Int J Appl Earth Obs Geoinformation 67 (2018) 114–122

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

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

Coefficient of variation for use in crop area classification across multiple climates

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ARTICLE INFO

Keywords:
SAR
Backscatter
Coefficient of variation
Time series
Agricultural land cover classification

ABSTRACT

In this study, the coefficient of variation (CV) is introduced as a unitless statistical measurement for the classification of croplands using synthetic aperture radar (SAR) data. As a measurement of change, the CV is able to capture changing backscatter responses caused by cycles of planting, growing, and harvesting, and thus is able to differentiate these areas from a more static forest or urban area. Pixels with CV values above a given threshold are classified as crops, and below the threshold are non-crops. This paper uses cross-polarized L-band SAR data from the ALOS PALSAR satellite to classify eleven regions across the United States, covering a wide range of major crops and climates. Two separate sets of classification were done, with the first targeting the optimum classification thresholds for each dataset, and the second using a generalized threshold for all datasets to simulate a large-scale operationalized situation. Overall accuracies for the first phase of classification ranged from 66%–81%, and 62%–84% for the second phase. Visual inspection of the results shows numerous possibilities for improving the classifications while still using the same classification method, including increasing the number and temporal frequency of input images in order to better capture phenological events and mitigate the effects of major precipitation events, as well as more accurate ground truth data. These improvements would make the CV method a viable tool for monitoring agriculture throughout the year on a global scale.

1. Introduction

As the earth is called upon to feed increasing numbers of people with a limited supply of arable land and water, accurate, up-to-date monitoring of global agriculture becomes an increasingly important part of world stability for reasons of food security, economic stability, climate change, and environmental degradation (Becker-Reshef et al., 2010; Jayne and Rashid, 2010; and Scherr and Sthapit, 2009). Remote sensing provides a way to monitor agriculture at a global scale, with reasonable time and manpower requirements while also providing a uniform system of measurement. Due to the dynamic and complex nature of agricultural landscapes, with hundreds of crop types growing on fields ranging from tenths to hundreds of hectares planted in numerous climatic conditions, remotely sensed measurements of agricultural land area vary drastically across the globe in their precision, accuracy, and timeliness, with global operationalization still proving elusive (Waldner et al., 2015). Most global land cover datasets include agricultural lands as part of mosaic or mixed classes, variably including pasture, which makes them challenging to use for agricultural applications (Bartholomé and Belward, 2005; Bontemps et al., 2011; Friedl et al., 2010). The few with dedicated agriculture classes struggle with accuracy (Gong et al., 2013) or otherwise highlight the uncertainty and challenges in estimating global cropland extent (Biradar et al., 2009; Pittman et al., 2010; Ramankutty et al., 2008; Yu et al., 2013). These discrepancies stem from a number of issues including the availability of cloud-free images at the desired spatial and temporal resolution of all the necessary regions of the globe, and the availability of detailed ground truth data for training classification algorithms (Matton et al., 2015 and Whitcraft et al., 2015).

As an active remote sensing system, synthetic aperture radar (SAR) can help mitigate some of the challenges of optical imagery, as the data are mostly independent of solar and atmospheric conditions, allowing for reliable data collection in areas of frequent cloud cover. Increasing numbers of SAR-based agricultural land cover classifications have been made using SAR as a standalone source, as well as in combination with optical data. Most of these works have focused on differentiating individual crops; however they primarily have been non-operational projects focused on small regions (Champagne et al., 2014; Haldar et al., 2012; Skriver et al., 2011). Operational projects primarily consist of Agriculture and Agri-Food Canada's annual end-of-season crop map

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https://doi.org/10.1016/j.jag.2017.12.014
Received 7 August 2017; Received in revised form 21 November 2017; Accepted 26 December 2017
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(Fisette et al., 2014) and a few rice monitoring projects in Asia (Chakraborty et al., 2006 and Nelson et al., 2014). Crop/non-crop classifications using SAR are not operationalized, and have primarily been related to monitoring agricultural land abandonment, but again over relatively limited regions and crops (Stefanski et al., 2014, and Yusoff et al., 2017).

Past work has found that L- and C-band are the most effective wavelengths for agricultural applications due to their sensitivity to both fine-scale structural characteristics of different crop types and growth stages, as well as to soil moisture and other soil characteristics (Ferrazzoli et al., 1997 and McNairn and Shang, 2016). Multi-temporal datasets have been found to be more effective at agricultural land cover classification due to their ability to capture agricultural phenology and related growth patterns (Blaes et al., 2005; Deschamps et al., 2012; Jiao et al., 2014). In order to capitalize on the changing radar signature over time exhibited by agricultural areas, as opposed to the relatively static signature of a forest or urban area, we introduce a statistical measurement known as the coefficient of variation (CV) to measure the variation in backscatter response over time for a single location. More commonly used to measure spatial variation, here the CV is used to measure temporal variation. It focuses on the overall variability and generally dynamic nature of crop planting, growing, and harvesting cycles, not specific phenological features of individual species. The significant changes in ground cover, physical structure, and backscatter of an agricultural area is expected to produce a wider range of backscatter values over time, and thus a higher CV (Cihlar et al., 1992). Once the CV has been computed for an entire region, a threshold can be used to classify pixels as a crop or non-crop, with crops having the higher range of CV values. Crop/non-crop classifications are valuable not only as a predecessor to classifications differentiating between individual crops, but also for what they can tell about land use patterns, such as continued farming in a conflict zone, or spotting new agricultural lands in a previously forested region. Other types of thresholds have been previously used for SAR-based classifications, as an example, for rice (Bouvet and Le Toan, 2011).

