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Classification of crops across heterogeneous agricultural landscape in Kenya using AisaEAGLE imaging spectroscopy data

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ABSTRACT

Land use practices are changing at a fast pace in the tropics. In sub-Saharan Africa forests, woodlands and bushlands are being transformed for agricultural use to produce food for the rapidly growing population. The objective of this study was to assess the prospects of mapping the common agricultural crops in highly heterogeneous study area in south-eastern Kenya using high spatial and spectral resolution AisaEAGLE imaging spectroscopy data. Minimum noise fraction transformation was used to pack the coherent information in smaller set of bands and the data was classified with support vector machine (SVM) algorithm. A total of 35 plant species were mapped in the field and seven most dominant ones were used as classification targets. Five of the targets were agricultural crops. The overall accuracy (OA) for the classification was 90.8%. To assess the possibility of excluding the remaining 28 plant species from the classification results, 10 different probability thresholds (PT) were tried with SVM. The impact of PT was assessed with validation polygons of all 35 mapped plant species. The results showed that while PT was increased more pixels were excluded from non-target polygons than from the polygons of the seven classification targets. This increased the OA and reduced salt-and-pepper effects in the classification results. Very high spatial resolution imagery and pixel-based classification approach worked well with small targets such as maize while there was mixing of classes on the sides of the tree crowns.

1. Introduction

The land use in the tropics is changing rapidly as the increasing populations are consuming more natural resources to support the human needs (Foley et al., 2005). This has led to an estimated 57% increase in the area of agricultural land in sub-Saharan Africa over the period of 1975–2000 (Brink and Eva, 2009). This increase is happening at the expense of forests and natural non-forest vegetation. In Kenya the population grew from 6 million in 1950 to 41 million in 2010 (United Nations, 2012), which has led to increase in the area of crop land (Imbernon, 1999; Baldyga et al., 2007). This change has been observed in the Taita Hills in south-eastern Kenya, which are a verdant mountainous region in the middle of dry savannah plains. The area has historically been covered with cloud forests, but have since been converted in large extent to agricultural use (Clark and Pellikka, 2009; Pellikka et al., 2009). During the last decades agricultural land has increased especially in the lowlands and foothills at the expense of shrub- and bushlands (Clark and Pellikka, 2009). Simulations made by Maeda et al. (2010) indicate that if the current trend set up from 1987 to 2003 continues, then in 2030 agricultural land would expand from 30% to 60% from 1987 to 2030. Until now, land cover and land use mapping in the area has been done on coarse thematic level where all agricultural targets are classified to the same class (Clark and Pellikka, 2009). However, the classification of the common agricultural crops on species level is needed for better understanding of the land use practices and the agricultural production.

The species level classification is possible by using high spatial resolution imaging spectroscopy (IS) data that has been used widely to map, for example tropical tree species (Feret and Asner, 2011), urban tree species (Alonzo et al., 2014), biodiversity (Baldec and Asner, 2013) and mangrove forests (Yang et al., 2009). In agricultural studies, IS has been used for assessment of the crop quality (Lelong et al., 1998; Mariotto et al., 2013), detecting diseases (Calderón et al., 2013) and the classification of crops (Mariotto et al., 2013). IS enables identification of plant species directly from their spectral response. Tropical tree species have been shown to have distinct chemical fingerprints (Asner and Martin, 2009). Kiang et al. (2007) showed that the spectral differences between higher taxonomic levels are greater than differences on lower taxonomic levels.

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High spectral resolution of IS data is an advantage when specific biochemical information is derived from the targets or the data is used for image classification on species level (Ustin, 2013; Asner and Martin, 2009). However, the highest number of input bands does not necessarily give the highest classification accuracy (Hughes, 1968; Belluco et al., 2006). This problem can be approached statistically by dimensionality reduction, where algorithms such as minimum noise fraction (MNF) are applied on the data and the noisy bands are excluded before the classification (Green et al., 1988). MNF has been proven to be efficient method for feature reduction and for improving the classification accuracy (Belluco et al., 2006; Ghosh et al., 2014; Zhang and Xie, 2012). MNF has been shown to perform better than principal component analysis (PCA) when combined with nonparametric classifiers such as spectral angle mapper (Mundt et al., 2005). Another approach would be to use vegetation indices that are calculated from the IS data and are related to the chemical and biophysical properties of the plants (Asner and Martin 2009; Galvão et al., 2012).

Mountrakis et al. (2011) concluded in their review article that support vector machine (SVM) algorithm outperformed other classification algorithms in many instances. SVM is a non-parametric machine learning algorithm based on statistical learning theory (Vapnik, 1998). In its simplest form SVM algorithm locates a linear hyperplane in the feature space that separates the data into classes. The optimal separating hyperplane maximizes the distance between the closest training samples of each class (support vectors) and the separating hyperplane (Melgani and Bruzzone, 2004). As the hyperspectral feature data is rarely linearly separable in the input space a soft margin method and kernel trick were introduced to solve the inseparability problem (Mountrakis et al., 2011). Applying MNF transformation before SVM classification has been shown to improve the classification results (Ghosh et al., 2014).

