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Effect of pan-sharpening multi-temporal Landsat 8 imagery for crop type differentiation using different classification techniques

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ABSTRACT

This study evaluates the potential of pan-sharpening multi-temporal Landsat 8 imagery for the differentiation of crops in a Mediterranean climate. Five Landsat 8 images covering the phenological stages of seven major crops types in the study area (Cape Winelands, South Africa) were acquired. A statistical pan-sharpening algorithm was used to increase the spatial resolution of the 30 m multispectral bands to 15 m. The pan-sharpened images and original multispectral bands were used to generate two sets of input features at 30 and 15 m resolutions respectively. The two sets of spatial variables were separately used as input to decision trees (DTs), *k*-nearest neighbour (k-NN), support vector machine (SVM), and random forests (RF) machine learning classifiers. The analyses were carried out in both the object-based image analysis (OBIA) and pixel-based image analysis (PBIA) paradigms. For the OBIA experiments, three image segmentation scenarios were tested (good, over and under segmentation). The PBIA experiments were carried out at 30 m and 15 m resolutions. The results show that pan-sharpening led to dramatic (∼15%) improvements in classification accuracies in both the PBIA and OBIA approaches. Compared to the other classifiers, SVM consistently produced superior results. When applied to the pan-sharpened imagery SVM produced an overall accuracy of nearly 96% using OBIA, while PBIA's overall accuracy was 1.63% lower. We conclude that pan-sharpening Landsat 8 imagery is highly beneficial for classifying agricultural fields whether an object- or pixel-based approach is used.

1. Introduction

Agricultural productivity is the foundation of developing economies and critical for food security (Awokuse and Xie, 2014). Accurate and timely crop maps are needed to update agricultural databases used in planning and for carrying out yield forecasting (Monfreda et al., 2008). Traditional approaches to crop mapping and yield forecasting involve routine field visits which are costly and often biased (Castillejo-Gonzalez and Lopez-Granados, 2009). Remote sensing offers an unbiased, cost effective, and reliable procedure of mapping crops at a local, regional, and national scale (Xin et al., 2015). The use of remotely sensed optical imagery for the identification and monitoring of crop types has gained popularity in recent years, mainly due to an increase in its availability (Vieira et al., 2012; Simms et al., 2014; Muller et al., 2015; Ozelkan et al., 2015; Wardlow et al., 2007; Zheng et al., 2015). Several authors have shown that, for land cover and crop type mapping, object-based image analysis (OBIA) often outperforms the traditional pixel-based image analysis (PBIA) approach, especially when high resolution imagery is used as input. For instance, Castillejo-Gonzalez and Lopez-Granados (2009) compared PBIA vs OBIA for the identification of crops using 2.6 m resolution Quickbird imagery and concluded that OBIA clearly outperformed PBIA. Also using Quickbird imagery, Myint et al. (2011) assessed OBIA and PBIA for urban land cover mapping and found that the former outperformed the latter by up to 27.6%. Similar conclusions were made by Bhaskaran et al. (2010) and Yan et al. (2015) who saw OBIA outperform PBIA by overall accuracies of 20% and 36% respectively. Weih and Riggan (2010) used 1 m resolution aerial photography and 10 m SPOT 5 imagery for supervised land use and land cover classification and showed that merging high and medium spatial resolution imagery significantly improved classifications. In their experiments OBIA outperformed both supervised and unsupervised PBIA by 10%. From the literature it is clear that OBIA is generally preferred when the objects of interest are significantly larger than the pixels of the imagery (Blaschke, 2010) and that the advantages of OBIA are reduced when lower resolution imagery is used. For instance, Duro et al. (2015) found that OBIA

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and PBIA did not produce significantly different results when using 10 m resolution SPOT 5 data for classifying agricultural landscapes.

Generally, high spatial resolution imagery is preferred for crop type mapping owing to the reduction of mixed pixels (Grzegozewski et al., 2016). However, low to medium resolution multi-temporal data have also been shown to be effective for crop identification as it can better represent crop phenology, with optical (as opposed to microwave radio detection and ranging) multi-temporal data being the preferred data source (McNairn et al., 2009). For instance, Grzegozewski et al. (2016) used very high temporal resolution, low spatial resolution MODIS EVI (250 m) imagery to map corn and soya bean. Their results showed that this approach works well provided that the pixels used for training the models were pure (i.e. representing homogenous fields of crops). Simms et al. (2014) also made use of multi-temporal MODIS normalized difference vegetation index (NDVI) 250 m images to monitor opium and cereal crops. The NDVI profiles generated from the images provided valuable insight into the temporal variations between crop types. Using higher resolution (30 m) multitemporal Landsat TM and ETM+ images, Vieira et al. (2012) demonstrated that accurate crop maps can be generated using expert knowledge of the phenological stages of crops. Similar observations were made by Zheng et al. (2015) and Muller et al. (2015) who also used multitemporal Landsat data for crop type differentiation.

