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Automatic classification of Google Earth images for a larger scale monitoring of bush encroachment in South Africa

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ABSTRACT

Bush encroachment of savannas and grasslands is a common form of land degradation in the rangelands of South Africa. To assess the carrying capacity of the land and to understand underlaying processes of bush encroachment, continuous monitoring of this phenomenon is needed. The aim of this study is to provide training sites for satellite-based monitoring of bush encroachment in South Africa on a medium spatial resolution satellite sensor (e.g. MODIS or Landsat) scale. Since field surveys are time consuming and of limited spatial extent, the satellite based creation of training sites using Google Earth images is intended. Training pixels for woody vegetation and non-woody land cover were manually digitized from 50 sample Google Earth images. A Random Forests model was trained to delineate woody from non-woody pixels. The results indicate a high performance of the model (AUC = 0.97). The model was applied to a further 500 Google Earth images with a spatial extent of 250 m × 250 m. The classified images form the database of training sites which can be used for larger scale monitoring of bush encroachment in South Africa.

1. Introduction

Bush encroachment of arid and semi-arid savannas and grasslands is seen as a common form of land degradation in the rangelands of South Africa. Bush encroachment is defined as the suppression of palatable grasses and herbs by woody vegetation which are palatable to browsers but not eaten by the majority of domestic livestock (Ward, 2005). The negative economic consequences are enormous since grass dependent livestock represents the main income for many local farmers who are now faced with a reduced carrying capacity of their land (Ward, 2005). Therefore, a monitoring of bush encroachment is needed for several reasons: it allows farmers to identify locations with upcoming bushes giving them a tool for management and allows them to assess the current carrying capacity of their land. It also serves scientists as a baseline to reveal the yet unknown causes of bush encroachment.

Since spatially extensive field surveys are very cost extensive, remote sensing represents the only way to meet the demand of a high resolution, quasi-continuous and area wide monitoring. There are a number of case studies aiming at monitor bush encroachment in South Africa using remote sensing data (Hudak and Wessman, 1998, 2001; Munyati et al., 2011; Symeonakis and Higginbottom, 2014). What these case studies have in common is that the spatial expansion of the product was limited by the availability of the ground truths. A variety of field surveys which provide ground truths were conducted in the South African rangelands on a local scale (Dreber et al., 2014; Skarpe, 1991; Wiegand et al., 2005; Britz and Ward, 2007; Roques et al., 2001; Buitenwerf et al., 2012). Though field surveys undoubtedly represent the most accurate way to identify training sites, they rarely match the spatial extent of medium resolution satellite systems (e.g. MODIS or Landsat) which are more suitable for operational monitorings. Therefore, satellite-based training sites with a spatial extent large enough to match at least one pixel of medium resolution satellite systems are needed to serve as ground truth in larger scale monitoring of bush encroachment.

There are a number of high resolution satellite products available which allow an accurate classification into woody vegetation and non-woody land cover to provide ground truths for larger scale monitoring. Gessner et al. (2013) classified Quickbird images from Namibia into woody and non-woody vegetation and used these classifications as ground truth for Landsat based estimations for the percentage of woody vegetation. WorldView images also provide a high resolution which enable delineation of woody from non-woody land cover. Though these images have not yet been explicitly applied in upscaling chains aiming at the estimation of woody vegetation, they have been successfully used as training sites for analysing grass cover based on WorldView-2 data on a

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Landsat and MODIS scale Lehnert et al. (2015). The drawback of high resolution images like WorldView and Quickbird are their relatively high costs, often a limiting factor for the accessibility of images for research projects. In contrast, Google Earth images are free of charge and offer a high spatial resolution which makes them perfectly suited for generating training sites. Though Google Earth images are often used as ancillary data source to digitize training sites, they are rarely used as a direct data source for land cover classifications (Aher et al., 2014; Almeer, 2012; Hu et al., 2013). This might be due to two central challenges: Firstly, Google Earth images are only available in RGB bands and feature no infrared channel which is commonly used for classifying vegetation. Secondly, they are only available at fixed dates which differ between locations. While the first drawback might be overcome by use of a visible vegetation index (VVI), the second issue is more challenging. However, as machine learning algorithms (e.g. Random Forests) are more extensively used an increasing number of monitoring strategies can build more general models between reflectance and percentage of a land class (e.g. Gessner et al. (2013)) rather than estimating woody vegetation from single scenes only. Following such approaches where training sites are taken from multiple scenes, the acquisition date of the Google image is less important so long as a Landsat/MODIS image is available for the date of the Google image.

This study aims to provide training sites for an upcoming satellite-based monitoring of bush encroachment on a medium spatial resolution scale (e.g. MODIS or Landsat) in South African savannas and grasslands. To pursue this target we use Google Earth images and Random Forests to automatically delineate woody vegetation from non-woody land cover. The classified images will form the database of training sites for the upcoming larger-scale monitoring.