According to land cover classification system (LCCS) developed by FAO (Gregorio and Jansen, 2005) a good classification system should be adapted to fully describe the whole variety of land cover types in the study area. However, in heterogeneous landscape with the great abundance of plant species, it is not always possible to fulfill this requirement when the classification is done at species level. SVM algorithm produces pixel-wise probabilities that indicate the probability of a pixel to belong to one of the classes. A probability threshold (PT) set by the user determines the level of confidence that any pixel needs to exceed to be classified. To our knowledge, it has not yet been studied whether increasing PT could be used to rule out pixels that do not belong to any of the target classes in highly heterogeneous environment where only a fraction of all the plant species is classified.

Collecting pixel-based ground reference data for very high spatial resolution remote sensing data is challenging. Matching a single pixel in the data to the same exact location on ground is not always possible. Thus it is practical to collect ground reference data as polygons that represent a single field or a tree. Then, the ground reference pixels for training data can be collected within these polygons. However, the polygons that correspond to the data collected in the field can be used to validate classifications, and the percentages of unclassified pixels within these polygons can be calculated and used to assess the impact of PT on the classification results.

In this study, our objective was to assess the prospects to map common crop species in highly heterogeneous agricultural landscape in the Taita Hills, Kenya using IS data. The pixel-based classification approach was selected to fully utilize the very high spatial resolution (0.6 m × 0.6 m) of the data. More specific objectives were: (1) to test how accurately crop species in this area can be classified using IS data with MNF transformation and SVM; (2) to test if selecting appropriate PT for SVM enables the mapping of only a few selected species in a species-rich study area; and (3) to assess the classifications using both pixel- and polygon-wise validation data.

2. Material and methods

2.1. Study area

The study area (1 km × 3.5 km) is located in the elevation range of 830–860 m in the foothills of the Taita Hills (3°29′S, 38°22′E) (Fig. 1). By elevation the study area belongs to livestock-millet agroecological zone (Jaetzold and Schmidt, 1983). The river flowing down from the hills through the study area in north–south direction makes this location suitable for diverse agricultural practices. The annual rainfall in the study area is estimated to be 500 mm. There are two rainy seasons with long rains occurring in the March–June and short rains in October–December. This area was selected as a test site as it consists primarily of agricultural land and acacia forests. Further away from the river, the land is drier with more bushland and shrubs.

2.2. Imaging spectroscopy data

The IS data was captured with airborne AisaEAGLE (Specim Ltd., Finland) imaging spectrometer in 21 January 2012. January was selected as time window since the possibilities for cloudless weather, needed for IS data acquisition, are better during the dry season. In addition, the phenological setting of most of the agricultural crops in January are favorable for species separation. In January the rainy season is just finished, but the crops are not yet harvested (Jaetzold and Schmidt, 1983). The sensor was installed on Cessna 208B Caravan I aircraft. Three flight lines were imaged to cover the study area under cloudless weather conditions. AisaEAGLE is a pushbroom scanner with instantaneous field of view of 0.648 mrad and field of view of 36.04°. The sensor was used in eight times spectral binning mode that produces output images with 64 bands and full width at half maximum of 8–10.5 nm in spectral range of 400–1000 nm. The output pixel size was 0.6 m. Nikon D3X digital camera was used simultaneously to capture very high spatial resolution (7 cm) aerial images.

2.3. Ground reference data

Five study plots were selected along the study area (Fig. 1b). Accessibility and knowledge of the agricultural practices were considered when the plots were selected. Field maps were drawn by hand on paper prints of Nikon D3X aerial images. For larger fields only the most common plant species were recorded. This produced, for example, maize field polygons that contained also small trees and cassava. The mapping was done mainly by local guides who had the best knowledge of the plant species found in the area. A total of 35 plant species were mapped. Agricultural crops included maize (*Zea mays*), mango (*Mangifera indica*), sugarcane (*Saccharum officinarum*), banana (*Musa acuminate*), yam (*Dioscorea* spp.), cassava (*Manihot esculenta*), coconut (*Cocos nucifera*), guava (*Psidium guajava*) and papaya (*Carica papaya*). Additionally acacia (*Acacia* spp.) and grevillea (*Grevillea robusta*) trees and some other rarer species were mapped.

The field maps were digitized and registered to an image mosaic created from the Nikon D3X images. There were geometric mismatches between the Nikon D3X images and the AisaEAGLE data. Thus the polygons were edited using AisaEAGLE mosaic to match the targets more accurately in the classification. Each tree was drawn as an individual polygon and the largest fields were split into smaller segments that included mainly a single crop. Polygons where target species were not visually detected were omitted. A subset of the polygons was created that contained only the most