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A sub-pixel method for estimating planting fraction of paddy rice in Northeast China

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ABSTRACT

Timely and accurate data regarding the distribution of paddy rice are valuable for various agricultural studies. In this study, we aimed to develop a sub-pixel method for estimating the planting fraction of paddy rice in Northeast China. This method assumes low seasonal variations in moisture in paddy rice fields compared with other upland crops due to the presence of flooding water throughout the growing season. We used the coefficient of variation (CV) of the land surface water index (LSWI) derived from the moderate resolution imaging spectroradiometer (MODIS) to indicate the water condition. High resolution images obtained by an unmanned aerial vehicle (UAV) were used to test this assumption and to develop the relationship between the CV of LSWI and the planting fraction of paddy rice. The results showed that the CV of LSWI could effectively indicate the planting fraction of paddy rice, where our method explained 84% of the variation in the planting fraction of paddy rice in the UAV survey sites. Validation based on the statistical data showed that this method explained 78% and 85% of the variations in the paddy rice area at the county and prefecture levels, respectively. Moreover, the performance of this method was good independent of the field survey data, and this alternative approach may facilitate mapping of the planting distribution of paddy rice over large areas.

1. Introduction

Paddy rice is one of the most important crop types throughout the world, where it accounts for > 12% of the global cropland area (FAO, 2010). Therefore, the geographic locations of paddy rice fields are important information for scientific studies, and especially for evaluating food security, monitoring water resources, and quantifying greenhouse gas emissions (Dong and Xiao, 2016). Paddy rice feeds nearly half of the world's population as a staple food (FAO, 2010) and the yield of rice greatly impacts food security. Most paddy rice requires irrigation and it consumes 24–30% of the world's developed fresh water resources (Bouman et al., 2007). Thus, accurate paddy rice mapping could be beneficial for protecting global water resources. In addition, paddy rice fields are important sources of methane (CH_4 is the second most important greenhouse gas) emissions because they are waterlogged environments (Tian et al., 2016). The global CH_4 emissions from paddies account for approximately 11% of the total CH_4 emissions (Montzka et al., 2011). During the past two decades, the planting practices for paddy rice have changed substantially in terms of the planting locations and intensity due to the effects of the market and policy changes (Qiu et al., 2016; Dong et al., 2016b).

It has been demonstrated that satellite remote sensing data including optical or synthetic aperture radar (SAR) images can be effective tools for estimating crop areas and yields (Mccloy et al., 1987; Turner and Congalton, 1998; Shao et al., 2001; Xiao et al., 2002; Yuan et al., 2016b). Many studies have used series of multi-spectral data (moderate resolution imaging spectroradiometer (MODIS), Landsat, NOAA-AVHRR, SPOT, and Chinese HJ-1A/B) to map paddy rice at regional and national scales (Singh et al., 2006; Nguyen et al., 2012; Wang et al., 2015; Clauss et al., 2016; Dong et al., 2016a). Weather-independent SAR data have also been used due to the effects of clouds and solar illumination on optical data (Chen et al., 2007; Bouvet and Toan, 2011; Rossi and Erten, 2015). However, SAR data have not been employed widely at a large scale because of their low temporal resolution and the limited availability of data (Bouvet and Toan, 2011; Dong and Xiao, 2016). Previously, MODIS time series data have proved the most effective for mapping paddy rice at large scales (Thenkabail, 2011; Bridhikitti and Overcamp, 2012; Clauss et al., 2016).

Numerous efforts have been made to discriminate paddy rice areas using various types of data and methods. Compared with natural

