ISPRS Journal of Photogrammetry and Remote Sensing 131 (2017) 77–91

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

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

Improving the prediction of African savanna vegetation variables using time series of MODIS products

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ARTICLE INFO

Article history:
Received 16 February 2017
Received in revised form 11 July 2017
Accepted 28 July 2017

Keywords:
Vegetation cover
Enhanced Vegetation Index (EVI)
Leaf Area Index (LAI)
Fraction of Photosynthetically Active Radiation (FPAR)
Partial Least Square Regression (PLSR)
Model transferability

ABSTRACT

African savanna vegetation is subject to extensive degradation as a result of rapid climate and land use change. To better understand these changes detailed assessment of vegetation structure is needed across an extensive spatial scale and at a fine temporal resolution. Applying remote sensing techniques to savanna vegetation is challenging due to sparse cover, high background soil signal, and difficulty to differentiate between spectral signals of bare soil and dry vegetation. In this paper, we attempt to resolve these challenges by analyzing time series of four MODIS Vegetation Products (VPs): Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Leaf Area Index (LAI), and Fraction of Photosynthetically Active Radiation (FPAR) for Etosha National Park, a semiarid savanna in north-central Namibia. We create models to predict the density, cover, and biomass of the main savanna vegetation forms: grass, shrubs, and trees. To calibrate remote sensing data we developed an extensive and relatively rapid field methodology and measured herbaceous and woody vegetation during both the dry and wet seasons. We compared the efficacy of the four MODIS-derived VPs in predicting vegetation field measured variables. We then compared the optimal time span of VP time series to predict ground-measured vegetation. We found that Multiyear Partial Least Square Regression (PLSR) models were superior to single year or single date models. Our results show that NDVI-based PLSR models yield robust prediction of tree density ($R^2 = 0.79$, relative Root Mean Square Error, rRMSE = 1.9%) and tree cover ($R^2 = 0.78$, rRMSE = 0.3%). EVI provided the best model for shrub density ($R^2 = 0.82$) and shrub cover ($R^2 = 0.83$), but was only marginally superior over models based on other VPs. FPAR was the best predictor of vegetation biomass of trees ($R^2 = 0.76$), shrubs ($R^2 = 0.83$), and grass ($R^2 = 0.91$). Finally, we addressed an enduring challenge in the remote sensing of semiarid vegetation by examining the transferability of predictive models through space and time. Our results show that models created in the wetter part of Etosha could accurately predict trees' and shrubs' variables in the drier part of the reserve and vice versa. Moreover, our results demonstrate that models created for vegetation variables in the dry season of 2011 could be successfully applied to predict vegetation in the wet season of 2012. We conclude that extensive field data combined with multiyear time series of MODIS vegetation products can produce robust predictive models for multiple vegetation forms in the African savanna. These methods advance the monitoring of savanna vegetation dynamics and contribute to improved management and conservation of these valuable ecosystems.

1. Introduction

Savanna ecosystems cover about fifth of the Earth's land surface and just under half of Africa's land area (Ciais et al., 2011; Shackleton and Scholes, 2011). These ecosystems provide pivotal ecosystem services including carbon sequestration, water filtration, soil stability, meat and dairy production, fuel wood provision, tourism, and recreation (Solbrig, 1996; Vågen et al., 2005). In addition, African savannas harbor rich biodiversity and provide habitat and connectivity for far-roaming wildlife (Sankaran et al., 2013).

Abbreviations: AVHRR, advanced very high resolution radiometer; DPM, Disc Pasture Meter; EVI, Enhanced Vegetation Index; FPAR, Fraction of Photosynthetically Active Radiation; GIS, geographic information systems; LAI, Leaf Area Index; MODIS, Moderate Resolution Imaging Spectroradiometer; NDVI, Normalized Difference Vegetation Index; NIR, near infrared; NPP, Net Primary Productivity; PCQ, point-centered quarter method; PLSR, Partial Least Square Regression; QC, quality control; RMSEP, Root Mean Squared Error of Prediction; rRMSE, relative Root Mean Square Error; SPOT, Satellite Pour l'Observation de la Terre (Satellite for observation of Earth); SWIR, shortwave infrared; VI, vegetation index; VP, vegetation product.

