ISPRS Journal of Photogrammetry and Remote Sensing 109 (2015) 17–29

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

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

Mapping tropical dry forest succession using multiple criteria spectral mixture analysis

Sen Cao [a,b], Qiuyan Yu [b,c], Arturo Sanchez-Azofeifa [a,*], Jilu Feng [a], Benoit Rivard [a], Zhujun Gu [a]

[a] Department of Earth and Atmospheric Sciences, University of Alberta, Edmonton T6G 2E3, Canada
[b] State Key Laboratory of Earth Processes and Resource Ecology, Beijing Normal University, Beijing 100875, China
[c] School of Geosciences, University of South Florida, Tampa 33620, USA

ARTICLE INFO

Article history:
Received 24 January 2015
Received in revised form 6 August 2015
Accepted 27 August 2015

Keywords:
Secondary tropical dry forest
Shortwave infrared
Spectral mixture analysis
Root mean square error
Spatial distance
Fraction consistency

ABSTRACT

Tropical dry forests (TDFs) in the Americas are considered the first frontier of economic development with less than 1% of their total original coverage under protection. Accordingly, accurate estimates of their spatial extent, fragmentation, and degree of regeneration are critical in evaluating the success of current conservation policies. This study focused on a well-protected secondary TDF in Santa Rosa National Park (SRNP) Environmental Monitoring Super Site, Guanacaste, Costa Rica. We used spectral signature analysis of TDF ecosystem succession (early, intermediate, and late successional stages), and its intrinsic variability, to propose a new multiple criteria spectral mixture analysis (MCSMA) method on the shortwave infrared (SWIR) of HyMap image. Unlike most existing iterative mixture analysis (IMA) techniques, MCSMA tries to extract and make use of representative endmembers with spectral and spatial information. MCSMA then considers three criteria that influence the comparative importance of different endmember combinations (endmember models): root mean square error (RMSE); spatial distance (SD); and fraction consistency (FC), to create an evaluation framework to select a best-fit model. The spectral analysis demonstrated that TDFs have a high spectral variability as a result of biomass variability. By adopting two search strategies, the unmixing results showed that our new MCSMA approach had a better performance in root mean square error (early: 0.160/0.159; intermediate: 0.322/0.321; and late: 0.239/0.235); mean absolute error (early: 0.132/0.128; intermediate: 0.254/0.251; and late: 0.191/0.188); and systematic error (early: 0.045/0.055; intermediate: −0.211/−0.214; and late: 0.161/0.160), compared to the multiple endmember spectral mixture analysis (MESMA). This study highlights the importance of SWIR in differentiating successional stages in TDFs. The proposed MCSMA provides a more flexible and generalized means for the best-fit model determination than common IMA methods.

1. Introduction

As one of the most disturbed and the least protected ecosystems on earth (Hoekstra et al., 2005; Janzen, 1988a,b), Tropical Dry Forests (TDFs) account for about 46% of tropical forests (Olson et al., 2001). Despite the worldwide coverage of TDFs, there are significant knowledge gaps regarding their ecological, biological, and biogeochemical dimensions as their rate of disturbance and deforestation far surpasses land use/cover change processes in other tropical biomes (Hoekstra et al., 2005). As a result of different socio-economic forces, the TDFs landscape is a mixture of forests undergoing different stages of ecological succession as well as different agricultural land uses. These land cover elements are integrated for management and conservation purposed under a term denominated "agro-landscapes". The concept of "agro-landscape" is a fundamental building block in establishing conservation and restoration policies of TDFs across the Americas.

Secondary TDFs presented in "agro-landscapes" can generally be divided into three levels of succession according to their horizontal and vertical structure, leaf area index (LAI), green canopy cover density, and species composition (Arroyo-Mora et al., 2005; Kalacska et al., 2005a, 2004a, 2005c). These three successional stages can be characterized as early, intermediate, and late. This nomenclature provides a way to better understand how TDFs recover after disturbances, and it has served as the framework

* Corresponding author.
E-mail address: arturo.sanchez@ualberta.ca (A. Sanchez-Azofeifa).

http://dx.doi.org/10.1016/j.isprsjprs.2015.08.009

for extensive collaborative inter-comparison studies across the Americas (e.g., Alvarez-Anorve et al., 2012; Castillo et al., 2011; Garcia Millan et al., 2014; Kalacska et al., 2007b).

In the context of quantifying ecological succession in TDFs, remote sensing approaches have been implemented in Mexico, Costa Rica, and Brazil with different degrees of success (e.g., Arroyo-Mora et al., 2005; Castillo et al., 2012; Garcia Millan et al., 2014; Grinand et al., 2013; Helmer et al., 2010; Kalacska et al., 2005a; Moura et al., 2012). Early studies mainly attempted to link spectral reflectance or vegetation indices with specific forest structural parameters (e.g., tree height, canopy openness, and LAI) (Arroyo-Mora et al., 2005; Kalacska et al., 2005a, 2005b, 2005c) or biodiversity parameters (e.g., Shannon diversity and Holdridge Complex Index) (Kalacska et al., 2007b). More recently, LiDAR (Castillo et al., 2012, 2011), and multi-angle (Garcia Millan et al., 2014, 2013) remote sensing have shown their superiority in exploring ecological restoration process. These previous studies have two common denominators. First, forest structure and biodiversity instead of "age since last disturbance" can better describe TDFs regeneration, because the growth of TDFs varies not only with forest age but with local factors such as precipitation, soil type, and previous land use (Alvarez-Anorve et al., 2012; Arroyo-Mora et al., 2005; Castro et al., 2003; Lucas et al., 2000). Second, the extent of TDFs can be better mapped during the dry season when biophysical parameters tend to be more pronounced and distinctive. This phenological feature is independent of which sensor is considered (multi-spectral, hyperspectral, multi-angle, or LiDAR), and it has been employed to map the extent of tropical dry forests across the Americas using MODIS (Portillo-Quintero and Sanchez-Azofeifa, 2010).

