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Mapping croplands, cropping patterns, and crop types using MODIS time-series data

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ABSTRACT

The importance of mapping regional and global cropland distribution in timely ways has been recognized, but separation of crop types and multiple cropping patterns is challenging due to their spectral similarity. This study developed a new approach to identify crop types (including soy, cotton and maize) and cropping patterns (Soy-Maize, Soy-Cotton, Soy-Pasture, Soy-Fallow, Fallow-Cotton and Single crop) in the state of Mato Grosso, Brazil. The Moderate Resolution Imaging Spectroradiometer (MODIS) normalized difference vegetation index (NDVI) time series data for 2015 and 2016 and field survey data were used in this research. The major steps of this proposed approach include: (1) reconstructing NDVI time series data by removing the cloud-contaminated pixels using the temporal interpolation algorithm, (2) identifying the best periods and developing temporal indices and phenological parameters to distinguish croplands from other land cover types, and (3) developing crop temporal indices to extract cropping patterns using NDVI time-series data and group cropping patterns into crop types. Decision tree classifier was used to map cropping patterns based on these temporal indices. Croplands from Landsat imagery in 2016, cropping pattern samples from field survey in 2016, and the planted area of crop types in 2015 were used for accuracy assessment. Overall accuracies of approximately 90%, 73% and 86%, respectively were obtained for croplands, cropping patterns, and crop types. The adjusted coefficients of determination of total crop, soy, maize, and cotton areas with corresponding statistical areas were 0.94, 0.94, 0.88 and 0.88, respectively. This research indicates that the proposed approach is promising for mapping large-scale croplands, their cropping patterns and crop types.

1. Introduction

Agricultural production in Brazil has grown rapidly over the past three decades due to rising global demand, favorable commodity prices, and technological advances (Cohn et al., 2016; Dias et al., 2016). The improvement in crop management practices and cropland expansion and intensification have made Brazil the leading exporter in soybeans, sugar, meat, coffee, and orange juice (FAO, 2015). These advances require updating crop distribution information and its dynamic change in a timely way. In the past decade, much research on mapping cropland distribution in Brazil has been conducted (Arvor et al., 2011; Arvor et al., 2012; Brown et al., 2013; Epiphanio et al., 2010; Gusso et al., 2014; Rudorff et al., 2010; Victoria et al., 2012; Zhu et al., 2016). Landsat imagery has been extensively used for crop mapping due to its long-term historical records at no cost and relatively fine spatial resolution (Maxwell et al., 2004; Odenweller, 1984; Vieira et al., 2012; Zheng et al., 2015; Zhong et al., 2014). However, the revisiting times (16 days) result in difficulty collecting cloud-free images, especially in

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Table 1
Summary of selected approaches for mapping large-scale cropland distribution.

