Remote Sensing of Environment 124 (2012) 653–665

Contents lists available at SciVerse ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Multi-sensor derivation of regional vegetation fractional cover in Africa

K. Guan *, E.F. Wood, K.K. Caylor

Department of Civil and Environmental Engineering, Princeton University, Princeton, NJ, 08544, USA

ARTICLE INFO

Article history:
Received 20 June 2011
Received in revised form 27 May 2012
Accepted 3 June 2012
Available online 17 July 2012

Keywords:
Vegetation fraction
Africa
NDVI
Backscatter coefficient
Vegetation optical depth
AVHRR
QuickSCAT
AMSR-E
TRMM

ABSTRACT

A spatially continuous field of landscape fractional covers of tree, grass and bare soil is required at regional and continental scales for earth system modeling and environmental monitoring. Climate and its variability drive vegetation fractional cover over time and space. For savanna ecosystems, precipitation plays the main role in shaping vegetation composition. In this study, we estimate land cover fraction at a satellite pixel scale by employing an existing 'Mean-Sensitivity Unmixing Algorithm' (MSUA), which is based on a state space defined by two key variables: (1) mean pixel values (referring to mean vegetation states), and (2) inter-annual sensitivity of pixel values to precipitation (referring to vegetation sensitivity to precipitation). We define these two variables through a multi-sensor assessment of three vegetation remote sensing datasets, namely (i) Normalized Difference Vegetation Index (NDVI), based on the visible and near-infrared bands from the Advanced Very High Resolution Radiometer (AVHRR); (ii) backscatter coefficients (dB) from the NASA QuikSCAT active-microwave scatterometer; and (iii) Vegetation Optical Depth (VOD) based on NASA Advanced Microwave Scanning Radiometer on EOS (AMSR-E) passive-microwave radiometry measurements. A merged satellite-gauge precipitation dataset from the Tropical Rainfall Measuring Mission (TRMM) version 3B42V6 is used. The three remote sensing datasets show generally similar but distinctive performances in characterizing the two key variables over various land cover types. NDVI and VOD perform better than dB in characterizing land cover variation based on mean pixel values; while dB represents more reliable and robust vegetation sensitivity to precipitation. By using NDVI for mean vegetation states and dB for inter-annual variability of vegetation to precipitation, we develop an improved fractional cover product. We find that our product agrees well with the tree fraction derived from high-resolution images for natural vegetation regions, and can reproduce the distinctive land cover pattern of grass and bare soil in the Moderate Resolution Imaging Spectroradiometer (MODIS) land cover product. For cropland-mixed regions, our tree fraction is overestimated since human impacts (e.g. irrigation) have not been accounted for in the MSUA. The improved performance from our approach is achieved by the synergistic use of the three vegetation remote sensing datasets, and their physical interpretations have been discussed to support the validity of this approach.

1. Introduction

Vegetation structure and composition play an important role in understanding ecosystem functioning (e.g. fire and grazing), as well as in managing ecosystem services (e.g. deforestation monitoring) (Hirota et al., 2011; K'efi et al., 2007; Mayaux et al., 2005; Miles et al., 2006). Vegetation fractional cover is also crucial for representing sub-pixel heterogeneity in climate and land-surface models (Avissar & Verstraete, 1990; Gutman & Ignatov, 1998; Zeng et al., 2000). Thus a spatially-continuous and reliable representation of vegetation fractional cover is required at regional and continental scales. This is especially true for savanna ecosystems, which are typically characterized as a mixture of woody and herbaceous vegetation (Sankaran et al., 2005; Scholes & Archer, 1997). Savanna ecosystems comprise approximately 20% of the global land area and up to 40% of the African continent (Scholes & Walker, 1993). This vast terrestrial extent makes savanna ecosystems a significant component in the global terrestrial carbon budget (Grace, 2004; Randerson et al., 1997). Possible degradations in savanna ecosystems induced by drought, overgrazing, fire regime shift, and woody encroachment in the context of a changing climate warrant a better quantification of the relative abundance of vegetation fractional covers.

