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Application of hyperspectral remote sensing for flower mapping in African savannas

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A B S T R A C T

We tested the suitability and accuracy of hyperspectral data to produce the first African flowering and short-term floral cycle map. The spatial distribution and abundance, as well as the floral cycle, of melliferous plants are of utmost importance for evaluating pollination effects and to understand the relationship between melliferous plants in the landscape and the quantity and quality of bee keeping products. For a study site in Kenya, airborne AISA/Eagle hyperspectral data with 60 cm pixel resolution (400 to 990 nm spectral ranges) was captured in January 2014, at the beginning of the prime flowering period, and during the prime flowering period in February 2013. Aerial digital imagery with 10 cm pixel size and Smartphone captures in the field were used for reference data collection. The flowering species were grouped into functional flowering plant groups. Linear spectral unmixing and Change Vector Analysis (CVA) were used on the bi-temporal AISA/Eagle data to produce a hard cover map showing the spatial distribution, abundance and short-term flowering cycle of melliferous plants. Overall accuracies were slightly higher in the February 2013 imagery at the prime flowering period; all flowering plant groups together ("All") could be mapped with an overall accuracy of 83% ($n = 512$). The "White forbs" flowering plant group was most accurately mapped in both AISA/Eagle acquisition dates. Based on Duncan's inter-class similarity test, the "White forbs" group was also most distinct from other flowering plant groups. There is a need to investigate the effect of spectral endmember variability and upscaling options for space-borne monitoring of the floral cycle at key sites in Africa. Floral cycle maps can help decision makers and bee keepers to understand how bee colonies interact with the floral environment and what to expect from an apiary in terms of honey flow.

1. Introduction

In Africa a significant part of the rural population draws their income from beekeeping (Qaiser, Tahir, Taj, & Ali, 2013), however information about the relationship between the abundance and distribution of flowering plants in the landscape and hive productivity is largely unavailable (Evans & Schwarz, 2011).

The floral cycle and flowering intensity in semi-arid Africa is spatially and temporally highly variable depending on the plant species as well as land form, and local climate and edaphic conditions (Raina & Kimbu, 2005). The floral cycle refers to the duration of the blossoming period and flowering intensity which includes the fractional coverage of flowering buds within a single tree, plant or vegetation community (McIntosh, 2002). In situ observations of the floral cycle of key melliferous plants are often used to produce floral calendars for a specific site (Raina, Kioko, Zethner, & Wren, 2011). Floral calendars categorize various flowers, their value to bees, abundance, season and duration of bloom for a given area. Melliferous plants produce nectar and pollen which is collected by honey bees and converted into honey (Decourtye, Mader, & Desneux, 2010).

Spatio-temporal information about the distribution and abundance of flowering plants can help to understand bee foraging behavior (Smith, Lopez Quintero, Moreno Patino, Roubik, & Wcislo, 2012) and ultimately, if a link can be established between ecosystem integrity and hive productivity, conservation incentives can be formulated (Abou-Shaara, 2014). Ecosystem integrity is a term used to describe the degree of self-maintenance of ecosystem functions within a particular ecosystem (Haines-Young & Potschin, 2010). A decrease in the fractional cover of melliferous plant communities within agro-ecological landscapes, due to for instance deforestation, would mean that ecosystem integrity in view of pollination and beekeeping is compromised. Lateral to that, long-term spatial data on landscape flowering patterns would also provide a critical understanding about nutritional, climate and

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ecological stresses which trigger pest and diseases in bee colonies (Aizen & Harder, 2009).

Earth observation (EO) is an effective tool to spatially assess plant traits, vegetation condition and ecological processes (Cho & Skidmore, 2006; Rocchini, 2010). Well validated remotely sensed data sets are more cost and time effective compared to sampling the same area using field based approaches (Weng, 2002). Moreover, when several well calibrated satellite images are used in time-series, phenological stages including the floral cycle can be effectively mapped (Ge, Everitt, Carruthers, Gong, & Anderson, 2006). EO mapping routines still have a vast unexplored potential to synoptically capture landscape ecological parameters in relation to pollinators and the distribution, temporal development and status of melliferous plants (Chen, Shen, Zhu, & Tang, 2009).

In airborne hyperspectral remote sensing dozens to hundreds of spectral bands are commonly used for the qualitative and quantitative analyses of various materials and targets across the visible (VIS), near-infrared (NIR) and short-wave infrared (SWIR) spectral ranges (Ustin, Roberts, Gamon, Asner, & Green, 2004; van der Meer et al., 2012). With its high spatial and spectral resolution, hyperspectral remote sensing can help map vegetation communities down to the species level, and detect elementary, biogeochemical and physiological vegetation properties such as cellulose and lignin content (Ustin et al., 2004). However, the large data volumes and high acquisition costs of specifically airborne hyperspectral data can be challenging to institutions and researchers alike (Higgins, Asner, Perez, Elespuru, & Alonso, 2014). Hyperspectral remote sensing data interpretation is often hampered by large data dimensionality, unavailability of multi-temporal and timely observations and, if spectral endmembers (EM) are used within a linear mixture modeling approach, high variability of spectral EM in time and space (Somers, Asner, Tits, & Coppin, 2011).