The methodology presented here is chosen because of its ability to be more statistically traceable than common methods of classifying a multi-temporal range of images, such as decision trees or the maximum likelihood classifier. As a simple hypothesis test using a statistics-based input layer, the CV classification allows one to estimate the effect on the classification error if a different threshold and/or number of input images were used. This characteristic makes this classification method useful both when designing data collection patterns for upcoming satellite missions, and for data users trying to select the minimum number of already collected images needed to produce a classification with a specified target accuracy. For crop/non-crop classifications, simple algorithms that do not depend on extensive training data and work in a wide range of climactic conditions have value for providing global measurements of agricultural area (Matton et al., 2015 and Waldner et al., 2015). The CV algorithm fits these preferred characteristics of being computationally simple, requiring minimal training data, and using consistent methodology across the globe.

An important application of this work is connected to NISAR, a joint project between NASA and the Indian Space Research Organization (ISRO). This mission, planned for launch in 2021 will be primarily collecting L-band HH/HV data over most land surfaces worldwide with a 12 day repeat cycle (Rosen et al., 2015). Its consistent, freely available (NASA, 2012) global coverage will provide a unique opportunity to investigate applications using longer and more frequent time series (some 30 images per year) than what has traditionally been feasible due to data cost and coverage (Fisette et al., 2014). Further investigation of applications techniques is encouraged by the NISAR project's Level 1 Science Requirements, which include the requirement that the satellite be able to seasonally classify global croplands at 80% or better at the one hectare scale (Sanchez, 2014). This paper not only tests the potential for the CV method in preparation for the NISAR satellite, it also shows how NISAR data could be used to improve global agricultural monitoring.

2. Data

Preliminary research has shown that cross-polarized L-band imagery is more effective at separating crop and non-crop regions using the CV classification method than C-band or co-polarized L-band observations (Siqueira, 2016). Because of these findings, cross-polarized (HV) imagery from the Japanese L-band ALOS satellite was used for this research, as it is one of the few available options for repeat-pass L-band SAR data. In addition, ALOS data spans a wide range of ecosystems and crop types, including coverage across all of the United States, and has previously been used for agricultural land cover classification (Haldar et al., 2012; McNairn et al., 2009 and Yusoff et al., 2017). Terrain corrected and ground projected images are available from the Alaska Satellite Facility (Alaska Satellite Facility Engineering Group, 2015). All images were acquired in fine beam dual mode (FBD), ascending orbits, with consistent viewing geometry including an off-nadir viewing angle of 34.3° and incidence range of 36.6°–40.9° (Rosenqvist et al., 2014). ALOS-1 had a very consistent orbit track, and hence incidence angles did not change over time. The consistent orbit also meant that data was repeatedly captured over the same strips of land, with significant overlap between neighboring strips. Using imagery from ASF provided consistent calibration and preprocessing, producing multilooked 30 m pixels with backscatter recorded in terms of gamma nought, which is a terrain-corrected version of the normalized radar cross section (Small, 2011). ALOS operated on a 46 day repeat cycle; however coverage locations varied between cycles. Each of the test locations has between six and fourteen images taken between 2007 and 2010 during the spring, summer, and fall months, with analysis using all dates that provided a complete image strip for the given location.

Ground truth information came from an agricultural land cover classification product known as the Cropland Data Layer (CDL), which is released annually by the United States Department of Agriculture National Agricultural Statistics Service (USDA NASS) (Boryan et al., 2011). The CDL was chosen as a relatively high resolution land cover database produced for a large region under consistent methodology; however its use did limit the possible study areas to the continental United States. Production of the CDL combines optical data primarily from Landsat 5 TM, Landsat 7 ETM+, and RESOURCESAT-1 AWiFS sensors with high quality ground truth data as input for sophisticated decision-tree classification software. The resulting product has an overall accuracy of around 80% for all agricultural land covers, with major crops such as corn, soybeans, wheat, cotton, and rice frequently having accuracies over 90%. While not 100% accurate, the CDL is a nationally available source of agriculturally-focused land cover data that is a more consistent source of data than if separate ground truth datasets had been used for the different regions of the country. At a national scale, classifying individual crops, with 30 m or 56 m pixels (depending on the year) it is one of the best publically available agricultural land cover databases available in the world, and as such has been used as training data for attempts at satellite-based global crop mapping (Matton et al., 2015; Pittman et al., 2010; Waldner et al., 2015).

Because this paper focused on a crop/non-crop classification rather than classifying individual crop types, the full CDL information was simplified into a multi-year crop/non-crop layer. Since the CDL is known to have difficulty classifying fields containing multiple crops in a single year, either due to interplanting of rows or double cropping that alternates summer and winter crops, a crop/non-crop version should reduce the influence of these types of errors (Boryan et al., 2011). It should also mitigate errors related to confusion between similar crops, such as oats or barley being misclassified as wheat. While the ALOS imagery spans 2007–2010 growing seasons, and production of the CDL began in the late 1990′s with a few key producing states, the CDL is

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