Remote Sensing of Environment 201 (2017) 165–180

Contents lists available at ScienceDirect

Remote Sensing of Environment

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

Detection of cropland field parcels from Landsat imagery[☆,☆☆,☆☆☆]

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A R T I C L E I N F O

Keywords:
Cropland
Field
Landsat
South America

A B S T R A C T

A slowdown in global agricultural expansion, spurred by land limitations, improved technologies, and demand for specific crops has led to increased agricultural intensification. While agricultural expansion has been heavily scrutinized, less attention has been paid to changes within cropland systems. Here we present a method to detect individual cropland field parcels from temporal Landsat imagery to improve cropland estimates and better depict the scale of farming across South America. The methods consist of multi-spectral image edge extraction and multi-scale contrast limited adaptive histogram equalization (CLAHE) and adaptive thresholding using Landsat Surface Reflectance Climate Data Record (CDR) products. We tested our methods across a South American region with approximately 82% of the 2000/2001 total cropland area, using a Landsat time series composite with a January 1, 2000 to August 1, 2001 timeframe. A thematic accuracy assessment revealed an overall cropland f-score of 91%, while an object-based assessment of 5480 fields showed low geometric errors. The results illustrate that Landsat time series can be used to accurately estimate cropland in South America, and the low geometric errors of the per-parcel estimates highlight the applicability of the proposed methods over a large area. Our approach offers a new technique of analyzing agricultural changes across a broad geographic scale. By using multi-temporal Landsat imagery with a semi-automatic field extraction approach, we can monitor within-agricultural changes at a high degree of accuracy, and advance our understanding of regional agricultural expansion and intensification dynamics across South America.

1. Introduction

In the latter half of the 20th century, growing food demand was met through intensification of agricultural production, while global agricultural expansion slowed down (Tilman et al., 2001). Farmers raised productivity through increased application of inputs such as fertilizers, herbicides, and pesticides, and by adopting modern plant varieties, mechanization, and new farming techniques (Deininger and Byerlee, 2012; Matson et al., 1997). While reduced land clearing for agriculture (Gibbs et al., 2010, 2015; Graesser et al., 2015) can contribute greatly to biodiversity preservation and habitat conservation (Foley et al., 2005), intensification can be environmentally harmful when inputs such as nitrogen and phosphorous are mismanaged (Barrett et al., 2001; Tilman et al., 2001, 2002). Thus, there is a critical need for agricultural monitoring to assess the environmental implications of agro-industrialization and intensification.

Timely and consistent monitoring of agricultural intensification is challenging because the availability of data that describe intensification over large areas is limited. For example, agricultural censuses provide information about farm size, machinery, and fertilizers, but these data lack the spatial and temporal resolution needed to consistently monitor detailed changes over large areas. Remote sensing, however, offers a unique solution to this problem. Remote sensing provides the capability to detect indicators of intensification, namely indicators of physical agricultural characteristics. For example, agricultural morphology, i.e., field shape or size, is observable with moderate- to high-resolution sensors, and would be an invaluable piece of information for multiple reasons. Field size is important in order to understand farm management practices such as crop diversity and rotation, and to assess tradeoffs between agricultural scale and efficiency, biodiversity monitoring, landscape fragmentation, and ecological diversity (Barrett

☆ Role of authors: JG contributed to ideas, work, writing, and stewardship, with an overall estimated contribution of 80%. NR contributed to ideas, work, writing, and stewardship, with an overall estimated contribution of 20%.
☆☆ Conflict of interest: The authors declare no conflict of interest.
☆☆☆ Role of the funding source: The funding source had no involvement in the research.

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http://dx.doi.org/10.1016/j.rse.2017.08.027
Received 27 April 2016; Received in revised form 1 July 2017; Accepted 16 August 2017

et al., 2001; Fahrig et al., 2015). Field size is also complementary to farm size. For example, if a farmer's capacity to expand land holdings is limited, farm size remains unchanged. But a farmer can still alter the landscape through changes in management such as field enlargement. Therefore, field size can provide important information about the planet's rapidly changing agricultural systems that would not otherwise be captured with farm size data from agricultural censuses and surveys. Fortunately, Landsat, one of the remote sensing community's long-standing pillars of global change monitoring, offers the geographic and temporal coverage as well as the spatial resolution necessary to detect cropland field parcels over large areas. The challenge is to exploit this vast resource and design practical and robust methods to accurately depict field parcels, which will complement growing information about agricultural expansion.

While the remote sensing community has remarkably improved the capacity to monitor extensive land cover changes, particularly into forests (Hansen et al., 2008; Hansen and Loveland, 2012; Potapov et al., 2012), less has been accomplished to remotely depict land use intensification such as field size changes. Part of the challenge is that traditional per-pixel based methods are not suitable for understanding landscape shape and context. Instead, image processing methods are essential to solving this problem. For example, contextual information, often referred to as image texture, can provide useful information about the structure and morphology of landscape context. This approach was used in combination with linear regression to estimate field sizes at a continuous scale in Eastern Europe (Kuemmerle et al., 2009). Though computationally simple and shown to produce accurate estimates, the method restricts the data output to large area units rather than individual field parcels. Similar to this work, European-wide field size estimates were conducted from interpolation of survey data (Kuemmerle et al., 2013). A very different approach from the previous studies made use of crowdsourcing to rapidly produce many field size samples from satellite imagery (Fritz et al., 2015). By doing so, the authors produced, to our knowledge, the first and only global estimate of field sizes, offering a first look at the major global patterns on the scale of food production. However, the methodology does not provide wall-to-wall estimates, instead interpolating between crowdsourced samples. Although somewhat expected in global studies, the result is an over-generalization of field sizes because of categorical field size classes and assumptions about field size patterns over interpolated space. Still, Argentina—particularly scrutinized because of our paper's regional focus—is a case in point of the limitations of this approach. Only remnants of small fields (although ‘small’ is not explicitly defined) were estimated, when in fact many small fields exist throughout the country, as we shall show later.

