Int J Appl Earth Obs Geoinformation 73 (2018) 493–502

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

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

Comparison of manual and automated shadow detection on satellite imagery for agricultural land delineation

Agnieszka Tarko*, Sytze de Bruin, Arnold K. Bregt

Laboratory of Geo-Information Science and Remote Sensing, Wageningen University and Research, Droevendaalsesteeg 3, 6708 PB Wageningen, The Netherlands

ARTICLE INFO

Keywords:
Photointerpretation
Risk-based classification
Data-driven approach
Land Parcel Identification System

ABSTRACT

Land cover identification and area quantification are key aspects in determining support payments to farmers under the European Common Agricultural Policy. Agricultural land is monitored using the Land Parcel Identification System and visual image interpretation. However, shadows covering reference parcel boundaries can hinder effective delineation. Visual interpretation of shadows is labor intensive and subjective, while automated methods give reproducible results. In this paper we compare shadow detection on satellite imagery obtained by expert photointerpretation to a proposed automated, data-driven method. The latter automated method is a thresholding approach employing both panchromatic and multispectral imagery, where the former has a finer spatial resolution than the latter. Thresholds are determined from automatically generated training data using a risk-based approach. Comparison of the total shadow area per scene showed that more pixels were labelled as shadow by the automatic procedure than by visual interpretation. However, the union of shadow area independently identified by twelve experts on a subscene was larger than the automatically determined shadow area. The limited intersection of the shadow areas identified by the experts demonstrated that experts strongly disagreed in their interpretations. The shadow area labelled by the automated method was in between the intersection and the union of the areas interpreted by experts. Furthermore, the automated shadow detection method is reproducible and reduces the interpretation effort and skill required.

1. Introduction

Shadows are present on the majority of remotely sensed images, and their presence can affect information abstraction. In photointerpretation, shadows can be indicative of land morphology or a feature's height and shape (Lillesand et al., 2015). Yet, shadows can complicate delineation of agricultural lands, hindering monitoring programs. A shadow covering a boundary of a reference parcel can affect delineation, impeding the updating of field geometries (European Commission, 2014a; LPIS TG ETS, 2017a). Since some agricultural subsidies are area-based, delineation of parcels may impact farm subsidies (Astrand et al., 2004), worth some €50,000 million in 2017 (European Commission, 2014b). Identification of shadows on images is therefore of key interest.

An example of a voluntary monitoring approach is the Land Parcel Identification System (LPIS) implemented by the European Union (EU) member states (European Commission, 2013). So-called reference parcels are delineated on the basis of very high resolution (VHR) images in the scope of the Control with Remote Sensing program (LPIS TG ETS, 2017b). Along with other sources such as farmers' declarations, VHR satellite images are used not only for LPIS updating but also for quality assurance of the system through the annual Executable Test Suite (ETS) (European Commission, 2014a; LPIS TG ETS, 2017a). Such testing is performed by EU member states using a limited number of VHR satellite images; this involves re-delineation of a sample of reference parcels. Shadows may influence the reference parcel boundary re-delineation, impacting ETS inspection. If too many parcel boundaries are masked by shadows, both sample randomness and sample size may be jeopardized, influencing the ETS results. Detection of cast shadows in a satellite scene can help to determine if available imagery is usable for the reference parcel monitoring process. Beyond the LPIS in the EU (IACS, 2017), knowledge of cast shadows is useful for other agricultural monitoring programs as well, such as those implemented by the US Farm Service Agency (FSA, 2017) and the Chinese GIS-based land registry system (Rabley and Yuen, 2009).

Traditionally, manual photointerpretation of agricultural systems based on aerial or satellite images has sought to delineate field boundaries, including those partly hidden by shadows on an image. To pinpoint reference parcel boundaries, image enhancement is performed and auxiliary data is used, such as additional images, maps and field visits. Although manual mapping performed by experts is subjective

* Corresponding author.
E-mail addresses: agnieszka.tarko@wur.nl (A. Tarko), sytze.debruin@wur.nl (S. de Bruin), arnold.bregt@wur.nl (A.K. Bregt).

https://doi.org/10.1016/j.jag.2018.07.020
Received 6 April 2018; Received in revised form 25 July 2018; Accepted 26 July 2018
0303-2434/

and has a low reproducibility (Van Westen, 2000), it is nonetheless still widely applied.

The results of manual mapping of shadows has been compared with the results of automated methods. In many such exercises, a manually digitized shadow mask serves as a reference to assess or test proposed shadow detection methods (Adeline et al., 2013; Tsai, 2006). As reviewed by Adeline et al. (2013) and Shahtahmassebi et al. (2013), there are various automated methods for shadow detection on a digital image. Some deterministic methods require additional input data, such as a digital surface model for model-based geometrical shadow detection methods (Adeline et al., 2013; Li et al., 2005). Physically based methods require additional information on the atmosphere and acquisition details (Adeline et al., 2013). Other methods, like machine learning, require users to input data such as training areas (Adeline et al., 2013). Invariant color model methods rely on RGB channels (for the colors red, green and blue) (Adeline et al., 2013; Tsai, 2006).

