Remote Sensing of Environment 144 (2014) 42–64

Contents lists available at ScienceDirect

Remote Sensing of Environment

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

Automated crop field extraction from multi-temporal Web Enabled Landsat Data☆

L. Yan *, D.P. Roy

Geospatial Science Center of Excellence, South Dakota State University, Brookings, SD 57007, USA

ARTICLE INFO

Article history:
Received 21 June 2013
Received in revised form 4 December 2013
Accepted 9 January 2014
Available online 5 February 2014

Keywords:
Agriculture
Fields
Landsat
Object oriented
WELD

ABSTRACT

An automated computational methodology to extract agricultural crop fields from 30 m Web Enabled Landsat data (WELD) time series is presented. The results for three 150 × 150 km WELD tiles encompassing rectangular, circular (center-pivot irrigation) and irregularly shaped fields in Texas, California and South Dakota are presented and compared to independent United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) cropland data layer (CDL) classifications. Coherent fields that are visually apparent were extracted with relatively limited apparent errors of omission or commission compared to the CDL classifications. This is due to several factors. First, the use of multi-temporal Landsat data, as opposed to single Landsat acquisitions, that enables crop rotations and inter-annual variability in the state of the vegetation to be accommodated for and provides more opportunities for cloud-free, non-missing and atmospherically uncontaminated surface observations. Second, the adoption of an object-based approach, namely the variational region-based geometric active contour method that enables robust segmentation with only a small number of parameters and that requires no training data. Third, the use of a watershed algorithm to decompose connected segments belonging to multiple fields into coherent isolated field segments and a geometry-based algorithm to detect and associate parts of circular fields together. A preliminary validation is presented to gain quantitative insights into the field extraction accuracy and to prototype a validation protocol including new geometric measures that quantify the accuracy of individual field objects. Implications and recommendations for future research and large-area applications are discussed.

1. Introduction

The spatial distribution of agricultural fields is a fundamental description of rural landscapes and the location and extent of fields is needed to establish the area of land utilized for agricultural yield prediction, resource allocation, and economic planning (Carfagna & Gallego, 2005; Johnson, 2013; Rudel, Schneider, Uriarte, Turner, Defries, Lawrence, et al., 2009). Since the era of the first Large Area Crop Inventory Experiment (LACIE) the potential for remote sensing in support of agricultural information retrieval has been demonstrated widely (Allen, 1990; Badhwar, 1984; Bauer, Hixson, Davis, & Etheridge, 1978; Becker-Reshef, Justice, Sullivan, Vermote, Tucker, Anyamba, et al., 2010; Jakubauskas, Legates, & Kastens, 2002; Johnson, 2013; Johnson & Mueller, 2010; MacDonald & Hall, 1980; Ozdogan, 2010; Pitts & Badhwar, 1980; Tucker, Elgin, McMurtrey, & Fan, 1979; Wardlow & Egbert, 2008). With the advent of free Landsat data and improved computing capacity it is now possible to implement processing algorithms that are applicable to continental scale 30 m Landsat data (Roy, Ju, Kline, Scaramuzza, Kovalskyy, Hansen, et al., 2010). Identifying agricultural fields from satellite data can be straightforward if undertaken visually by a capable interpreter, for example, by screen digitizing or by interactive thresholding of spectral vegetation indices (Basnyat, McConkey, Meinert, Gatkze, & Noble, 2004; Ferguson, Badhwar, Chhikara, & Pitts, 1986; Lobell, Asner, Ortiz-Monasterio, & Benning, 2003). However, interactive techniques are impractical for large area application and are not amenable to automation. Semi-automated approaches, such as land cover classification, are challenged by factors including within-field spectral variability (caused by spatial variations in soil moisture, salinity, fertility and nutrient limitations, pesticide, herbicide and fertilizer treatment, pollution, pests and diseases) and the temporal variability and spectral similarity between crops and non-crops as a function of their phenological stage, degree of soil background, and the time of satellite observation (Chang, Hansen, Pittman, Carroll, & DiMiceli, 2007; Hall & Badhwar, 1987; Johnson, 2013;

* Corresponding author at: South Dakota State University Geospatial Science Center of Excellence Brookings, South Dakota 57007, USA. Tel.: +614-886-3172

E-mail addresses: lin.yan@sdstate.edu (L. Yan), david.roy@sdstate.edu (D.P. Roy).

0034-4257/$ – see front matter © 2014 The Authors. Published by Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.rse.2014.01.006

Rao, 2008). Moreover, they do not extract field objects and to do so requires contextual association of classified pixels to individual fields which is non-trivial. Object-based classification approaches do not operate directly on individual pixels but rather on objects consisting of many pixels that have been grouped together in a meaningful way by image segmentation; when undertaken with geospatial data this is often termed Geographic Object-Based Image Analysis (GEOBIA) (Hay & Castilla, 2008). Commercial software, such as the eCognition package (Definiens, 2009), provide object-based classifiers but they are supervised and require human intervention. A number of automated and semi-automated approaches have been developed to extract objects from satellite data, particularly for high spatial resolution data (Benediktsson, Pesaresi, & Arnason, 2003; Evans, Jones, Svalbe, & Berman, 2002; Huang & Zhang, 2008; Mayer, 2008; Myint, Gober, Brazel, Grossman-Clarke, & Weng, 2011; Shackelford & Davis, 2003), but no automated field extraction methodology applicable to regional or continental scale Landsat data has been developed.

