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Automatic and adaptive paddy rice mapping using Landsat images: Case study in Songnen Plain in Northeast China

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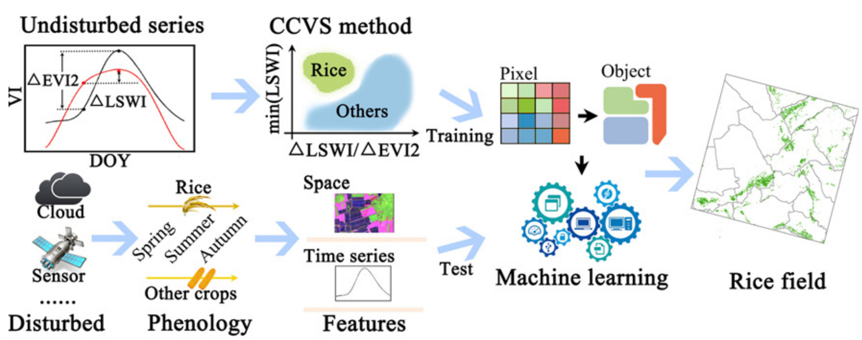
HIGHLIGHTS

- Study area was subdivided into undisturbed/disturbed regions based on data availability.
- Object-oriented CCVS method was applied in undisturbed region.
- Feature extraction was conducted considering spectral separability and spatiotemporal coverage.
- Rice fields were extracted by pixel and object-integrated phenology-based strategy.
- Practical strategy for training samples was provided by incorporating finer time series observations.

GRAPHICAL ABSTRACT



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ABSTRACT

Spatiotemporal explicit information on paddy rice distribution is essential for ensuring food security and sustainable environmental management. Paddy rice mapping algorithm through the Combined Consideration of Vegetation phenology and Surface water variations (CCVS) has been efficiently applied based on the 8 day composites time series datasets. However, the great challenge for phenology-based algorithms introduced by unpromising data availability in middle/high spatial resolution imagery, such as frequent cloud cover and coarse temporal resolution, remained unsolved. This study addressed this challenge through developing an automatic and Adaptive paddy Rice Mapping Method (ARMM) based on the cloud frequency and spectral separability. The proposed ARMM method was tested on the Landsat 8 Operational Land Imager (OLI) image (path/row 118/028) in the Songnen Plain in Northeast China in 2015. First, the whole study region was automatically and adaptively subdivided into undisturbed and disturbed regions through a per-pixel strategy based on Landsat image data availability during key phenological stage. Second, image objects were extracted from approximately cloud-free images in disturbed and undisturbed regions, respectively. Third, phenological metrics and other feature images from individual or multiple images were developed. Finally, a flexible automatic paddy rice mapping strategy was implemented. For undisturbed region, an object-oriented CCVS method was utilized to take the full advantages of phenology-based method. For disturbed region, Random Forest (RF) classifier was exploited using training data from CCVS-derived results in undisturbed region and feature images adaptively selected with full considerations of spectral separability and the spatiotemporal coverage. The ARMM method was verified by 473 reference sites, with an overall accuracy of 95.77% and kappa index of 0.9107. This study provided an efficient strategy to accommodate the challenges of phenology-based approaches through transferring knowledge in parts of a satellite scene with finer time series to targets (other parts) with deficit data availability.

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1. Introduction

Rice produces food for more than half of the world's population, especially in monsoon Asia (Bouvet and Le Toan, 2011; Nuarsa et al., 2012; Tornos et al., 2015). Owing to continuously increasing population and limited arable land, food security is always a big challenge to the whole world (Dong and Xiao, 2016). Paddy rice fields release Greenhouse gasses (GHGs) and consume huge amount of water resources (Minami and Neue, 1994). Spatio-temporal explicit information on paddy rice fields is important for both food security and environmental sustainability (Gumma et al., 2014; Kuenzer and Knauer, 2013; Mosleh et al., 2015; Nuarsa et al., 2012; Qin et al., 2015).

Research efforts have long been concentrated on rice mapping fields for this reason (Dong and Xiao, 2016; Manfron et al., 2013; McCloy et al., 1987; Mosleh and Hassan, 2014; Qin et al., 2015; Xiao et al., 2005; Zhang et al., 2017; Zhang et al., 2015). The developments of paddy rice mapping algorithms have experienced four stages (Dong and Xiao, 2016): Stage 1: reflectance data and image statistic-based approaches; Stage 2: vegetation index and enhanced image statistic-based approaches; Stage 3: vegetation index or RADAR backscatter-based temporal analysis approaches; and Stage 4: phenology-based approaches through remote sensing recognition of key growth phases. Increasing recent research interests have been drawn on developing a more straightforward phenology-based approach for agricultural crops and other land cover mapping (Dong and Xiao, 2016; Tong et al., 2017; Zhong et al., 2016).

