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# Fractional vegetation cover estimation by using multi-angle vegetation index

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ABSTRACT

The vegetation index-based (VI-based) mixture model is widely used to derive green fractional vegetation cover (*FVC*) from remotely sensed data. Two critical parameters of the model are the vegetation index values of fully-vegetated and bare soil pixels (denoted $V_x$ and $V_n$ hereafter). These are commonly empirically set according to spatial and/or temporal statistics. The uncertainty and difficulty of accurately determining $V_x$ and $V_n$ in many ecosystems limits the accuracy of resultant *FVC* estimates and hence reduces the utility of VI-based mixture model for *FVC* estimation. Here, an improved method called MultiVI is developed to quantitatively estimate $V_x$ and $V_n$ from angular VI acquired at two viewing angles. The directional VI is calculated from the MODIS Bidirectional Reflectance Distribution Function (BRDF)/Albedo product (MCD43A1) data. The results of simulated evaluation with 10% added noise show that the root mean square deviation (RMSD) of *FVC* is approximately 0.1 (the valid *FVC* range is [0, 1]). Direct evaluation against 34 globally-distributed *FVC* measurements from VAlidation of Land European Remote sensing Instruments (VALERI) sites during 2000 to 2014 demonstrated that the accuracy of MultiVI *FVC* ($R^2$ = 0.866, RMSD = 0.092) exceeds than from SPOT/VEGETATION bioGEOphysical product version 1 (GEOV1) *FVC* ($R^2$ = 0.795, RMSD = 0.159). MultiVI *FVC* also exhibits higher correlation to the VALERI reference *FVC* than does the MODIS fraction of photosynthetically active radiation product (MCD15A2H; $R^2$ is 0.696). A key advantage of the MultiVI method is obvious in areas where fully-vegetated and/or bare soil pixels do not exist in moderate-coarse spatial resolution imagery when compared to the conventional VI-based mixture modelling. The MultiVI method can be flexibly implemented over regional or global scales to monitor *FVC*, with maps of $V_x$ and $V_n$ generated as two important byproducts.

## 1. Introduction

Fractional vegetation cover (*FVC*), represents the planar fraction of the land surface covered by green foliage (Lu et al., 2003). *FVC* is an important vegetation biophysical parameter that is linearly related to the fraction of photosynthetically active radiation absorbed by foliage (fPAR) (Asrar et al., 1984; Carlson and Ripley, 1997) and is therefore a controlling factor in transpiration, photosynthesis, global climate change and other terrestrial processes, geochemical cycles, and climate models (Arneth, 2015; Barlage and Zeng, 2004; Gutman and Ignatov, 1998; Jiang et al., 2006; Jiapaer et al., 2011; Jiménez-Muñoz et al., 2009). Measures of *FVC* are widely used to monitor vegetation quality and ecosystem change.

Remote sensing provides the most efficient way to monitor regional and global *FVC*. Most *FVC*-estimation approaches based on remote sensing at medium to coarse resolution can be summarized into five approaches (Guan et al., 2012): (i) spectral-based supervised classifications (Gessner et al., 2013; Goel and Strebel, 1984; Teillet et al., 1982); (ii) spectral-based unmixing techniques (Hall et al., 1995; Iordache et al., 2014; Okin et al., 2013; Van Der Meer, 1999); (iii) climate and environment variability based methods (Guan et al., 2012; Scanlon et al., 2002; Waldner et al., 2015); (iv) multi-angle remote sensing models (Chopping et al., 2012; Chopping et al., 2008; Knyazikhin et al., 1998; Myneni and Williams, 1994; Xiao et al., 2016);