2. Methods

The work flow of this study (Fig. 1) first requires example 50 Google Earth RGB images as baseline. From these images (i) training pixels for woody and non-woody areas were manually digitized and (ii) derivated predictor variables were calculated from the Google Earth RGB images. A Random Forests model was then trained to delineate woody from non-woody pixels using a subset of the training pixels. The model was validated using the hold out samples. In a further step, the model was applied to 500 randomly chosen Google Earth images. The reliability of each classification was assessed using the predicted probabilities for woody vegetation. Using the reliable classifications only, the predicted percentage of woody vegetation will serve as input for the upcoming larger scale monitoring of bush encroachment. The following sections describe these steps in detail.

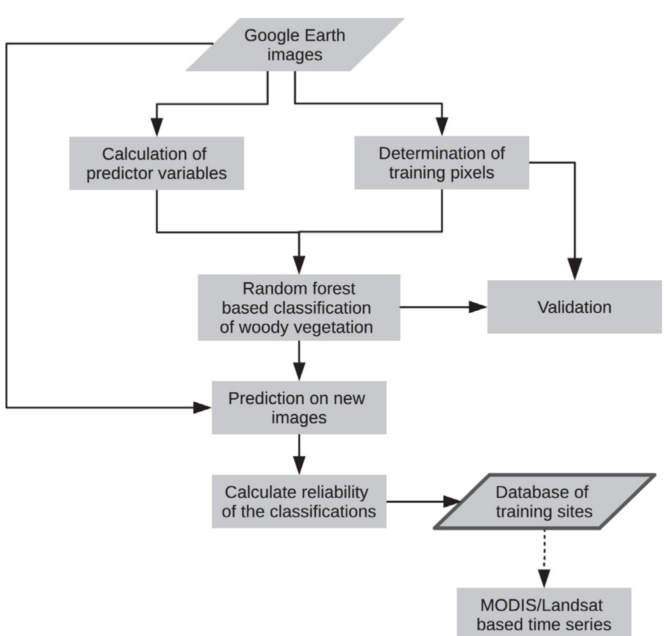

Fig. 1. Overview of the processing flow.

All steps of modeling and analysis were performed using the R environment for statistical computing (R Core Team, 2014). The caret package (Kuhn, 2014) as a wrapper package for machine learning algorithms implemented in R was applied for model tuning, training and prediction.

2.1. Study area

The areas of interest in this study are the savanna and grassland biomes of South Africa, Lesotho and Swaziland (Fig. 2). Both biomes, savannas and grasslands, are characterized by a mixture of grasses and sparse trees or bushes and affected by the problem of bush encroachment. See Mucina et al. (2006) for further description on the vegetation of South Africa.

The determination of the study area was done on the basis of the biome classification of Mucina et al. (2006). Only areas classified as savanna or grassland were taken into account. In a second step, all anthropogenic areas as defined by the MODIS land cover product were masked so that only savanna and grassland areas were considered for further analysis.

2.2. Data and variables

50 Google Earth images were downloaded at randomly chosen locations within the study area. Each image had a spatial extent of 250 m $\times$ 250 m which corresponds, or exceeds the size of a pixel from medium spatial resolution satellite sensors (e.g. MODIS or Landsat). The images were downloaded as georeferenced RGB images using the gmap function from the dismo package in R (Hijmans et al., 2015). The highest available spatial resolution for each respective image was used, corresponding to a pixel size of approximately 30 by 30 cm. For all images, the RGB values as well as the HSV values and a visible vegetation index (VVI, described in e.g. Joseph and Devadas (2015)) were used as predictor variables. The vegetation index takes advantage of the spectral properties of vegetation in the visible spectrum of light to distinguish between vegetated and non-vegetated surfaces. Additionally, texture measures were included by calculating the mean and standard deviation (sd) values in a 3×3 environment of all 7 spectral variables. The two-level variable “Biome” was further included to account for differing land cover characteristics between grasslands and savannas. In total, 22 predictor variables were used.

Training sites for woody vegetation and non-woody land cover were manually digitized from the 50 Google Earth images (in total 220,507 pixels for woody vegetation and 283,289 pixels for non-woody land cover). The values of the predictor variables at each of the training pixels were extracted from the raster data.

2.3. Random Forests classification

Random Forests was used to create a model which delineates woody vegetation from non-woody land cover. The Random Forests (RF) algorithm of Breiman (2001) is based on the concept of regression and classification trees. Random Forests repeatedly builds trees from random samples of the training data. In classification models, the class which is most often predicted from the individual trees is taken as the final estimate. To overcome the correlation between trees, a subset of predictors (mtry) is randomly selected