Although significant advances concerning the characterization of the state and extent of TDFs have been achieved, accurate classification of these TDFs as a function of successional stages remains an important area of concern for research due to two properties in secondary TDFs: the similar spectral response between successional stages and the wide variation of forest pathways within the same successional stage (Helmer, 2000; Lucas et al., 2000; Neeff et al., 2006). The solution to the former requires a wavelength selection process that can well differentiate successional stages. Since a succession stage is driven by species composition which is, in turn, driven by different types of propagation mechanisms (Castillo et al., 2011), the spectral reflectance of TDFs is consequently tied to them (Hesketh and Sanchez-Azofeifa, 2012). From this point of view, wavelengths that reflect these propagation mechanisms or related ecological variables have a higher capacity to differentiate succession stages. Asner (1998) demonstrated the relative importance of biophysical (e.g., leaf and stem area and foliage clumping) and biochemical (e.g., foliar lignin and nitrogen) factors on forest canopy reflectance in visible, near, and shortwave infrared (SWIR) spectral ranges. His research confirmed previous observations (Fourty et al., 1996; Woolley, 1971) that organic features in leaf spectra were largely obscured by water in the SWIR. This conclusion was then successfully employed to map vegetation in arid and semi-arid (Asner and Lobell, 2000) and coniferous (Lobell et al., 2001) ecosystems. In this context and during the middle of dry season, TDFs present a similar landscape pattern to arid and semi-arid ecosystems, where most of green leaves fall and exposed wood, litter, and bare soil dominate the forests' spectral signatures. Therefore, it is essential to explore the spectral features of this ecosystem in the SWIR to better map the TDFs.

The secondary TDFs' spectral signature is also affected by the wide variation of forest pathways (Alvarez-Anorve et al., 2012; Hesketh and Sanchez-Azofeifa, 2012; Kalacska et al., 2007b), resulting in the so-called spectral variability that introduces great uncertainty in forest mapping. To address spectral variability, two categories of strategies have been proposed (Somers et al., 2011). The first is spectral feature analysis (SFA) (e.g., Debba et al., 2006; Dennison et al., 2006; Somers et al., 2010, 2009). The second is an iterative mixture analysis (IMA) (Asner and Lobell, 2000; Roberts et al., 1998; Song, 2005). Both of these strategies are built on the basis of spectral mixture analysis (SMA), which treats the spectra of each pixel as a composition of several spectral signatures (endmembers) (Roberts et al., 1998). However, the fundamental principles behind these strategies are totally different. SFA tries to reduce or eliminate spectral variability before pixel unmixing. It could efficiently generate pure endmembers with higher between-class variation and lower in-class variation, but it would also lose useful information or introduce greater uncertainty in its results (Somers et al., 2011). This shortcoming in SFA can be well overcome by IMA. IMA never attempts to optimize endmember purity before the unmixing process. Instead, it directly tests all possible endmember combinations (or endmember models) for a given pixel and then selects the one with the best fit.

As the first and the most representative IMA technique, multiple endmember SMA (MESMA) (Roberts et al., 1998) has been widely and successfully applied in vegetation mapping applications (e.g., Liu and Yang, 2013; Roberts et al., 1998; Sonnentag et al., 2007; Youngentob et al., 2011). Some similar techniques have also been proposed, such as Bayesian SMA (BSMA) (Song, 2005) and auto Monte Carlo spectral unmixing model (AutoMCU) (Asner and Lobell, 2000). Nevertheless, there are still some problems present with the IMA approach. The first one exists in endmember extraction. Although the research community has recognized that representative endmembers, rather than spectrally purest endmembers, could better explain within-class spectral variation (Deng and Wu, 2013; Powell et al., 2007), the priorities of existing endmember extraction techniques such as spatial-spectral endmember extraction (SSEE) (Rogge et al., 2007) and automatic endmember bundle extraction for MESMA (Somers et al., 2012) are still searching vertexes or signature bundles near vertexes as endmember candidates, but within a spatial context. Their strategy is reasonable, however it functions best under conditions wherein the vertexes are present for a given land cover. In secondary TDFs, there may be no significant vertexes. The second problem in IMA refers to the best-fit model selection. On the one hand, existing IMA methods may solely or mainly adopt one fitness indicator to calculate the best-fit model. For example, the probability distribution of endmember signatures and unmixing fractions is the only indicator considered in BSMA and AutoMCU, respectively. In MESMA the unmixing residual is, in fact, the most influential indicator. On the other hand, even though MESMA employs a very complex procedure to exclude those ill-fit models by combining some other indicators such as spatial adjacency, it is a stepwise filtering technique. Models that have been excluded in former steps cannot be involved in future steps despite the fact they may show great fitness later on. Furthermore, MESMA cannot incorporate any additional indicators due to its tight algorithm structure.

Based on previous work in TDFs succession quantification and existing forest mapping strategies, the objective of this paper is to demonstrate a methodology for better mapping TDFs in different successional stages. This study analyzed the spectral signature and variability of different successional forests, extracted SWIR as efficient spectrum range, and then proposed a multiple criteria spectral mixture analysis (MCSMA) approach. To account for the great variability in TDFs, the study's approach adopted a multi-classifiers and spatial homogeneity based technique on endmember extraction. Then, specifically, the study constructed a fitness evaluation framework to select the best-fit endmember model among all possible models by simultaneously considering three indicators: root mean square error (RMSE); spatial distance (SD); and fraction consistency (FC).