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and (v) relative vegetation measurement approaches scaled by maximum and minimum ('greenness') vegetation index (VI) based mixture model (Gutman and Ignatov, 1998; Jiapaer et al., 2011). Of these methods, the simplest is the VI-based mixture model, which is based on the strong linear relationship between a 'greenness' VI and *FVC* (Gamon et al., 1995; Tucker, 1979) with the most commonly used VI being the Normalized Difference Vegetation Index (NDVI (Rouse et al., 1973; Tucker, 1979)). This VI-based mixture model identifies the NDVI values that represent no foliage cover (bare soil) and full cover, and rescales NDVI linearly between these two thresholds to yield *FVC* (Carlson and Ripley, 1997; Gutman and Ignatov, 1998; Kogan, 1990):

$$FVC = \frac{V^0 - V_n^0}{V_x^0 - V_n^0} \tag{1}$$

where *FVC* is green fractional vegetation cover (0–1), $V_x$ and $V_n$ are the maximum and minimum NDVI values, respectively, and $V$ is the NDVI value being rescaled. The superscript 0 stands for the observational zenith angle 0° (nadir).

The weakness of the VI-based mixture model is that $V_x$ and $V_n$ need to be known a priori and that the NDVI-*FVC* relationship is very sensitive to $V_n$ (Asrar et al., 1984), which is a challenging value to identify. Conventionally, $V_x$ and $V_n$ are obtained by: (i) interrogation of the imagery to find the maximum and minimum VI values within a geographic area (Donohue et al., 2008; Gutman and Ignatov, 1998) or within a location's historical time-series (Zeng et al., 2000); or (ii) independent field-based observations or high-resolution products (Jiapaer et al., 2011; Zhang et al., 2013). Image interrogation relies on there being representative bare soil and full cover values within an image or time-series, which is not often the case in heavily or sparsely vegetated landscapes. Further, $V_n$ is known to vary with soil types and properties (e.g., soil color) (Baret et al., 1993; Huete, 1988; Montandon and Small, 2008; Myneni and Williams, 1994; Rondeaux et al., 1996); hence the relationship between NDVI and *FVC* (and fPAR) changes with each combination of these variables. To avoid addressing these issues, a simplifying assumption often used is that $V_n$ is invariant across space (Gutman and Ignatov, 1998), which is roughly synonymous with assuming a precise 'global' soil line (Baret et al., 1993; Huete, 1988). Montandon and Small (2008) found soil NDVI to vary substantially, between 0.1 and 0.4. Since it is common to use global $V_n$ values that are at the lower end of this range (for example, 0.05), *FVC* of sparse vegetation areas can be overestimated by up to 0.2 (Ding et al., 2016; Montandon and Small, 2008), which represents an error of *at least* 20%. Donohue et al. (2014) compared the effects of using a global $V_n$ and locally derived $V_n$ on estimates of gross primary productivity (GPP) and found 30–60% overestimation of GPP at sparsely vegetated sites (Donohue et al., 2014) when using a global $V_n$ value. The formidable, and usually prohibitive, alternative to assuming a global $V_n$ is to determine $V_n$ for each soil type or even location.

Here, we provide an alternative method (MultiVI) to identify $V_n$ and $V_x$ that does not require any prior knowledge of soil background color. This method utilizes multiple viewing geometries to reconstruct the directional VIs, which reflect vegetation structural information and soil characteristics (Chen et al., 2005; Diner et al., 1999; Sandmeier and Deering, 1999; Verrelst et al., 2008), and establishes equations to solve $V_x$ and $V_n$. With multi-angle observations, the determination of $V_x$ and $V_n$ does not require the VI statistics over space and/or time and can be flexibly applied to different spatial resolutions and extents. Specific objectives include to:

(1) derive a framework for the estimations of $V_x$ and $V_n$ using directional VIs;

(2) assess the performance and feasibility of the method with simulated and real data;

(3) analyze the sensitivity of MultiVI *FVC* estimates to possible error sources and their uncertainty.

## 2. Methods

### 2.1. Theory

The method proposed here requires directional reflectance at two viewing angles over at least two remote sensing pixels, where $V_x$ and $V_n$ are respectively assumed to be the same for the two pixels. The basic idea of this method is to extract $V_x$ and $V_n$ by simultaneously solving equations which are established by combining the multi-angle gap fractions and VI. It is built on three steps.