An automated Landsat agricultural crop field extraction methodology is presented. The methodology is object-based, requires no training data, no human interaction, can be parameterized with only a small number of parameters, and is sufficiently computationally efficient and structured to be scalable to continental scale application. Most object-based classifiers purposefully over-segment the scene, typically by applying a multi-scale (hierarchical) iterative segmentation algorithm to generate a set of segmentation solutions (Mason, Corr, Cross, Hoggs, Petrou, Lawrence, et al., 1988; Pavlidis & Liow, 1990; Rydberg & Borgefors, 2001). Rules are then used to group segments to associate them to the same object and to label the objects using image understanding approaches (Shackelford & Davis, 2003; Ton, Sticklen, & Jain, 1991). In this paper the established computer vision based variational region-based geometric active contour segmentation method is used because it requires only a small number of parameters to iteratively generate a segmentation with control over the smoothness of the segment boundaries and segmentation noise (Chan & Vese, 2001). Spatially explicit maps of the probability of crop agriculture and crop field edge presence are derived from Web Enabled Landsat Data (WELD) 30 m time series (Roy et al., 2010) and used as input to the segmentation method. Satellite time series data are used to reduce the impacts of ambiguities due to the phenological stage and the spatial arrangement of field boundaries (irrigation ditches, tracks and roads, fences and hedges, weed and grass swards, trees and shrubs) that in single date satellite images may not be spectrally separable from field interiors (Duveiller & Defourny, 2010; Ozdogan & Woodcock, 2006; Rydberg & Borgefors, 2001). Further, and importantly, time series reduce the influence of missing, shadowed and atmospherically contaminated Landsat observations (Roy, Qin, Kovalskyy, Vermote, Ju, Egorov, et al., 2014; Roy et al., 2010; Zhu & Woodcock, 2012) and enables specific crop and non-crop phenologies to be considered as part of the algorithm implementation. A watershed algorithm is used to decompose connected segments belonging to multiple fields into coherent isolated fields segments. A geometry-based algorithm is used to detect and associate parts of circular fields that are particularly challenging to deal with due to their shape. Results are presented for 150 km × 150 km agricultural regions (each composed of 5000 × 5000 30 m pixels) in Texas, California and South Dakota that encompass rectangular, circular, and irregular fields and a variety of crop types. The results are compared with annual United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) cropland data layer classifications (Johnson & Mueller, 2010). A preliminary validation by detailed comparison with field boundaries manually digitized from Landsat 5 Thematic Mapper (TM) data are presented to gain quantitative insights into the field extraction accuracy and to prototype a validation protocol. Implications and recommendations for algorithm refinement and large-area application are discussed.

2. Data and study area

2.1. Landsat data

The methodology requires consistently processed, long-term, geolocated Landsat time series. In this study the weekly Web Enabled Landsat Data (WELD) products were used (Roy et al., 2010). The WELD products enable the development of turnkey approaches to land cover and land cover change characterization (Hansen, Egorov, Potapov, Stehman, Tyukavina, Turubanova, et al., 2014; Hansen, Egorov, Roy, Potapov, Ju, Turubanova, et al., 2011) due to the systematic Landsat processing, including conversion of digital numbers to calibrated top of atmosphere reflectance and brightness temperature, cloud masking, and reprojection into a gridded continental map projection (Roy et al., 2010). Weekly WELD Version 1.5 products were obtained from the USGS EROS (http://e4ftl01.cr.usgs.gov/WELD/). The products store for each 30 m pixel location the six reflective top of atmosphere Landsat 7 Enhanced Thematic Mapper Plus (ETM+) bands, the two top of atmosphere thermal bands, bit packed band saturation information, Normalized Difference Vegetation Index (NDVI), two cloud masks, the day of year that the pixel was sensed on, and the number of Landsat observations considered in the week (Roy et al., 2010). The weekly WELD products were generated from all Landsat 7 ETM+ Level 1T data with cloud cover ≤80%. The most recent Landsat calibration knowledge is used in the Level 1T processing to ensure a consistently calibrated Landsat time series with a 5% reflective band calibration uncertainty (Markham & Helder, 2012). The L1T ETM+ geolocation error in the CONUS is less than 30 m even in areas with substantial terrain relief (Lee, Storey, Choate, & Hayes, 2004).

The WELD products are defined in the Albers Equal Area conic projection in separate tiles of 5000 × 5000 30 m pixels referenced using a two digit horizontal and vertical tile coordinate system. Fig. 1 illustrates WELD tile spatial subsets of four weekly WELD products over an agricultural region of Texas. The Landsat 7 ETM+ has a 16 day repeat cycle and each ETM+ L1T scene may be sensed up to 22 or 23 times per year depending on the first January overpass date (Ju & Roy, 2008). The weekly WELD products contain the Landsat 7 ETM+ data sensed in consecutive seven day periods and so at CONUS latitudes they may contain no data, as no Landsat overpassed in that seven day period, or only one Landsat observation. The weekly products have along scan stripes of missing data due to the Landsat 7 ETM+ scan line corrector that failed in 2003 and reduces the usable data in each ETM+ scene by about 22% (Markham, Storey, Williams, & Irons, 2004).

2.2. Independent comparison data

The Cropland Data Layer (CDL) is generated by the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) using Landsat-like resolution satellite imagery and extensive agricultural ground truth via a supervised classification approach (Boryan, Yang, Mueller, & Craig, 2011; Johnson & Mueller, 2010). The CDL defines annually about 110 land cover and crop type classes at 30 m for all the conterminous United States and is used to provide acreage estimates and digital, crop-specific, georeferenced information (Johnson & Mueller, 2010). In this study, the annual CDL for 2008, 2009 and 2010 were obtained from http://nassgeodata.gmu.edu/CropScape/ and used for qualitative comparison with the field object segmentation results and to provide information on the study area crop types. For 2008, 2009, and 2010 the conterminous United States CDL crop classification accuracy was 76.9%, 80.0%, and 84.3%, respectively (Johnson, 2013). Prior to 2008 the CDL was not available for all the conterminous United States.