From the above overview of using single-date high resolution imagery (e.g. Quickbird) and multitemporal medium resolution (e.g. MODIS and Landsat) imagery for mapping crop types, it would seem that high resolution, multitemporal imagery would be ideal for crop type mapping. However, acquiring and processing such data over large areas is often prohibitively expensive. Pan-sharpening, the process of fusing lower resolution multispectral data with higher resolution panchromatic imagery, may offer a solution to increase the spatial detail of medium resolution multi-temporal imagery such as Landsat. The technique, also known as pan-fusion, has been shown to be effective not only for visual enhancements of imagery (Ghodekar et al., 2016) but also for quantitative analyses such as land cover mapping (Ai et al., 2016). Pan-sharpening essentially combines the superior spatial resolution of a panchromatic band (required for accurate description of texture and shapes), with the spectral information of the lower resolution multispectral bands (required for accurate discrimination of informational classes) (Ghassemian, 2016). Although many different pan-sharpening methods exist, not all are suitable for quantitative analyses. It is inevitable that some of the spectral fidelity of the original multispectral information is lost during the fusion process, but some algorithms are designed to maximize spectral preservation. Zhang and Mishra (2012) reviewed a range of commercially available pansharpening techniques and concluded that the PANSHARP algorithm, available in the software package PCI Geomatica, retained most of the spectral information of the original imagery and consistently produced superior results for all the types of sensors, images and spectral bands considered (Zhang, 2002a, 2002b). MS-split, a new pan-sharpening technique introduced by Guo-dong et al. (2015) also shows promise, but the technique is not yet available in commercial software. Johnson (2014) analysed the effects of pan-sharpening on two Landsat 8 vegetation indices (NDVI and simple ratio) using fast intensity-hue-saturation, Bovey transform, additive wavelet transform, and smoothing filter-based intensity modulation. The results showed that these pan-sharpening algorithms were able to downscale both single-date and multi-temporal Landsat-8 imagery without introducing significant distortions of index values.

Non-parametric machine learning algorithms has recently gained much popularity in remote sensing as they have the ability to use known data (training samples) to classify large sets of imagery, while incorporating ancillary spatial data. Their capacity to handle input variables that are not normally distributed is one of their main strengths (Jwan et al., 2013), but they are also very effective for classifying different types of input data (e.g. nominal, ordinal, ratio, and interval) and have been shown to be relatively robust under conditions of high dimensionality (Zheng et al., 2015). Popular algorithms include decision trees (DTs), k-nearest neighbour (k-NN), random forests (RF), and support vector machine (SVM). Decision trees perform well for land cover classification as demonstrated by Waheed et al. (2006) and Yang et al. (2003), while random forests have been used successfully for crop identification, vegetation classification and change analysis (Pal and Mather, 2003; Gislason et al., 2006). Alganci et al. (2013) and Zheng et al. (2015) showed that SVM is effective for agricultural classification and Myburgh and Van Niekerk, 2014 found that SVM is a cost-effective solution for mapping land cover over large areas. K-NN has been used in many studies, partly because it was for long the only classifier available in the popular OBIA software eCognition. Examples include Myint et al. (2011), Mountrakis et al. (2011), and Myburgh and Van Niekerk, 2014.

This study investigates the value of pansharpened, multitemporal Landsat 8 imagery and machine learning for crop differentiation. The aim is to determine whether pan-sharpening Landsat 8 imagery (from 30 m to 15 m resolution) has any effect on crop classification accuracies. The multitemporal imagery was used to generate an extensive set of spatial features (including vegetation indices and texture measures), which were then used as input to DTs, k-NN, RF, and SVM. The four classifiers were trained and assessed using in situ data collected during field surveys. A series of experiments were carried out in both the PBIA and OBIA paradigms to assess whether the increase in spatial resolution that pan-sharpening provides outweighs the loss of spectral fidelity; and whether OBIA is more effective in classifying the fused imagery into crop types. The results are interpreted in the context of finding an operational solution for monitoring crop types over extensive areas.

2. Material and methods

2.1. Study area

The study was carried out in the Cape Winelands region of South Africa (Fig. 1). The 1040 km^2 study site, which extends from 33°34′39″ to 33°52′17″S and 18°32′24″ to 18°54′43″E, was chosen owing to the availability of multitemporal cloud free Landsat 8 imagery and the variety of winter and summer crops that are produced in the region. The study site has a Mediterranean climate with cool wet winters and warm dry summers, an average annual rainfall of 550 mm, and the mean annual temperature minima and maxima are 11 °C and 22 °C respectively (Tererai et al., 2015).

The area produces a wide range of crops, the most common of which are canola, grapes (mainly for wine production), lucerne (alfalfa), lupine, olives, managed pasture, and wheat. The phenological and agricultural production stages phases of these crops are shown in Fig. 2. The annuals canola, lupine, pasture grasses and wheat are grown during Southern hemisphere winter (April to August), while grapes are harvested during summer months (December to February). Lucerne is cut throughout the year, while olives are harvested during the early winter months.

2.2. Satellite imagery acquisition and pre-processing

Five Landsat 8 level 1T images captured on 7 February, 11 May, 12 June, 31 August, and 5 December 2015 were acquired from the USGS (United States Geological Survey). The image dates were cho-