Remote Sensing of Environment 198 (2017) 490–503

Contents lists available at ScienceDirect

Remote Sensing of Environment

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

MODIS phenology-derived, multi-year distribution of conterminous U.S. crop types

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ARTICLE INFO

Article history:
Received 3 August 2016
Received in revised form 12 April 2017
Accepted 28 June 2017
Available online xxxx

Keywords:
Generalized classifier
Adjusted kappa
NDVI time-series
MOD09Q1
Cropland mapping
United States croplands
Cropland data layer

ABSTRACT

Innovative, open, and rapid methods to map crop types over large areas are needed for long-term cropland monitoring. We developed two novel and automated decision tree classification approaches to map crop types across the conterminous United States (U.S.) using MODIS 250 m resolution data: 1) generalized, and 2) year-specific classification. The classification approaches use similarities and dissimilarities in crop type phenology derived from NDVI time-series data for the two approaches. The year-specific approach uses the training samples from one year and classifies crop types for that year only, whereas the generalized classification approach uses above-average, average, and below-average precipitation years for training to produce crop type maps for one or multiple years more robustly. We produced annual crop type maps using the generalized classification approach for 2001–2014 and the year-specific approach for 2008, 2010, 2011 and 2012. The year-specific classification had overall accuracies >78%, while the generalized classifier had accuracies >75% for the conterminous U.S. for 2008, 2010, 2011, and 2012. The generalized classifier enables automated and routine crop type mapping without repeated and expensive ground sample collection year after year. The resulting crop type maps for years prior to 2007 are new and especially important for long-term cropland monitoring and food security analysis because no other map products are currently available for 2001–2007.

1. Introduction

Cropland mapping with sufficient accuracies via open, reproducible, and rapid methods are required to develop well-informed strategies for global food security and to anticipate shortfalls (Thenkabail et al., 2010). The United States (U.S.) is a major food producer in the world accounting for ~30% of the world grain exports (USDA, 2016). Environmental variables that influence the U.S. agricultural production also impact food prices at global markets with important implications for global food security. In addition, since crop cultivation accounts for nearly 80% of all water-use, having comprehensive, long-term, and accurate information regarding U.S. crop types and their spatial distribution is critical in accurately quantifying agricultural production and crop water-use estimates towards food security (Thenkabail et al., 2012). Remote sensing techniques can provide such information repeatedly, consistently, and accurately over space and time (Pervez and Brown, 2010).

This study proposes two new, open, reproducible, and rapid methods to produce annual crop type maps for the U.S. in an automated manner for the years 2001–2014 because:

1) Cropland mapping algorithms currently available in the U.S. are developed for either a small region or a few selective years and cannot be used to map crop types annually in an automated manner without extensive ground data every year.
2) The ground data collection is expensive and the United States Department of Agriculture (USDA) is currently the only institution that can access the Farm Service Agency's (FSA) Common Land Unit (CLU) dataset to produce Cropland Data Layer (CDL) (FSA, 2012).
3) Annual maps for crop types at MODIS 250 m resolution are lacking for the years 2001–2007 for the conterminous U.S.
4) We present new annual crop type data products for the years 2001–2014. The crop type maps produced using our algorithms can be used as critical base maps for long-term cropland monitoring and change detection to address food security concerns and water use demands.

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http://dx.doi.org/10.1016/j.rse.2017.06.033
0034-4257/

Previous studies in the U.S. mapped croplands at county, state, regional, and country levels using a wide range of satellite sensors. The land-use and land-cover maps derived from Landsat TM and ETM+ data such as the Gap Analysis Program (GAP) datasets (Eve and Merchant, 1998), and the United States Geological Survey (USGS) National Land Cover Dataset (NLCD) (Homer et al., 2004; Vogelmann et al., 2001; Homer et al., 2007; Homer et al., 2012) have classified cropland extent for multiple but limited number of years. While most crop type maps have been produced at county and state levels using Landsat data (Mosiman, 2003; Price et al., 2002; Wardlow and Egbert, 2008), the USDA National Agricultural Statistics Service (NASS) has produced the cropland data layer (CDL) annually for the conterminous U.S. since 2008 (Johnson and Mueller, 2010; Boryan et al., 2011; Han et al., 2012; Boryan et al., 2014). There is currently no spatial data product available for the conterminous U.S. crop types prior to 2008. Landsat data with its high spectral and spatial resolutions, but moderately-low temporal resolution is suitable for mapping crop types. However, large computational costs, time, and data storage required for Landsat data make crop type mapping at the country scale a major challenge.

The Advanced Very High Resolution Radiometer (AVHRR) with its coarse resolution (1 km) and near-daily revisit time has been used in multiple large-scale studies to map land cover types based on temporal variations in vegetation indices such as Normalized Difference Vegetation Index (NDVI). The studies range from a country scale (Loveland et al., 1991; Loveland et al., 1995) to a global scale (DeFries and Townshend, 1994; Loveland and Belward, 1997; DeFrics et al., 1998; Hansen et al., 2000; Loveland et al., 2000; Asrar et al., 1989; Baret and Guyot, 1991). Some of the crop-specific studies that used AVHRR data include: Gallo and Flesch, 1989; Tucker et al., 1980; Das et al., 1993; Doraiswamy and Cook, 1995; and Lee et al., 1999. Most AVHRR-derived land cover classifications represent croplands as either cropland extents or a mixed class of croplands and other natural vegetation. While the coarse resolution of AVHRR is suitable for mapping natural vegetation, the spatial heterogeneity and field boundaries in agricultural systems require finer resolution remote sensing data (Turner et al., 1995).

