study boundaries from producing spurious differences in FVC.

2 Methods for Estimating Fractional Vegetation Cover from UAV Imagery

2.1 Threshold Segmentation, Two-Endmember Pixel Modeling, and Spectral Unmixing

RGB thresholding distinguishes vegetation from the background using color channels or vegetation indices. Thresholds may be determined manually or selected automatically using Otsu's method, clustering, or Gaussian fitting. This method is computationally efficient and readily interpretable and is suitable for imagery in which green vegetation contrasts strongly with bare soil. However, a fixed threshold has limited transferability under shadows, flowering conditions, senescent vegetation, or variable soil colors.

A two-endmember pixel model is commonly applied to multispectral imagery. The linear form proposed by Gutman and Ignatov is

The model has a simple structure but assumes that each pixel is a linear mixture of only vegetation and soil and that the endmembers remain stable. Bias may arise when canopy chlorophyll content changes or when shadows and non-green vegetation are substantial.

Spectral or color unmixing represents each pixel as a combination of multiple endmembers and produces continuous abundance estimates, thereby reducing the misclassification of mixed pixels caused by hard thresholds. Yan et al. proposed a color-mixture analysis method in the HSV color space. Vegetation and background endmembers were extracted from low-altitude, close-range UAV images, and FVC was subsequently calculated using maximum a posteriori estimation. For both field datasets, the root mean square error (RMSE) was below 0.007 and the mean absolute error (MAE) was below 0.01 [3]. Nevertheless, systematic errors may still occur if the probability distributions of the endmembers fail to represent variations in crop cultivars, soil conditions, or illumination.

2.2 Machine-Learning and Deep-Learning Methods

In supervised learning, quadrat-level FVC values or pixel labels serve as target variables, while band reflectance, vegetation indices, texture, color, and canopy height are used as inputs. Random forests can model nonlinear relationships and interactions among variables and are relatively robust for small- and medium-sized datasets. Support vector regression is suitable for continuous estimation with limited samples. Backpropagation neural networks can establish nonlinear mappings between UAV-derived labels and satellite features.

In a study of winter wheat, Yang et al. found that a random forest model based on UAV multispectral data achieved an (R^2) of 0.9359 and an RMSE of 0.0544 for FVC estimation, outperforming the NDVI-based two-endmember model, which achieved an (R^2) of 0.8405 and an RMSE of 0.0765 [4].

Deep learning can perform semantic segmentation directly and generate pixel-level classes for green vegetation, litter, soil, and shadows. Convolutional networks are effective at extracting local textures, while vision Transformers can model large-scale canopy structures. Hybrid architectures can reduce speckle noise and fragmented boundaries by combining these capabilities. However, such models require large volumes of high-quality annotated data, and their generalization performance can decline across locations and seasons. Blocked cross-validation, transfer learning, domain adaptation, and uncertainty estimation should therefore be used, while rule-based or spectral methods should be retained as interpretable baselines.

3 Principal Factors Affecting Estimation Error

3.1 Errors in Aerial Image Acquisition and Preprocessing

Flight altitude determines both ground resolution and the area covered during a single mission. Flying too low increases the number of images, mosaicking errors, and ghosting caused by wind-induced crop movement. Flying too high increases the number of mixed pixels. Insufficient forward or side overlap, rolling-shutter effects, and exposure variations can produce seams in orthomosaics. Unevenly distributed ground control points may cause positional errors to concentrate near image boundaries. If multispectral cameras are not corrected for dark current, lens vignetting, and reflectance, digital values from different dates cannot be compared directly.

Flights should be conducted under similar solar elevation angles, low-wind conditions, and periods without rapidly changing cloud shadows. Flight parameters and calibration procedures should be kept consistent. Quality control should be completed before modeling and should include removing blurred images, checking geometric errors, validating reflectance ranges, and creating quality masks for mosaic seams and invalid areas. Classification models should not be expected to absorb processing errors passively.

3.2 Effects of Vegetation Condition, Background, and Shadows

Growth stage alters leaf color, canopy structure, and the proportion of exposed soil. During the seedling stage, vegetation is sparse and mixed pixels are common. After canopy closure, green vegetation indices may become saturated. During maturation, leaf yellowing can cause green FVC to underestimate total FVC. Diseases, weeds, and lodging can also alter texture and spectral characteristics.

Background materials such as dry and wet soil, crop residues, gravel, and plastic mulch may resemble the target vegetation. Self-shadowing in trees and tall crops can divide the same canopy into illuminated and shaded classes.

Potential solutions include defining endmembers or models separately for different phenological stages, explicitly adding shadow and non-green vegetation classes, and using red-edge, near-infrared, or three-dimensional height features to support classification. If total FVC is the intended variable, all non-green pixels should not be classified directly as bare ground. If green FVC is the objective, the boundary of the indicator must be clearly stated in the reported results.

3.3 Spatial-Scale and Mixed-Pixel Effects

UAV imagery can resolve individual leaves and small vegetation patches, whereas satellite pixels spatially average these features. Simply aggregating a binary UAV-derived vegetation map to a satellite grid is susceptible to grid misregistration, boundary pixels, and inconsistencies in sampling support areas.

In a study of alpine grasslands on the Qinghai–Tibetan Plateau, Chen et al. found that UAV-derived FVC at the satellite-pixel scale was more accurate than estimates based on a limited number of ground quadrats. The accuracy of ground-based estimates increased with the number of quadrats and decreased as surface heterogeneity increased [2].