Climate variability shapes the landscape structure at various spatial and temporal scales, with precipitation being the major driving force in characterizing vegetation composition in savanna ecosystems (Good & Caylor, 2011; Rodriguez-Iturbe & Porporato, 2004; Scanlon & Albertson, 2003). Different vegetation types respond differently to precipitation patterns. In particular, herbaceous plants utilize dense and shallow root systems to use ephemerally available water in the upper soil layer, while woody plants have a root system which can penetrate deeper soil layers and access a more stable supply of soil water (Scanlon et al., 2002). In addition, herbaceous plants in dry/semi-dry savanna ecosystem have a photosynthetic pathway (C4) that synthesizes more carbon per unit of water than do C3 woody plants (Ehleringer & Monson, 1993). For these reasons, herbaceous plants are more sensitive to

* Corresponding author. Tel.: +1 609 258 6383.
E-mail address: kguan@princeton.edu (K. Guan).

0034-4257/$ – see front matter
doi:10.1016/j.rse.2012.06.005

precipitation and have a relatively low above-ground biomass. Woody plants, on the other hand, are less sensitive to precipitation variability with a relatively high above-ground biomass (Scanlon et al., 2002; Scholes & Walker, 1993). Thus it is possible to estimate sub-pixel fractional covers by leveraging the differences in trees and grasses in terms of their above-ground biomass and their sensitivity to precipitation.

Remote sensing (RS) provides the most efficient way to derive fractional covers at regional and global scales. At medium to coarse resolutions (>250 m), representative RS-based approaches for deriving vegetation fractions include:

(i) spectral-based supervised classification (hereafter referred as 'SC', e.g. Friedl et al., 2002; Hansen et al., 2003);
(ii) spectral-based linear unmixing techniques ('SU', e.g. DeFries et al., 1999; Okin, 2007);
(iii) relative vegetation abundance approach scaled by maximum and minimum vegetation index ('RA', e.g. Gutman & Ignatov, 1998; Zeng et al., 2000);
(iv) multi-angle geometric-optical model ('GO', e.g. Chopping et al., 2008, 2009); and
(v) 'Mean-Sensitivity Unmixing Algorithm' (MSUA) based on the different responses of land covers to precipitation variability (Scanlon et al., 2002).

The spectral-based approaches (SC and SU) require spectral characterizations of each land cover component, which are usually determined from training datasets and associated empirical knowledge (Friedl et al., 2002). The RA approach constructs a ratio scaled by maximum and minimum vegetation index values, and this approach does not account for the heterogeneity of different plant functional types within each pixel. The GO approach takes the three-dimensional structure of landscape into account by using multi-angle geometric-optical models, and has shown great potential for representing savanna structure (Chopping et al., 2008), but local calibration from high-resolution imagery is usually required. These four methods are either unable to extract sub-pixel fractional covers or require calibration and/or empirical knowledge. The 'Mean-Sensitivity Unmixing Algorithm' developed by Scanlon et al. (2002) provides a different linear unmixing algorithm for sub-pixel fractional cover that does not require calibration or other empirical inputs. The algorithm utilizes the knowledge that different plant functional types have different vegetation responses to precipitation, and constructs a state space formed by two key variables for linearly decomposing sub-pixel fractional covers:

(1) the mean vegetation states;
(2) the inter-annual sensitivity of vegetation to precipitation.

The algorithm objectively determines the endmembers on the basis of an optimal fit to the observed data. Scanlon et al. (2002) applied the MSUA concept to a Kalahari savanna transect with a precipitation gradient of 300–1600 mm/yr using Normalized Difference Vegetation Index (NDVI) as the vegetation dataset. In tropical regions with extensive cloud cover, the MSUA's effectiveness may be limited if it only uses the visible–near infrared (Vis–NIR)-based NDVI.

