

A half-Gaussian fitting method for estimating fractional vegetation cover of corn crops using unmanned aerial vehicle images

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ARTICLE INFO

Keywords:

Fractional vegetation cover (FVC)

Unmanned aerial vehicle

(UAV)

Low-altitude remote sensing (LARS)

Digital photography

Half-Gaussian distribution

Histogram threshold

ABSTRACT

Accurate estimates of fractional vegetation cover (FVC) using remotely sensed images collected using unmanned aerial vehicles (UAVs) offer considerable potential for field measurement. However, most existing methods, which were originally designed to extract FVC from ground-based remotely sensed images (acquired at a few meters above the ground level), cannot be directly used to process aerial images because of the presence of large quantities of mixed pixels. To alleviate the negative effects of mixed pixels, we proposed a new method for decomposing the Gaussian mixture model and estimating FVC, namely, the half-Gaussian fitting method for FVC estimation (HAGFVC). In this method, the histograms of pure vegetation pixels and pure background pixels are firstly fit using two half-Gaussian distributions in the Commission Internationale d'Eclairage (CIE) $L^*a^*b^*$ color space. Then, a threshold is determined based on the parameters of Gaussian distribution to generate a more accurate FVC estimate. We acquired low-altitude remote-sensing (LARS) images in three vegetative growth stages at different flight altitudes over a cornfield. The HAGFVC method successfully fitted the half-Gaussian distributions and obtained stable thresholds for FVC estimation. The results indicate that the HAGFVC method can be used to effectively and accurately derive FVC images, with a small mean bias error (MBE) and with root mean square error (RMSE) of less than 0.04 in all cases. Comparatively, other methods we tested performed poorly (RMSE of up to 0.36) because of the abundance of mixed pixels in LARS images, especially at high altitudes above ground level (AGL) or in the case of moderate vegetation coverage. The results demonstrate the importance of developing image-processing methods that specially account for mixed pixels for LARS images. Simulations indicated that the theoretical accuracy (no errors in fitting the half-Gaussian distributions) of the HAGFVC method reflected an RMSE of less than 0.07. Additionally, this method provides a useful approach to efficiently estimating FVC by using LARS images over large areas.

1. Introduction

Fractional vegetation cover (FVC) plays a key role in land surface processes, including carbon and water cycles (Jung et al., 2006) and energy transfer (Sellers, 1997). It is also an important data product in numerical weather prediction (Gutman and Ignatov, 1997) and high-precision agricultural analysis (Hunt et al., 2014; Matese et al., 2015). To meet the requirements of FVC mapping and validation using satellite

products, rapid and accurate measurements of FVC are necessary (Mu et al., 2015; Song et al., 2017). Hence, various methods have been developed to measure FVC for these applications including visual estimation, direct sampling and digital photography (Muir et al., 2011). Among these methods, photography provides the best performance in terms of efficient and accurate validation of satellite remote sensing products for high-precision applications (Yan et al., 2012).

Proximal (very close range, i.e. a few meters) sensing methods have

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<https://doi.org/10.1016/j.agrformet.2018.07.028>

Received 22 November 2017; Received in revised form 18 July 2018; Accepted 27 July 2018

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a clear advantage over satellite remote sensing in terms of spatial resolution and flexibility. The data obtained from proximal sensing can provide highly accurate estimates of FVC directly from images (Liu and Pattey, 2010; Macfarlane and Ogden, 2012; Song et al., 2015) while the satellite remote sensing images will typically require that FVC be estimated based on calibrations of vegetation indices against independent estimates of FVC from proximal sensing methods (Carlson and Ripley, 1997). However, traditional proximal sensing methods, lacking the spatial coverage needed for mapping FVC over large regions, are potentially labor intensive even over medium-scale areas and local conditions may limit site access. Recent technological innovations have led to an increase in the availability of unmanned aerial vehicles (UAVs) (Watts et al., 2012), which potentially overcome many limitations of both traditional proximal and satellite imagery platforms. Low-altitude remote-sensing (LARS) UAVs are advantageous because of their flexibility, operational ability in a variety of environmental conditions, and capacity for mapping at intermediate spatial scales. The application of UAVs has extended to crop monitoring, precision agriculture and other Earth science studies (Bhardwaj et al., 2016; Zarco-Tejada et al., 2012). Researchers widely agree that commercial cameras mounted on UAVs are powerful tools for assessing FVC (Chianucci et al., 2016; Torres-Sánchez et al., 2014).

UAVs are flexible in terms of their flight altitude, which facilitates the collection of imagery at a range of spatial scales (Mesas-Carrascosa et al., 2014). For example, Chapman et al. (2014) deployed UAVs fitted with a fixed, wide angle lens at heights ranging from 20 m to 80 m, in order to evaluate various plant breeding trials. Generally, as UAVs are required to map FVC rapidly over larger areas, the flight altitude must be increased, which reduces the spatial resolution. Spatial resolution could be maintained by narrowing the camera focal length as altitude increases but this would increase the number of flights required by what are frequently UAVs with only short flight time, which would negate one of the main advantages of UAVs. As a result, UAVs are often flown at varied altitudes but constant focal length (e.g., Samseemoung et al., 2012). However, reducing the spatial resolution of LARS imagery increases the proportion of mixed pixels, which is likely to reduce the accuracy of medium-scale FVC mapping (Hsieh et al., 2001; Jones and Sirault, 2014).