To the best of our knowledge there are currently no remote sensing studies in Africa that specifically aim at mapping the abundance, distribution and the short-term flowering cycle of melliferous plants on a landscape scale. Some earlier studies in North America mapped the floral cycle and phenological characteristics of specific invasive weeds within the landscape mosaic using airborne and ground based hyperspectral data (Ge et al., 2006). Invasive species often exhibit a distinct floral cycle, which enhances their spectral differentiation at certain periods within the phenological cycle (Lawrence, Wood, & Sheley, 2006; Parker Williams & Hunt, 2002). Carvalho, Schlerf, van der Putten, and Skidmore (2013) used hyperspectral-based spectroscopy to assess the flowering and leaf phenology of *Jacobaea vulgaris* in northern Europe as a means of obtaining an insight into the chemical characteristics of the plant. Chen et al. (2009) used hyperspectral data and spectral mixture modeling to develop an accurate flowering coverage index for *Halerpestes tricuspis* in Tibetan plateau grasslands. The authors found that yellow flowering *H. tricuspis* were best mapped using the 500–670 nm spectral region (visible to near-infrared wavebands) while no apparent flowering effect was found in the NIR spectral region. Shen, Chen, Zhu, Tang, and Chen (2010) found that flowering in the same species (*H. tricuspis*) significantly affects the robustness of the Enhanced Vegetation Index (EVI) which is often used in wide-area vegetation monitoring studies. In a study in European orchards, hyperspectral data and waveband selection was employed to detect the spatial abundance and distribution of floral pear buds (Wouters, De Ketelaere, De Baerdemaeker, & Saeys, 2013). In nearly all studies reviewed, in situ hyperspectral data sets at plot level, from hand held devices, were used for flower or floral bud mapping and in most cases only a single observation period was considered.

In this study multi-temporal (bi-temporal) AISA/Eagle hyperspectral aircraft data was used as input. Two commonly used spectral mapping algorithms were used in sequence, namely linear spectral unmixing and Change Vector Analysis (CVA) (Dubovyk, Menz, Conrad, Thonfeld, & Khamzina, 2013). Linear spectral unmixing is widely used on hyperspectral data for landscape feature mapping (Clark & Roush, 1984) mainly due to the relative simplicity of the spectral mixture model used and easy interpretation of results (Dobigeon et al., 2014). Linear spectral unmixing results are considered to be robust if well defined and stable reference spectra (or spectral endmembers — EM) are utilized in the model approximation. Linear spectral unmixing has some uncertainties mainly due to its inability to accurately consider non-linear spectral mixing effects (Altmann, Dobigeon, McLaughlin, & Tourneret, 2013) within highly heterogeneous landscapes (Higgins et al., 2014; Somers et al., 2011). CVA was, thus, utilized to fine-tune the attained linear unmixing results. In CVA the two-dimensional distance (magnitude) and direction between spectra or spectral derivatives is computed (Chen, Gong, He, Pu, & Shi, 2003). Albeit the difficulties in interpreting CVA results, CVA is considered a state-of-the-art change detection algorithm that is able to accurately map fine scale spectral changes in multi-temporal imagery (Landmann, Schramm, Huettich, & Dech, 2012).

2. Methodology

2.1. Study site

The study site is located in the Mwingi Central Sub County, Kitui County in Kenya (Fig. 1). It covers an area of 100 km^2. Mwingi is a semi-arid area with two rainfall peaks in April (147 Mean Annual Precipitation) and November (270 Mean Annual Precipitation). The average maximum temperature is 31 °C while the minimum is 15 °C. The hottest months are February–March and September–October, with the coldest months being July to August. The main woody species in Mwingi include *Acacia* spp., *Melia volkensii*, *Azadirachta indica*, *Zizyphus abyssinica*, *Albizia gummifera* and *Markhamia lutea*. The main flowering plants include *Acacia* spp., *Terminalia brownie*, *Aspilia mozambensis*, *Cassia diambotia*, *Cassia semea*, *Solonium incunum*, and *Boscia* and *Grewia* spp. The main flowering period for most of these plants is from January to May (Raina & Kimbu, 2005) with a few plants flowering in December. Relatively high rainfall amounts in November to December trigger the flowering of most plants from January onwards. This flowering trend is sustained by further rainfall during March and April.

The study area is mostly an agro-ecological mosaic, whereas the main crops are maize (*Zea mays*) and sorghum (*Sorghum bicolor*), and additional income is generated from beekeeping. Deforestation of the few patches of near-natural vegetation leads to the reduction of the diversity of melliferous plants and consequently reduction in honey production (Delaplane, 2010). The main flowering species are *Acacia* spp. which bloom from February to April with a pronounced flowering peak in February, while the two main crops (maize and sorghum) have their main flowering period in January (Nagarajan, Audi, Jones, & Smale, 2007).

2.2. Hyperspectral data acquisition and pre-processing

AISA/Eagle imaging spectrometer (Specim Limited., Finland) was used to cover the study area with hyperspectral data from an airborne platform using a maximum flight altitude of 860 m above ground level. AISA/Eagle is a pushbroom scanner with instantaneous field of view of 0.037°, field of view of 36.04° and 969 pixels across the spatial axis. The sensor was used in 8 times spectral binning mode, which produces output images in 64 bands with a full width at half maximum (FWHM) of 8–10.5 nm in the spectral range of 400–1000 nm. Spatial resolution was 0.6 m after geo-referencing. The flight campaign in year 2013 carried out on the 14th of February during the maximum flowering period and in year 2014 on the 11th of January at the beginning of the main floral period. Fig. 2 shows the various input data sets used in this study as dashed rectangles, processing routines as rounded rectangles and derived data sets as solid line rectangles.

Radiometric calibration and geolocating was performed using the CaliGeoPro tool (Pre-processing in Fig. 2) (Specim Limited., Finland).