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http://dx.doi.org/10.1016/j.isprsjprs.2017.07.012
0924-2716/

However, savanna ecosystems face degradation due to changes in land use, climate change, fire, and management regimes (Mathieu et al., 2009; Mitchard and Flintrop, 2013; Vogel and Strohbach, 2009). Monitoring rapid changes in savannas requires a method that maintains sufficiently high temporal resolution over large spatial extents. Remote sensing is a viable tool to predict biophysical measurements of cover, density, and biomass of savanna vegetation (Ban et al., 2015; Boschetti et al., 2013; Choudhury, 1992; Dube and Mutanga, 2015; Naidoo et al., 2012; Rahimzadeh-Bajgiran et al., 2012; Zhu and Liu, 2015). For convenience, we use the term "prediction" hereafter to refer to the modeled relationship between reflectance data and field-based vegetation measurements.

Savannas are extensive, and often remote and inaccessible, complicating protocols for their monitoring. Field methodologies for measuring vegetation change are typically limited in extent, expensive, and time consuming. Therefore, the use of low and moderate resolution remote sensing, including Moderate Resolution Imaging Spectroradiometer (MODIS), has been applied to characterize savanna vegetation throughout Africa (Eisfelder et al., 2012). Nonetheless, the sparse vegetation in these arid and semi-arid areas and high reflectance of soil background continue to present a major challenge to the use of remote sensing to predict continuous vegetation variables (Ali et al., 2016; Ghulam et al., 2007; Rahimzadeh-Bajgiran et al., 2012; Svoray et al., 2013). Moreover, savanna vegetation is senesced during prolonged periods of the year (Eisfelder et al., 2012). Low chlorophyll content of senescent vegetation reduces the red-to-near infrared (NIR) spectral contrast, which impairs our ability to distinguish vegetation from background soil. These characteristics present additional challenges when using remote sensing to directly predict dry biomass (Homer et al., 2013; Huete, 1988; Mayr and Samimi, 2015; Meyer and Okin, 2015). One approach to addressing these challenges is to use spectral products targeted at enhancing vegetation that use red, near infrared (NIR), and shortwave infrared (SWIR) wavelengths which are particularly sensitive to vegetation changes (Houborg et al., 2007).

MODIS provides four preprocessed vegetation products. Two of these products are vegetation indices, Normalized Difference Vegetation Index (NDVI), and Enhanced Vegetation Index (EVI). The other two are vegetation quantities derived partly from spectral vegetation indices: Leaf Area Index (LAI), and Fraction of Photosynthetically Active Radiation (FPAR) (Knyazikhin et al., 1999). We refer to these four MODIS-derived products as "Vegetation Products" (VPs). These MODIS VPs are freely available, atmospherically and geometrically corrected, and based on extensive field validation campaigns (Solano et al., 2010). Therefore, these VPs are readily available to practitioners, and particularly valuable for savanna conservation applications (Li et al., 2015a; Tsalyuk et al., 2015).

NDVI has been widely applied to predict vegetation cover, above-ground biomass and greenness (Jacquin et al., 2010). While the relationship between NDVI and above-ground green biomass is well established (Eisfelder et al., 2012; Li et al., 2012; Zhu and Liu, 2015), research has indicated the limited capacity of NDVI to predict senesced vegetation (Xu et al., 2014). Conversely, the EVI index is sensitive to a wider range of canopy cover than NDVI (Huete et al., 2002). The EVI index includes the red and IR bands of NDVI, and additionally incorporates a blue band, soil adjustment factor, and atmospheric resistance terms, which correct the influence of aerosol on the red band (Sjostrom et al., 2011). This correction is specifically useful in open canopies such as savanna and shrublands, where the background signal may have prominent effect on radiometric measurements of vegetation (Huete et al., 2002). There is a strong correlation between EVI and gross primary productivity (GPP) in African ecosystem (Jin et al., 2013; Sjostrom et al., 2011). Li et al. (2012) show a strong relationship between EVI, Net Primary Productivity (NPP), and forage production in rangelands. Time series of MODIS EVI was successfully used to classify land cover in Northern China (Zhang Xia et al., 2008), identify maize crop cultivation areas (Zhang et al., 2014), and monitor global crop yield (Zhang and Zhang, 2016).

