Int J Appl Earth Obs Geoinformation 66 (2018) 116–125

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

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

Research Paper

Bamboo mapping of Ethiopia, Kenya and Uganda for the year 2016 using multi-temporal Landsat imagery

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ARTICLE INFO

Keywords:
East Africa
Bamboo
Multi-temporal
Landsat

ABSTRACT

Mapping the spatial distribution of bamboo in East Africa is necessary for biodiversity conservation, resource management and policy making for rural poverty reduction. In this study, we produced a contemporary bamboo cover map of Ethiopia, Kenya and Uganda for the year 2016 using multi-temporal Landsat imagery series at 30 m spatial resolution. This is the first bamboo map generated using remotely sensed data for these three East African countries that possess most of the African bamboo resource. The producer's and user's accuracies of bamboos are 79.2% and 84.0%, respectively. The hotspots with large amounts of bamboo were identified and the area of bamboo coverage for each region was estimated according to the map. The seasonal growth status of two typical bamboo zones (one highland bamboo and one lowland bamboo) were analyzed and the multi-temporal imagery proved to be useful in differentiating bamboo from other vegetation classes. The images acquired in September to February are less contaminated by clouds and shadows, and the image series cover the dying back process of lowland bamboo, which were helpful for bamboo identification in East Africa.

1. Introduction

Bamboos are a variety of perennial woody grasses. They play an increasing role in ecosystem services, biodiversity conservation, and socio-economic development. They have been recognized to be an important carbon sink and has potential for mitigating climate change (Song et al., 2011; Dubey et al., 2016; Agarwal and Purwar, 2017). Bamboos have also been proven to have an ecological function of soil and water conservation (Zhou et al., 2005). Bamboo is an irreplaceable habitat for a lot of wildlife, being their food source and escape cover (Schaller, 1985; Kratter, 1997; Reid et al., 2004; Linderman et al., 2005). Due to its versatile application and rapid re-growth, bamboo provides materials for household use, construction, and industries (Kaur et al., 2016; Sofiana et al., 2017), which is an alternative material to wood products facing the environmental concerns. It is a key component in lifting rural people out of poverty by providing job opportunities (Mishra, 2015; Chen et al., 2017). For example, bamboo weaving is a good income-earning opportunity for disadvantaged groups (Das, 2017).

Bamboo is widely distributed in Asia, Latin America and Africa, mainly in the tropical and subtropical area. In Africa, Ethiopia, Kenya and Uganda possess most of the bamboo resources, according to the world bamboo resources assessment report (Lobovikov et al., 2005). Among the three countries, 86% of the African bamboo resource is distributed in Ethiopia (Kelbessa et al., 2000). Two indigenous species of bamboo in East Africa are *Yushania alpina* K. Schumach (highland bamboo) and *Oxytenanthera abyssinica* A. Rich (lowland bamboo).

However, the natural bamboo forests are under threat from deforestation and degradation. People are clearing them away to have more space for agricultural activities and residential plots, due to lack of sustainable management and control. For example, lowland bamboos in Benishangul Gumuz Region of Ethiopia were found converted to

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https://doi.org/10.1016/j.jag.2017.11.008
Received 4 September 2017; Received in revised form 16 November 2017; Accepted 17 November 2017

agricultural land, and if the same trend continues, the bamboo resource will vanish soon (Bessie et al., 2016). The same situation also arises in highland bamboo areas. The highland bamboo has been converted into croplands, grazing lands and human settlements, which caused increasing habitat loss and fragmentation for wild animals, such as Bale monkeys (Mekonnen et al., 2017). Timely mapping the distribution of bamboo is necessary for biodiversity conservation, resource management and policy making for rural poverty reduction.

Remote sensing has its advantage on mapping and monitoring the Earth surface, providing an up-to-date, comparatively cheap and dynamic information for many applications. However, bamboo is very difficult to be identified using remote sensing in comparison with other land cover classes. Firstly, some of them are understory layer or mixed with other canopy (Reid et al., 2004; Doležal et al., 2009). Secondly, bamboos have similar spectral properties with other vegetation classes, implying that spectrum is not adequate to separate bamboo from other vegetation (Singh, 1987; de Carvalho et al., 2013). Thirdly, many bamboos are distributed in patches owing to local climate conditions or human interventions, which require high resolution imagery to find them (Ghosh and Joshi, 2014). Finally, they are among the fastest-growing plants on Earth and frequently changing, which heightens the difficulties on sample collection (Mertens et al., 2008; McMichael et al., 2013). A few attempts have been made to identify bamboo using remotely sensed data. Wang et al. (2009) mapped the understorey bamboo in part of the Xinglongling and Tianhuashan giant panda habitats in the Qinling Mountains of China. They used an ASTER image acquired in May when the leaves on the canopy of the trees started to emerge. Han et al. (2014) mapped Moso bamboos in the northeast of Anji County, Zhejiang Province of China. The data used in their study was a SPOT-5 image. Due to the high spatial resolution, they used an object-based image analysis method and texture measures derived from gray level co-occurrence matrices. Ghosh and Joshi (2014) also made good use of high resolution data in mapping bamboo. They used the WorldView 2 imagery, which provides 2 m multi-spectral and 0.5 m panchromatic spatial resolution. The study area was in lower Gangetic plains in West Bengal, India and they used an image acquired in the season of returning monsoons. Temporal information was not used in these bamboo mapping studies since they only used one single image. Li et al. (2016) tried to map the distribution of bamboo in Zhejiang Province of China using 4 Landsat images, and the importance of temporal information in bamboo mapping was proven. These mapping works were limited to small study areas, and there is no study focused on mapping bamboo at a national scale.