The most representative and widely utilized phenology-based rice mapping method was the transplanting-based algorithm (Xiao et al., 2005; Zhang et al., 2017). It was proposed through evaluating the differences between the Normalized Difference Vegetation Index (NDVI)/Enhanced vegetation index (EVI) and the Land Surface Water Index (LSWI) during the paddy rice transplanting period (Xiao et al., 2005). The input variables of optimal remote sensing-based method experienced an evolution from reflectance data, to NDVI/EVI, then to NDVI/EVI and LSWI and finally to other combined indicators (e.g. Qiu et al. 2015) (Dong and Xiao, 2016). A novel rice mapping algorithm was developed based on Combined Consideration of Vegetation phenology and Surface water variations (CCVS) (Qiu et al., 2015). The phenology-based CCVS method has been proved to be efficient in extracting paddy rice fields using 8 day composites Moderate Resolution Imaging Spectroradiometer (MODIS) time series datasets (Qiu et al., 2015; Qiu et al., 2016b). However, data availability is a great limitation for the newly developing and promising phenology-based algorithms (Qin et al., 2015). For a phenology-based algorithm such as the CCVS, there were at least the following two aspects needed to be further investigated. On the one hand, its capability on time series images with finer spatial resolution and coarse temporal resolutions has not been testified (Dong and Xiao, 2016). On the other hand, could the CCVS method efficiently deal with the greatest challenges of phenology-based algorithms introduced by unpromising data availability, e.g. frequent cloud cover?

Although the MODIS data is an important source for rice mapping, it has some limitations due to its coarse spatial resolution since the paddy rice fields are often patchy and fragmented (Dong and Xiao, 2016; Zhang et al., 2017). Moderate resolution sensors like Landsat have sufficient spectral bands and fine spatial resolution are freely available and successfully utilized in paddy rice mapping (Qin et al., 2015; Zhang et al., 2015; Zhou et al., 2016). The vegetation indices temporal profiles could be seriously disturbed by cloud contaminations, even for the hyper-temporal MODIS data (Dong and Xiao, 2016; Qiu et al., 2013; Tong et al., 2017). It might be more difficult to provide sufficient good-observations for Landsat time series images with temporal gap of 16 days (Zhang et al., 2017). Given that specific phenological stage (from tillering to heading dates) utilized in the CCVS method was within one and a half months, could it overcome this challenge? If not, a more robust automatic method is necessary to overcome the data availability and cloud contamination issues.

In land use/cover classification fields, automated and accurate methods are highly desirable by taking account of large data volumes and time-consuming data processing, integration and interpretation (Rogan et al., 2008). Machine learning algorithms such as the Random Forest (RF) classifier (Breiman, 2001) could fulfill the requirements in remote sensing community (Belgiu and Drăguţ, 2016; Schneider, 2012; Shih et al., 2015; Yan and Roy, 2015; Zhu and Woodcock, 2014b). Training data are often needed in machine learning algorithms (Schneider, 2012; Shih et al., 2015). However, the generation of training samples is a time intensive, expensive and subjective task (Ghimire et al., 2012). Land cover mapping of large areas with medium-resolution imagery is often constrained by the lack of good training and validation data (Knorn et al., 2009). It is therefore important to find out solutions in order to generate reliable training samples efficiently and objectively.

The objectives of this study are three-folds: 1) to examine the capability of the CCVS rice mapping methods on relatively cloud-free Landsat 8 Operational Land Imager (OLI) images with temporal gap of 16 days; 2) to evaluate the influences and uncertainty of cloud cover with different frequency on the spectral separability of the CCVS method; 3) to develop an automatic and Adaptive paddy Rice Mapping Method (ARMM) which could relief the challenges introduced by limited data availability particularly the cloud contaminations and offer a flexible resolution strategy through incorporating regions with sufficient good observations. The adaptive paddy rice mapping algorithm and its applications in Northeast China were illustrated in the following sections.

2. Study area and data source

2.1. Study area

We choose a pilot study area at the border of Heilongjiang and Jilin provinces (Landsat: Path/row: 118/028) (Fig. 1). The study area is located between 47°05′10.44″–44°58′3.81″N, 128°04′0.27″–124°50′35.24″E, covering four municipalities (Harbin, Suihua, and Daqing in Heilongjiang province and Songyuan in Jinlin province). It is a part of the Songnen plain (Fig. 1), an alluvial plain formed by Songhua River and Nen River. The Songhua River wandered through in the middle, accompanied with the Tongken River in the north and A'shi River in the south (Fig. 1). As part of the Northeast plain, the Songnen plain is one of the major grain producing areas in China. The average annual precipitation is approximately 550 mm, primarily in July and August. The mean annual temperature is around 4 °C, with the lowest temperature occurring in January at around −18.5 °C, and the highest temperature in July at 23.3 °C. The elevation is within 100–375 m. Cropland is the main land cover in the study area with reference to the GlobelLand30 in 2010 (Fig. 1) (Chen et al., 2015). It is primarily cultivated with paddy rice, maize, bean and some vegetables (e.g. *Capiscum annuum*). There is only one crop per year due to temperature limit.

2.2. Datasets

All available Landsat 8 Operational Land Imager (OLI) images (23 images) for the study area (Path/row: 118/028) in 2015 were downloaded from the USGS Earth Explorer data portal (http://earthexplorer.usgs.gov/). Each image was atmospherically corrected to surface reflectance using the Provisional Landsat 8 Surface Reflectance Code (LaSRC) (Vermote et al., 2016). And cloud cover and cloud shadow for each Landsat image were identified through the following two procedures (Zhu and Woodcock, 2014a): the first step is based on a single-date algorithm called Fmask (Function of mask) that initially screens most of the clouds, cloud shadows, and snow; the second step benefits from the extra temporal information from the remaining"clear" pixels and further improves the cloud, cloud shadow, and snow mask. Ten images acquired on day of year (DOY) 7, 23, 55, 103, 167, 199, 247, 263,