Vis–NIR RS has the longest history of vegetation monitoring. For example, the Vis–NIR-based vegetation index record from the AVHRR is from 1981 till present (Tucker et al., 2005). But the accuracy of Vis–NIR RS products is affected by a number of factors include incomplete atmospheric corrections (Tanre et al., 1992; Viovy et al., 1992), the inability of the bidirectional reflectance distribution function (BRDF) to represent the surface anisotropy property (Chopping et al., 2002), and cloud cover that prevents Vis–NIR surface measurement especially for tropical regions. Cloud fractions significantly increase during the rainy season in tropical Africa (Fig. 1), which overlaps with the growing season. An analysis of the MODIS reflectance product MOD09 shows that the daily NDVI suppression is correlated with cloud fraction during the growing season in Africa (results not shown here), and similarly for the AVHRR-based product (Tang & Oki, 2007). Maximum-value compositing (MVC) (Holben, 1986; Viovy et al., 1992), temporal/spatial averaging (Zhao et al., 2005), or the stricter cloud-pixel-screening approaches (Heidinger et al., 2002) when applied to Vis–NIR RS datasets can overcome this problem to a certain extent. But cloud residual noise is still hard to separate from the true vegetation signals, and regions with extensive cloudiness often have large gaps (or significant noise) in their product during the growing seasons. The low signal-to-noise ratio in vegetation products causes problems in quantifying intra- and inter-annual sensitivity of vegetation states to climate variability, particularly in these regions. Thus, alternative measurements are required, such as those from microwave sensors that have the ability to penetrate clouds.

In this paper, we apply the MSUA algorithm to derive the vegetation fractional covers over a tropical savanna region with a broad precipitation gradient ranging from 200 to 2000 mm/yr. We utilize and assess the capability of three independent RS products to determine two key variables needed by the MSUA: the mean vegetation states and the vegetation sensitivity to precipitation. The three RS datasets are: (i) NDVI, based on Vis–NIR bands in AVHRR; (ii) backscatter coefficients (dB) from NASA's QuikSCAT active-microwave scatterometer; and (iii) Vegetation Optical Depth (VOD) based on NASA's AMSR-E passive-microwave radiometry measurements. Based on a comprehensive assessment of the multi-sensor vegetation datasets with the TRMM 3B42v6 satellite-gauge merged precipitation product, we find that NDVI is most suitable in characterizing mean vegetation states, while dB provides the most robust estimation of vegetation sensitivity to precipitation. By combining these two products, essentially a synergistic use of optical-microwave sensors, a new approach is proposed for deriving fractional vegetation covers. A physical interpretation for how each product responds to vegetation cover and its sensitivity to precipitation is provided to support the validity of the approach.

2. Materials and methods

2.1. Study area

The study domain (Fig. 1) is approximately 700 km wide and 2,800 km long, running southwest from the Ethiopia-Kenya border (4° N) to the Botswana–South Africa border (24° S), and covers a total area of approximately 2.4 million km^2 (including large parts of Kenya, Tanzania, Malawi, Zambia, Zimbabwe, and Botswana). The mean annual precipitation (MAP) across the domain ranges from 200 to 2000 mm/yr (Fig. 1), resulting in widely varying distributions of grass and tree fractions. The MAP is highest in the central portion, and decreases to the southern and northern parts of the domain. The land cover product from MODIS MCD12Q1 shows a similar gradient with the central portion having more woodland, while the southern portion having more shrubland and grassland, and the northern portion being mainly composed of bare ground and grassland.

2.2. Datasets

Table 1 provides an overview of the datasets used in this study. Normalized Difference Vegetation Index (NDVI) is the most extensively-used RS data for vegetation monitoring (Tucker et al., 2005). NDVI is formulated based on the different absorption of chlorophyll-a and -b in green leaves in the red (~690 nm) and near-infrared (~850 nm) frequency bands (Glenn et al., 2008). This results in a unique vegetation spectral feature distinctive of other land cover types (e.g. soil, water and snow). NDVI is defined as:

$$\mathrm{NDVI} = (\rho_{\mathrm{NIR}} - \rho_{\mathrm{Red}})/(\rho_{\mathrm{NIR}} + \rho_{\mathrm{Red}}) \quad (1)$$

where ρ_{Red} and ρ_{NIR} refer to the reflectance at red and near-infrared frequency, corresponding to AVHRR Band one (0.58–0.68 um) and Band two (0.72–1.0 um) in this study. The Global Inventory Modeling and Mapping Studies (GIMMS) NDVI based on AVHRR measurements is