First, a linear relationship exists between the directional *FVC* and VI at observational zenith angle $\theta$ (Tang et al., 2009). Eq. (1) is the special case of Eq. (2) at nadir view.

$$F^\theta = \frac{V^\theta - V_n^\theta}{V_x^\theta - V_n^\theta} \tag{2}$$

where $F^\theta$, $V^\theta$, ${V_x}^\theta$ and ${V_n}^\theta$ are respectively the directional *FVC*, VI, $V_x$ and $V_n$ at observational zenith angle $\theta$. $F^\theta$ in this study is defined to be complementary to the directional gap fraction, and $F^0$ is *FVC* commonly referred to. We have Eq. (3) based on Beer's Law (Nilson, 1971):

$$F^\theta = 1 - e^{-G(\theta)\cdot\Omega\cdot LAI/\cos\theta} \tag{3}$$

where $G$ and $\Omega$ are the mean projection of the unit foliage area and clumping index, respectively, $LAI$ is the leaf area index and $e^{-G(\theta)\cdot\Omega\cdot LAI/\cos\theta}$ is the gap fraction. With Eqs. (2) and (3), the formula of the directional gap and VI is expressed as:

$$\frac{V_x^\theta - V^\theta}{V_x^\theta - V_n^\theta} = e^{-G(\theta)\cdot\Omega\cdot LAI/\cos\theta} \tag{4}$$

Second, multi-angle observations are used to eliminate $LAI$, $G$ and $\Omega$. Kernel-driven Bidirectional Reflectance Distribution Function (BRDF) models enable the reconstruction of observations at any viewing angle from multi-angle observations (Hu et al., 1997; Lucht, 1998; Privette et al., 1997). Here, we establish equations of gap fraction and VI at viewing zenith angles (VZN) of 55° and 60°. In particular, the value of $G$ is approximately constant around the zenith angle of 57°, despite the change of leaf angle distributions (Weiss et al., 2004). Another important reason to choose the angles around 57° is that many operational, multi-angle satellite sensors have viewing angles smaller than 60° (Kramer, 2002; Xin et al., 2012). More errors occur when reconstructing the directional observation at the viewing angles beyond this range of observational angles (Liu et al., 2009; Wang et al., 2015). Without the loss of generality, VZNs of 55° and 60° in the forward hemisphere and the solar principal plane are selected to construct equations that closely bracket 57°. The backward hemisphere is not recommended due to the influence of the hot-spot effect (Chen and Cihlar, 1997; Maignan et al., 2004). Variations in $G$ and $\Omega$ are not large in contrast to the reciprocal of cos$\theta$, which means that we can assume $G$ and $\Omega$ are invariant between viewing angles of 55° and 60°; the impact of this assumption is assessed later (see Section 5 Analysis of the Method). Assuming that the multi-angle ground surface reflectance observations and the reconstructed directional observations are obtained over a given remote sensing pixel (pixel $i$), equations can be derived for pixel $i$ from Eq. (4) with two directional observations:

$$\frac{V_x^{55^\circ} - V_i^{55^\circ}}{V_x^{55^\circ} - V_n^{55^\circ}} = e^{-0.5\cdot\Omega\cdot LAI_i/\cos 55^\circ} \tag{5}$$

$$\frac{V_x^{60^\circ} - V_i^{60^\circ}}{V_x^{60^\circ} - V_n^{60^\circ}} = e^{-0.5\cdot\Omega\cdot LAI_i/\cos 60^\circ} \tag{6}$$

where the subscript "$i$" stands for the given pixel and the superscripts "55°" and "60°" represents the viewing angles. If we assume that differences in $V_n$ between 55° and 60° are negligible, as are those in $V_x$, then Eqs. (5) and (6) can be combined to obtain an equation to estimate $V_x$ and $V_n$ without recourse to $LAI$, $G$ and $\Omega$:

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