The Moderate Resolution Imaging Spectroradiometer (MODIS) instrument aboard the Terra and Aqua satellite with its near-daily global coverage allows dense time-series that are well suited and extremely useful for crop mapping at resolutions of 250 m and above (Wardlow et al., 2007). This balance in spatial and temporal resolution of MODIS data provides a unique capability that allows development of temporally generalized methods that can distinguish annually recurring temporal patterns to classify crop types year after year without the need for expensive ground data. In addition to a dense time-series, the near-daily coverage of MODIS data allows cloud-free composites. MODIS data has been extensively used for cropland mapping as the 250 m spatial resolution of the red (620–670 nm) and near infrared (841–876 nm) surface reflectance bands are adequate to map U.S. crop fields which are comparable in size (Wardlow et al., 2007). Cropland maps produced in the U.S. with MODIS data include those developed for Kansas for 2001 (Wardlow et al., 2007; Wardlow and Egbert, 2008), the Great Lakes basin for 2005, 2006, and 2007 (Lunetta et al., 2010), the Great Plains for 2000–2011 (Howard and Wylie, 2014), irrigated crops for 2001 (Ozdogan and Gutman, 2008), and irrigated crops for 2002, 2007, and 2012 (Brown et al., 2009; Pervez and Brown, 2010; Brown and Pervez, 2014). Furthermore, MODIS time-series based classification methods have been developed and widely used to map croplands at regional and state levels (Wardlow et al., 2007).

MODIS-based NDVI time-series data in 250 m resolution has been widely used in phenology-based studies. In 250 m spatial resolution, MODIS NDVI enables generalized classification at much higher accuracies than the two spectral bands, red and near-infrared, themselves for the following reasons:

1) While MODIS data has high overall spectral stability and calibration accuracy (Salomonson et al., 1989; Vermote et al., 2002), the normalization between the red and near-infrared bands in NDVI further reduces any effect of degradation of the satellite calibration from 10 to 30% for a single channel to approximately 4% for the normalized index (Holben et al., 1990; Kaufman and Holben, 1990).
2) NDVI significantly reduces the angular dependency of the surface reflectance and of the atmospheric effects (Holben and Fraser, 1984), which in turn allows texture independent values unlike the single bands.
3) Scattering and absorption effects by atmospheric aerosol and gases including water vapor and small undetected clouds is significantly reduced by compositing maximum value NDVI from several consecutive images for each pixel (Tanre et al., 1992; Kaufman, 1987). The narrow channels of MODIS sensor in the electromagnetic spectrum further reduce the disturbances in NDVI by atmospheric water vapor.
4) Identifying differences in the two surface reflectance bands in a time-series dataset requires significantly more computing time, whereas identifying differences in a single NDVI product is much faster and utilize the information from both the red and near infrared bands at the same time.

Previous studies have used NDVI time-series data to characterize and classify an entire crop growing season or up to a year. The Large Area Crop Inventory Experiment (LACIE) and Agriculture and Resources Inventory Surveys through Aerospace Remote Sensing (AgRISTARS) programs undertaken by National Aeronautics and Space Administration (NASA) in 1975 and 1980, respectively, laid the foundations of mapping crops using time-series data from Landsat sensors in selected locations of the U.S (Hogg, 1986; MacDonald and Hall, 1980).

Existing cropland classification algorithms use both supervised (NDVI thresholds, Mahalanobis distance, maximum likelihood, decision trees, neural networks, random forest) and unsupervised (K-means, Isodata) approaches that rely on ground-based data for training and labeling output classes, respectively. While ground-based data is needed for accurate classification, such data collection is expensive in terms of time and cost, and poses a major challenge for researchers. In the U.S., for example, the USDA is the only institution that has access to a large, ground-based FSA CLU dataset. While the USDA can produce accurate crop type maps using this dataset (for example, CDL), no other researcher or institution can replicate the classification algorithm without the expensive ground-based data. Therefore, the ability to automate crop type classification without extensive ground data is critical.

Significant improvement in mapping economy and speed can be achieved by developing a temporally generalized classifier, which can be used for multiple years without the need to collect temporally-specific ground-based data every year (Zhong et al., 2014). Generalized classifiers require training data from multiple years and multi-temporal images that are comparable from year to year. There have been many studies that used spatial and temporal generalization at smaller spatial extents since the LACIE program (Botkin et al., 1984). Generalized classifiers have been successfully applied in vegetation studies (Botkin et al., 1984; Woodcock et al., 2001; Baraldi, 2011; Hestir et al., 2012) as well as in cropland mapping (Zhong et al., 2011; Zhong et al., 2014; Waldner et al., 2015; Thenkabail et al., 2009; Teluguntla et al., 2015). Temporal metrics such as emergence, maturity, and harvest based on time-series of multispectral images have also been successfully used for inter-annual classification via generalized classifiers (Reed et al., 1994; Zhang et al., 2003; Zhong et al., 2011; Sakamoto et al., 2013; Zhong et al., 2012; Zhong et al., 2014).

Taking advantage of quantitative temporal metrics such as image dates, differences in time-series curves, and corresponding time-series values overcome common challenges associated with single date spectral characteristics and signatures of crop types (Zhong et al., 2011). Classification approaches that focus on normalized time-series data provide much greater advantages. First, a normalized and differenced index such as NDVI is less susceptible compared to the individual spectral