The limitations (reliance on third-party data, coarse field estimates) of the approaches above warrant a solution that can produce wall-to-wall, large-scale estimates of individual fields. Yan and Roy (2014) developed a novel procedure to detect individual parcels from multi-temporal Landsat imagery by combining image-processing techniques such as image morphology and segmentation. The authors employed temporal Web-enabled Landsat Data (WELD) (Roy et al., 2010) to extract fields over a five-year period in the United States and presented the first large-scale estimate of individual fields. More recently, the authors reduced the timeframe to one year, refined the methods, and applied their algorithm to the contiguous US (Yan and Roy, 2016). Their approach, utilizing a combination of image processing methods, is more promising than previous approaches. Another European-wide study illustrated the potential for ‘field patch’ segmentation from satellite imagery (Weissteiner et al., 2016). However, whereas the estimates of Yan and Roy (2016) were kept at the field level, Weissteiner et al. (2016) aggregated their data to a much coarser scale than individual fields.

In this study, we present an image processing method to detect individual field parcels from multi-temporal Landsat imagery, with some key differences from the Yan and Roy studies, and with application over different agricultural landscapes across much of South America. South America's agricultural landscape has changed rapidly over the past several decades (Berduegué and Fuentealba, 2011; Dros, 2004; FAO, 2015; Graesser et al., 2015; Martinelli, 2012). Better estimates of cropland and data that describe the nature of the agricultural changes are needed in order to accurately monitor and understand the consequences of these rapid changes. Field-size data, in particular, would greatly enhance the capacity to monitor the scale of these changes. This study addresses two questions: 1) Is Landsat a reliable sensor for cropland observations? and 2) Can individual field parcels be detected at the continental scale from multi-temporal Landsat imagery over a broad range of crop types and field configurations? To characterize cropland, we used all available Landsat images over a 1.5-year period, from 2000 to 2001. We then estimated cropland at a parcel level using multi-temporal Landsat imagery and contemporary edge-based methods, and tested the robustness of our methods over a large and complex agricultural region of South America.

2. Data and study area

2.1. Study area

We identified individual crop field parcels across a selected region of South America, broadly defined as cropland south of the Amazon River and north of Patagonia (Fig. 1). The test region was chosen from Landsat scenes that intersected selected world ecoregions (Olson et al., 2001) in order to include a wide range of crop types and landscapes. This selected region contained approximately 82% of the 2001 South American cropland area (Graesser et al., 2015). Argentina and Brazil comprise the majority of the agricultural land within the study region.

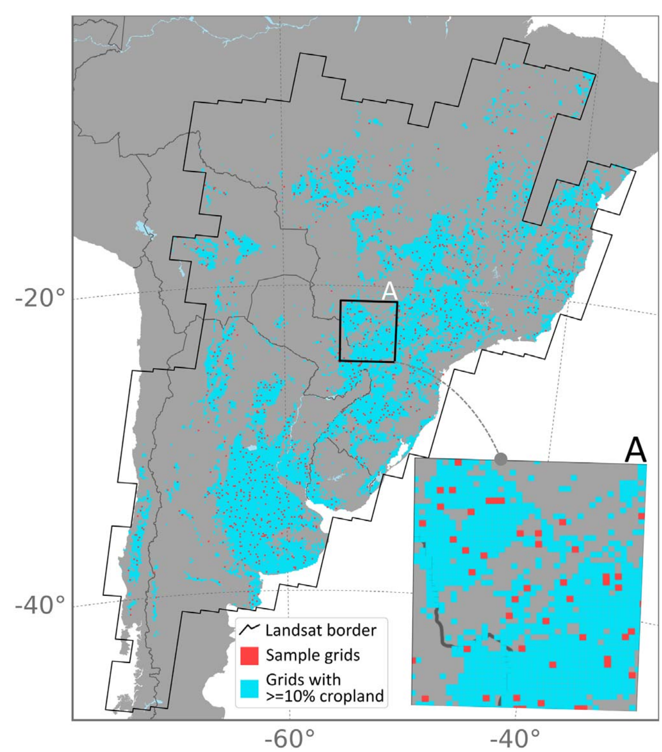

Fig. 1. South America test region for semi-automatic crop-field extraction. The study area (shown in black outline) consists of Landsat scenes that intersect selected ecoregions. For field parcel validation, 10 km × 10 km grids were generated to cover the test region. The grids were then restricted to those with ≥ 10% cropland area (shown in cyan). Finally, we randomly sampled 1000 grids (shown in red) from this ≥ 10% cropland grid to use for crop field parcel validation. Inset A illustrates a larger-scale view of the sample grids. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)