	Method	Description of examples	Key references
Pixel-based approaches	Traditional classifiers and machine learning classifiers	(1) Maximum likelihood classifier based on MODIS EVI time-series data to map crop types and cropping system in Mato Grosso, Brazil	Arvor et al. (2011)
		(2) Spectral angle mapper based on MODIS EVI time-series to map crop types in Paraná, Brazil	Grzegozewski et al. (2016)
		(3) Decision tree classifier based on MODIS NDVI and EVI time-series data to classify agricultural land use data in Mato Grosso, Brazil; based on MODIS NDVI time-series data to identify crop types in Kansas, USA or the conterminous USA; and based on LSWI, EVI, and NDVI time-series data to identify paddy rice in the southern China	Brown et al. (2013), Wardlow and Egbert (2010), Massey et al. (2017), Xiao et al. (2005)
		(4) Neutral network based on MODIS NDVI time-series data to classify crop types across Laurentian Great Lakes Basin, USA	Lunetta et al. (2010)
		(5) Classification and regression trees approach to extract crop types based on MODIS NDVI time-series in Manitoba, Canada	Chen et al. (2016)
		(6) Random Forest classifier to extract crop area in USA based on MODIS time-series	Hao et al. (2015), Zhong et al. (2016)
	Data transform algorithms	(1) Fourier analysis based on MODIS NDVI time-series data to map crop type distribution in northern China	Zhang et al. (2008)
		(2) Wavelet analysis based on MODIS EVI time-series data to map cropland distribution in Mato Grosso, Brazil	Galford et al. (2008)
	Temporal profile fitting method	(1) Temporal best-fitting classifier based on MODIS EVI time-series data to extract crop types in Rondônia, Brazil	Brown et al. (2007)
		(2) Dynamic Time Warping distance-based similarity measure approach based on MODIS NDVI time-series to map cropping system in Vietnam	Guan et al. (2016)
	Phenology Method	(1) Optimizing threshold by comparing key phenology metrics derived from MODIS with that from ground data to extract crop types in central Germany	Xu et al. (2017)
		(2) Quantifying the relationship between crop phenology index time-series and winter wheat area	Pan et al. (2012)
	Hybrid method	(1) Automated Cropland Classification/Mapping Algorithm (ACCA, ACMA) based on clustering classifers and spectro-temporal characteristics from MODIS NDVI time-series	Thenkabail and Wu (2012), Xiong et al. (2017)
		(2) Decision tree algorithms and spectral matching techniques for season rice cropland mapping in Bangladesh and irrigated area mapping in India	Dheeravath et al. (2010), Gumma et al. (2014)
		(3) Object-oriented method and supervised classification to map crop area.	Vintrou et al. (2012)
		(4) Data fusion with Landsat 8 imagery and support vector machine to map crop types in Midwest USA	Zhu et al. (2017)
Subpixel-based approaches	Temporal unmixing technique	(1) Probabilistic temporal unmixing methodology using time-series MODIS red and near infrared data in identifying crop proportion area in northwest Mexico and southern Great Plains, USA	Lobell and Asner (2004)
		(2) Unsupervised signal processing algorithm to temporally decompose MODIS data to automatically map major crop types in Kansas and Nebraska, USA and in Turkey	Ozdogan (2010)
		(3) Spatially constrained phenological mixture analysis (SPMA) to extract crop percent covers using MODIS NDVI time-series data in the Midwest USA	Zhong et al. (2015)
	Regression technique	(1) Regression model with adaptive parameters based on MODIS EVI time-series data to extract winter wheat proportion map in China	Pan et al. (2012)
		(2) Nonlinear regression technique based on MODIS time-series data for mapping fractional corn and soybean distribution at national scale in USA	Chang et al. (2007)
		(4) Linear regression model based on MODIS EVI time-series and Landsat data to produce fractional cropland map in Mato Grosso, Brazil	Zhu et al. (2016)

Note: MODIS, Moderate Resolution Imaging Spectroradiometer; NDVI, normalized difference vegetation index; EVI, enhanced vegetation index; LSWI, land surface water index.

tropical areas. At regional and global scales, many previous studies on cropland mapping used MODIS (Moderate Resolution Imaging Spectroradiometer) data or integration of MODIS and Landsat data to effectively use phenological characteristics from the high temporal resolution (Arvor et al., 2011; Kumar et al., 2008; Lobell and Asner, 2004; Thenkabail and Velpuri, 2006; Wardlow et al., 2007; Xiao et al., 2005). MODIS normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI) time-series data are commonly used for crop classification (Arvor et al., 2011; Gumma et al., 2016; Lobell and Asner, 2004; Ozdogan, 2010; Pan et al., 2012; Thenkabail et al., 2005; Wardlow and Egbert, 2008; Xiao et al., 2005; Zhu et al., 2016, 2017). The approaches can be grouped into two broad categories: pixel-based and subpixel-based methods. Table 1 provides examples for cropland mapping using MODIS time-series data.

Coarse spatial resolution images such as MODIS are often used to map large-scale cropland or single-crop type distribution (Galford et al., 2008; Lobell and Asner, 2004; Teluguntla et al., 2017; Thenkabail and Wu, 2012; Xiao et al., 2005) without taking different cropping patterns and multi-crop types into account. However, the spatial distribution of cropping patterns and crop types at regional and global scales are required for reducing the uncertainty of crop yield estimation and for making better decisions in crop planting to achieve food security. The