Scale conversion should begin with high-accuracy image registration, followed by aggregation according to the satellite point-spread function or area-weighted averaging. Training and validation regions must be spatially independent. For highly heterogeneous grasslands, shrublands, and field boundaries, multiresolution sensitivity analyses should be conducted. Changes in the mean and variance of FVC with pixel size should be reported, rather than directly extending an optimal threshold obtained at one flight altitude to other spatial scales.

4 Accuracy Validation and Comparison of Representative Studies

4.1 Reference Data and Evaluation Design

Reference data can be obtained from manually interpreted, ultra-high-resolution near-ground images; vertical quadrat photographs; point-grid methods; or pixel labels reviewed by experts. Ground photographs should be acquired as close as possible to nadir and synchronized with the UAV overflight. Oblique photography introduces lateral views of leaves and parallax and may therefore overestimate reference FVC.

Quadrats should be selected using stratified random or systematic sampling to cover different vegetation types and cover levels. Sampling only near roads or within uniform fields should be avoided.

Continuous FVC estimates are generally evaluated using the coefficient of determination ((R^2)), RMSE, MAE, and bias. Classification results should also report overall accuracy, producer's accuracy, user's accuracy, and the F_1-score. Model comparisons must use the same independent test set and should report the sample size and confidence intervals. When neighboring pixels are strongly correlated, random splitting can cause spatial data leakage. Training and test data should instead be partitioned by plot, flight strip, or acquisition date.

4.2 Quantitative Results and Method Applicability

Table 1. Representative studies of fractional vegetation cover estimation and their quantitative results

Reference	Study object and data	Method	Principal findings
Gutman and Ignatov [1]	NOAA/ AVHRR vegetation indices	Linear vegetation–soil two-endmember model	Established a linear expression relating FVC to NDVI endmembers
Chen et al. [2]	Alpine grasslands on the Qinghai–Tibetan Plateau; 21 sampling sites	Comparison of UAV-derived FVC with ground quadrats and satellite vegetation indices	The (R^2) between UAV-derived FVC and vegetation indices was significantly higher than that obtained from ground quadrats (($p<0.05$)); ground-estimation accuracy increased with the number of quadrats
Yan et al. [3]	Two UAV RGB field datasets and synthetic imagery	HSV color-mixture analysis	RMSE (<0.007) and MAE (<0.01) for both field datasets
Yang et al. [4]	UAV and satellite imagery of winter wheat acquired over two growing seasons	Random forest, NDVI-based two-endmember model, and BPNN-based scale conversion	UAV random forest: ($R^2=0.9359$), RMSE (=0.0544); independent validation of the satellite BPNN: RMSE (=0.059)

Table 1 shows that thresholding and two-endmember models are suitable for rapid mapping and small-sample scenarios.

Color unmixing can reduce mixed-pixel effects in RGB imagery, while random forests and neural networks can use multidimensional features but depend on representative training samples.

It is particularly important to note that the errors reported by Yan et al. were obtained from specific field datasets and internal methodological comparisons and should not be interpreted as demonstrating that errors below one percentage point can be achieved in all regions. Similarly, the high (R^2) reported by Yang et al. was obtained specifically for winter wheat at the corresponding growth stages using standardized multispectral data.

5 Optimization Framework and Future Directions

Reliable UAV-derived FVC products should be developed within a closed-loop framework of “indicator definition–standardized acquisition–multimethod estimation–independent validation–uncertainty mapping.”

First, researchers should determine before data acquisition whether the intended variable is green or total vegetation cover, define the output resolution and application target, and establish quadrats covering the complete FVC gradient.

Second, standardized flight and radiometric-calibration procedures should be established. In addition to orthomosaics, the original images, quality masks, digital surface models, and processing parameters should be retained.

Third, threshold segmentation or a two-endmember pixel model should be used as a baseline. Color unmixing, random forests, or semantic segmentation may then be introduced for complex backgrounds or cross-scale applications. Ablation experiments should be used to identify the actual contributions of spectral, textural, and height features.

Future research can be advanced in four areas. First, self-supervised learning can exploit large volumes of unlabeled multitemporal imagery and reduce the cost of pixel-level annotation. Second, RGB, multispectral, thermal-infrared, and point-cloud data can be integrated to distinguish green vegetation, litter, bare soil, and shadows. Third, external validation across regions, crops, and sensors should be conducted to develop transferable endmember libraries and domain-adaptation methods. Fourth, high-accuracy UAV-derived FVC can be used as training and validation data for satellite products, with rigorous image registration and upscaling or downscaling models supporting continuous regional monitoring.

Published products should also provide pixel-level confidence estimates or error ranges, enabling users to identify areas of low reliability.

Conclusion

UAV remote sensing can provide high-resolution and repeatable information on fractional vegetation cover at the intermediate scale between ground quadrats and satellite observations. RGB threshold segmentation is inexpensive, the two-endmember pixel model is simple and interpretable, and color unmixing and machine learning improve performance in complex backgrounds and scale-conversion applications.

However, illumination, shadows, phenology, endmember selection, and spatial scale jointly affect estimation results. High accuracy obtained from a single internal validation cannot be interpreted directly as evidence of universal performance. Future studies should standardize concepts and sampling procedures, strengthen multitemporal and multisensor data fusion, conduct spatially independent validation, and explicitly represent uncertainty. These measures will support the transition of FVC estimation from local algorithm experiments to comparable, reproducible, and operational monitoring.

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