Leaf Area Index (LAI) provides information on plant canopy structure by measuring the total green leaf area per unit ground-surface area (Lotsch et al., 2003). FPAR is a unitless fraction, measuring the proportion of radiation absorbed by the canopy out of the total available radiation in the photosynthetically active wavelengths of the spectrum 400–700 nm. FPAR is an important measure of carbon cycling and energy budget (Huete et al., 2002). Both LAI and FPAR have been measured in the field as prominent indicators of vegetation condition. Research has demonstrated that both these vegetation properties have higher correlations with senesced grass biomass than does NDVI (Asner et al., 1998; Butterfield and Malmstrom, 2009). FPAR was shown to correlate with both green grass biomass and litter canopy, indicating its ability to predict dry vegetation biomass (Machwitz et al., 2015). Recently, LAI and FPAR have being used as satellite-derived products for calculating surface photosynthesis, evapotranspiration, land cover, and net primary productivity (Huete et al., 2002; Knyazikhin et al., 1999; LP DAAC, 2002-2012; Myneni et al., 2002).

The MODIS-based algorithm of LAI/FPAR products was designed to use up to seven spectral bands of MODIS surface reflectance (648, 858, 470, 555, 1240, and 2130 nm) (Knyazikhin et al., 1998). However, until recently only the red (648 nm) and infrared bands (858 nm) were used (Yan et al., 2016), similar to NDVI. The relationships among NDVI and LAI and NDVI and FPAR have received attention (Myneni et al., 2010). However, these relationships are influenced by land cover and the vegetation canopy structure (Lotsch et al., 2003). To deal with this, MODIS LAI/FPAR algorithm uses NDVI bands and relies on world classification of six biomes together with extensive field validation to define vegetation structure (Lotsch et al., 2003). The algorithm links surface bi-directional reflectance factor (BRT) to structural and spectral properties of vegetation and soil (Yan et al., 2016). Importantly, LAI/FPAR in situ measurements show a good correlation with MODIS-derived values (Fensholt et al., 2004; Zhao et al., 2007).

An additional challenge in applying remote sensing in savannas is encompassing the high inter- and intra-annual variability of the vegetation in these ecosystems. Capturing seasonal and inter-annual variation is especially important in savannas, where vegetation biomass is highly dependent on variable rainfall (Scanlon et al., 2005). Time series of VPs capture vegetation phenology over time; and, therefore, they can improve the prediction of vegetation variables (Rao et al., 2015; van Hoek et al., 2016; Zhu and Liu, 2015). Indeed, integrated (summed) values and maximum annual NDVI and FPAR values over the growth year show strong correlations with above-ground herbaceous biomass (Li et al., 2015a; Zhang et al., 2016). Annually integrated VI data show better correlations with field measured herbaceous biomass than a single-date VI value (Verbesselt et al., 2006; Yi et al., 2008; Zhou et al., 2013). Time series information, such as times of green up and senescence/dormancy onset and the length of the growing season have been used to describe vegetation phenology (Lu et al., 2014a, 2014b; Zhang et al., 2003), and to differentiate between growing cycles of trees or grasses (Archibald and Scholes, 2007). Time series of MODIS-derived EVI predict maize (Zhang et al., 2014) and winter wheat (Qiu et al., 2017) cultivated areas across China with considerable accuracy.

In spite these recent developments, remote sensing of biophysical variables of savanna vegetation remains a challenge (Mayr and Samimi, 2015; Meyer and Okin, 2015). A major hindrance in the application of remote sensing data for monitoring and management is transferability of models between sites, when trying to apply models developed for one area to predict vegetation