Image analysis methods developed for proximal sensing methods are poorly suited to estimate FVC from LARS when mixed pixels are abundant in the images. Hsieh et al. (2001) established a simulation scheme to assess the effect of the spatial resolution on classification accuracy and found that the classification errors increased rapidly with decreasing spatial resolution. Jones and Sirault (2014) reported that a low spatial resolution has a significant negative influence on image classification. Torres-Sánchez et al. (2014) observed the decrease in accuracy of FVC estimates in the early growth stages of wheat when the spatial resolution of LARS imagery was reduced.

Early image analysis methods depended on supervised

classification, which requires human intervention, has low operational efficiency and produces noisy results. Later, automatic classification methods were based on unsupervised clustering algorithms, category tree methods and threshold-based methods (Yan et al., 2012). Researchers developed numerous threshold-based methods based on vegetation indices in the red-green-blue (RGB) color space; such indices include the excessive green index (Woebbecke et al., 1995; Liu and Pattey, 2010), normalized difference index (Pérez et al., 2000), green leaf algorithm (Chianucci et al., 2016), etc. Other color spaces, such as the Commission Internationale d'Eclairage (CIE) $L^*a^*b^*$ and hue saturation intensity (HSI), have also been used for classification (Liu et al., 2012; Macfarlane and Ogden, 2012). These automatic algorithms have modestly improved the efficiency of validation. However, they were specifically developed for proximally-sensed images and unsuited to images containing many mixed pixels. In addition, previously reported studies tended to use UAV-based commercial cameras to collect images over sparse scenes, such as early crop and rangeland areas (Rango et al., 2009; Torres-Sánchez et al., 2014), while densely vegetated scenes (FVC > 0.7) have seldom been studied.

In this study, we propose an image analysis method, HAGFVC for estimating FVC that is scale invariant and specifically addresses the problem of large and variable numbers of mixed-pixels in LARS images acquired from varying altitudes. The theory and implementation of the half-Gaussian fitting method for extracting FVC are described in Section 2. Three published methods, LAB2 (Macfarlane and Ogden, 2012), Shadow-Resistant Algorithm for Extracting the Green FVC (SHAR-LABFVC; Song et al., 2015) and excess green vegetation index (ExG; Woebbecke et al., 1995) are introduced for comparison as well. Section 3 describes the real data and simulated data used to validate and analyze the HAGFVC method. In Section 4, the results of the HAGFVC method and the three other methods are compared, and an uncertainty analysis is presented. Sections 5 and 6 present the discussion and conclusions, respectively.

2. Methods

2.1. Gaussian mixture model for FVC

For vegetated surfaces, the CIE a^* distribution of an image usually was considered as a Gaussian mixture model (GMM) distribution (Coy et al., 2016; Liu et al., 2012). In proximally sensed images, assuming almost no mixed pixels in these images, the GMM derives from the distributions of pure vegetation and pure background material and exhibits a distinct bimodal distribution mode (Liu et al., 2012; Song et al., 2015). This mixture distribution function $H(x)$ can be given by:

$$H(x) = \omega_v N(\mu_v, \sigma_v^2) + \omega_b N(\mu_b, \sigma_b^2) \quad (1)$$

where ω , μ and σ are weight, mean value and standard deviation, respectively; subscripts v and b indicate vegetation and background,

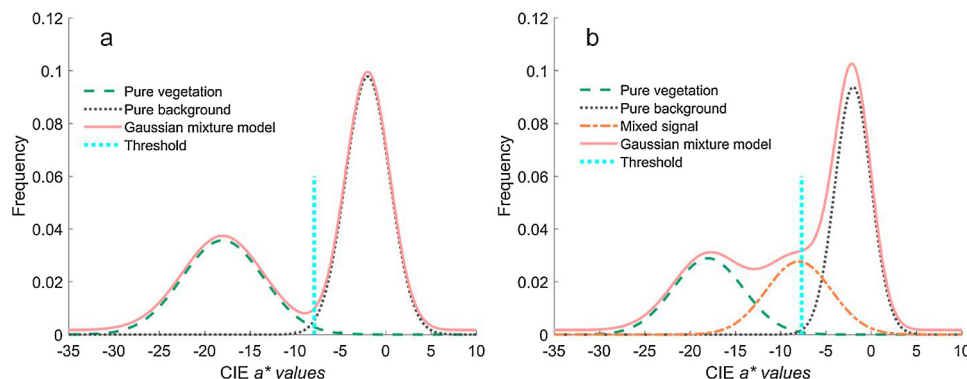


Fig. 1. Schematic diagrams of GMM distribution of CIE a^* values at different spatial resolutions, (a) a^* distribution at a high spatial resolution (i.e. proximal sensing), (b) a^* distribution at a lower spatial resolution (i.e. low-altitude remote sensing).

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