Histogram thresholding is among the most popular methods for automated shadow detection due to its simplicity, independence from auxiliary data and good overall performance. However, setting a proper threshold is an issue with these methods. Yamazaki et al. (2009) proposed threshold determination by visual interpretation. Dare (2005) identified the threshold as the mean value between two peaks of a panchromatic (PAN) band histogram, while Otsu (1979) proposed an automatic threshold estimator for grey-level images. The best thresholding results were obtained using first valley detection on Nagao's modified intensity (Adeline et al., 2013; Nagao et al., 1979). However, the valley detection algorithm fails if intensity histograms lack a bimodal distribution (Nagao et al., 1979).

Most automated methods have focused on urban zones and city centers with high buildings and urban valleys (Adeline et al., 2013; Dare, 2005; Li et al., 2005; Sarabandi et al., 2004; Tsai, 2006; Yamazaki et al., 2009). An exception is the use of aerial imagery of an alpine terrain in Central Taiwan in which shadows were identified by first valley detection thresholding using Nagao's modified intensity (Wu et al., 2014). Another exception concerns aerial imagery covering a rural area in Italy on which RGB band spectral ratioing and Otsu's threshold finding method were used (Movia et al., 2015).

While there are several automated methods for shadow detection on remotely sensed imagery, they either require user interaction for threshold detection, or depend on detailed ancillary data, such as a digital surface model. Such data may not be available for many rural areas. Therefore, this study proposes a relatively simple thresholding method for shadow detection with limited ancillary data requirements. The method is compared to manual visual interpretation of shadows in the context of agricultural land delineation.

The aim of the comparison is to assess whether the results of the proposed automated procedure for shadow detection are similar to those of visual interpretation and whether the former are suitable for quick labelling of image scenes that, due to too much shadow, have limited usability for agriculture monitoring. The objective of this paper is twofold: (1) to propose a reproducible method for shadow detection on satellite images using a readily available auxiliary training area and (2) to compare the method with expert manual interpretation of shadows. While shadow detection can be used in a processing chain prior to image enhancement operations, the latter are beyond the scope of this paper.

2. Methods

This chapter first describes the manual method, then explains the automated procedure and our case-study. Finally the comparison method is briefly presented.

2.1. Manual method

Twelve experts independently interpreted and digitized shadows on an agricultural study area. No specific instructions for the photointerpretation were provided and the experts were free to choose their preferred software for image display (including image enhancement) and digitizing. Following Tarko et al. (2015), the experts were asked to set their own preferred image enhancement, which could be adapted while interpreting (e.g., color stretching). Shadows could be digitized as polygons in a vector layer or by labelling pixels in a raster. The used zooming level was left to the expert's discretion; for the used input data the typical mapping scale would be 1:100–1:1000 The experts were encouraged to use widely accessible open-layer images (such as Google Earth, Google Maps and Bing Maps) to assist in identification of potential shadows (these are referred to as auxiliary data). The provided data were PAN images with 0.5 m pixel size and a polygon indicating the area to be photointerpreted (see green frame in Fig. 2). Multispectral (MS) imagery were not included, because the 2 m pixel size of MS bands was deemed too coarse for visual identification of shadow boundaries. Any received vector layer was rasterized. Rasterizing error (Bregt et al., 1991) was found to be within 0.1% of the shadow area. The intersection and the union of the shadow layers produced by the individual experts were also computed. Apart from the shadow detection on the smaller subscene done by the twelve experts (including the first author), the first author also manually digitized shadows on all scenes tested in the automated method.

2.2. Automated method

Our method employed thresholds adjusted to an acceptable rate of erroneously labelled shadows, determined using a minimum set of training data. Section 2.3 describes a case study in which such data were acquired without user interaction. Two thresholds were applied: one for VHR PAN images and the other for high resolution (HR) MS images. For the former, based on a PAN version of the training data, the darkest objects in a scene were identified using the PAN spectrum. Regarding the latter, while MS training data have coarser resolution, they contain spectral information for a selected spectrum part holding information about land cover types (Belgiu et al., 2014). Moreover the near infrared (NIR) band spectrum is beyond the PAN spectrum. To enable use of a single threshold on the MS data, the dimensionality of the MS bands had to be reduced. A potentially suitable choice for this operation is principal component analysis (PCA). In our approach, the first principal component (PC1) was computed on the covariance matrix of the training data; it was enforced to be positively loaded on NIR. While this may suggest that a single threshold could be applied to the NIR band, PC1 was chosen because it is more discriminative for bare soil, which commonly occurs in imagery acquired early in the growing season and in areas affected by drought. Hence, a threshold was determined on the training area and applied to the area of interest.

The intersection of shadows labelled in two versions of the scene (PAN and MS) allowed the integration of the finer spatial resolution of PAN, resulting in sharper detail, while shadow confirmation from the PC1 allowed shadow detection on vegetated land beyond the PAN band wavelengths. Fig. 1 presents a flow diagram of the overall procedure.

2.2.1. Determine thresholds

The first step was preparation of the vector layer delineating approximated agricultural land that was deemed shadow free. Training data were obtained by overlaying the imagery and the vector layer. The thresholds were determined from the training data using an acceptable risk level. A relatively low risk level of 5% was applied. This choice was made taking into account the quality of the used images. Our imagery was acquired under favorable light and viewing angle conditions, and therefore the amount of shadow on the scenes was expected to be minimal. However, the input training data were not perfect. The 5% quantile was considered a suitable compromise.

To obtain a single threshold T_{PAN} for the VHR PAN images, a threshold corresponding to the selected quantile on the histogram of the