The objective of this study is to determine the effectiveness of multi-temporal image series in bamboo mapping, and to produce a validated bamboo map of Ethiopia, Kenya and Uganda for the year 2016 using Landsat 8 imagery. The classification process, accuracy assessment, estimated area of bamboo cover are all presented. The hotspots with large amounts of bamboo were identified according to the map. The phenological characteristics of bamboo and other vegetation classes were analyzed to examine the function of multi-temporal images.

2. Methodology

Fig. 1 is a flow chart of the bamboo mapping process in this study, including data preparation, sample collection, image classification, post-processing, and accuracy assessment.

2.1. Data preparation

In this study, we queried all Level 1 terrain-corrected (L1T) Landsat 8 images acquired between 2013 and 2017 from USGS Earth Resources Observation and Science Center. Since the bamboo mapping is for the year 2016, the images acquired in 2016 were used in the highest priority. We combined a multi-temporal feature set of 12 months in the mapping process, so we used 12 scenes of Landsat imagery for each path/row in Worldwide Reference System-2 (WRS-2). For some of the months, the images acquired in 2016 were not enough because of the absent of L1T product or high cloud cover over 90%, then images from adjacent years were used as alternatives. We downloaded the CFmask layer (Zhu and Woodcock, 2012; Zhu et al., 2015) together with the spectral reflectance of Landsat. Landsat images of other years were also used in the analysis of seasonal variation of bamboo samples.

Ancillary data includes MODIS Normalized Difference Vegetation Index (NDVI) time series, climate data, and topography data. MOD13Q1 NDVI data is provided every 16 days with a spatial resolution of 250 m. For climate data, we selected WorldClim Version2, a dataset contains a collection of average monthly climate data (including minimum temperature, maximum temperature, average temperature, precipitation, radiation, wind speed, and water vapor pressure) for the years 1970–2000 at a resolution of 30 s (Fick and Hijmans, 2017). The 30 m resolution of Shuttle Radar Topography Mission (SRTM) elevation data was also prepared, and topographic variables (e.g., slope, southness, eastness) were derived. All ancillary layers were geo-registered and resampled to the same 30 m pixels as Landsat 8 data.

2.2. Sample collection

The map we designed to produce in this study includes 10 classes: 9 level-1 classes (croplands, forests, grasslands, shrublands, wetlands, water bodies, impervious surfaces, bare lands, snow and ice) in the classification scheme of FROM-GLC (Gong et al., 2013), and bamboos. Ground truth samples were collected during several field trips Fig. 2. We conducted the first field trip in these three countries in January of 2017, accompanied by local experts, and collected 31 bamboo samples mainly at Kiambu (Kenya), Migori (Kenya), Kabale (Uganda), Asosa (Ethiopia), and Butajira (Ethiopia). Some field photos of bamboo are also presented in Fig. 2. We also collected samples of other land cover classes during the field trip in order to better differentiating bamboo from other vegetation. Since the distribution of bamboo is scattered, local experts continued to contribute field samples to the dataset after this field trip. Totally, local experts contributed 268 sample sites of bamboos for three countries (65 from Kenya, 37 from Uganda, and 166 from Ethiopia).

The field samples unsuitable for training or validation were carefully screened from the dataset. Bamboo patches which were too small to be a pure Landsat 30 m × 30 m pixel were removed. Bamboo growing in the understory of forests, which is invisible on most of the satellite imagery, were also removed. After screening, the field samples were randomly partitioned into 2 subsets, one for training and the other for validation.

We also collected more training samples (mainly bamboo samples, with a few samples of other land cover classes surrounding bamboo samples) by manual interpretation of high resolution images on Google Earth, according to the interpretation keys we summarized from the field samples. To compensate for the deficiencies in training samples of other land cover classes, we employed all samples located in Ethiopia, Kenya and Uganda from an all-season sample set, i.e., FROM-GLC-Africa sample set (Li et al., 2017). Each sample from this dataset was double-checked, especially to distinguish bamboo samples from other vegetation types. With the multi-temporal Landsat image series, the temporal information was greatly enlarged from 4 seasons to 12 months. For each sample in the training dataset, we measured the extended radius from the center point to be a homogeneous sample, which determined how many pixels we could spatially expand in training. The reason for expanding the training sample temporally and spatially is to enrich the spectral diversity of the training dataset (Zhao et al., 2016).

2.3. Classification and post-processing

Random Forest Classifier with 100 trees was used in this study