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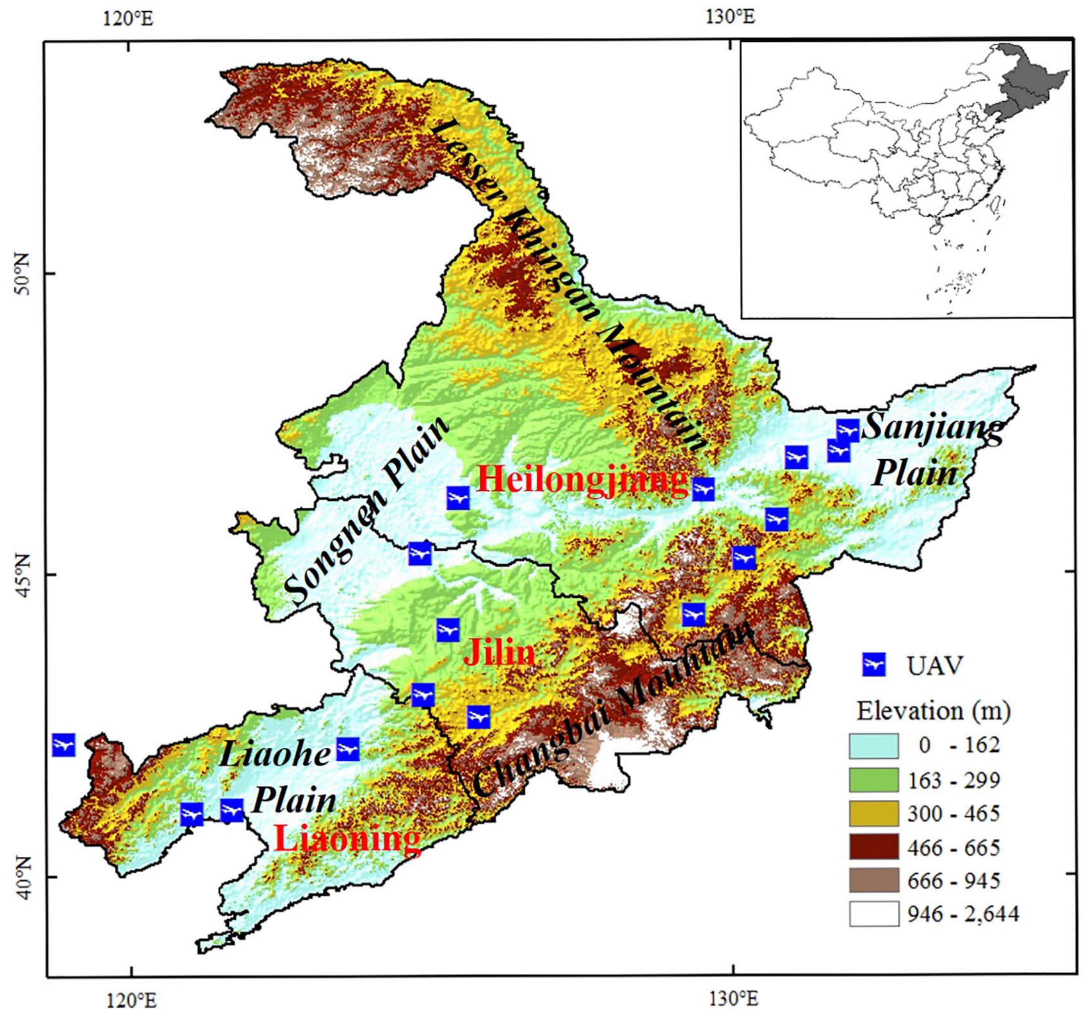

Fig. 1. Digital elevation model (DEM) of northeast China. UAV stands for the sites where aerial images were taken by unmanned aerial vehicle (UAV). The study area covers three provinces of Heilongjiang, Jilin, and Liaoning in Northeast China.

vegetation, paddy rice exhibits unique phenology and developmental stages due to crop management strategies (such as cropping system and water and fertilizer management) (Kuenzer and Knauer, 2013). In order to map paddy rice, early studies analyzed the band reflectance with traditional supervised and unsupervised classifiers, especially the maximum likelihood classifier (Mccloy et al., 1987; Fang, 1998). However, the rice growth calendar varies in different regions. Thus, studies that use reflectance with a specific time window have limited applications at large scales (Panigrahy and Parihar, 1992; Tennakoon et al., 1992). Other methods have been developed using multi-temporal images and vegetation indexes (VIs) (Wang, 2009; Nuarsa et al., 2012; Gumma et al., 2014). For example, Chen et al. (2011b) obtained a paddy rice map for southern China by recognizing temporal changes in normalized difference vegetation index (NDVI) data for rice fields using 30-m HJ-1A/B images acquired between January and July. A paddy rice map of continental China was also established with a support vector machine using time series of MODIS products (Clauss et al., 2016). In recent years, several phenology-based methods have been developed using multiple VIs (i.e., NDVI, enhanced vegetation index (EVI), and land surface water index (LSWI)) by depicting the transplanting characteristics of paddy rice (Xiao et al., 2002; Peng et al., 2011; Bridhikitti and Overcamp, 2012; Dong et al., 2015). Xiao et al. (2002) identified paddy rice based mainly on the relationship between the NDVI (EVI) and LSWI during the transplanting period when the LSWI values are temporarily greater than those of the NDVI or EVI. In addition to this transplanting-based approach, Qiu et al. (2015) used the "ratio of change amplitude of LSWI to EVI2" (RCLE) between the tillering and heading phases as an indicator in order to map paddy rice. Compared with other crops, paddy rice exhibits relatively smaller variations in the LSWI, thereby yielding lower RCLE values. These methods have improved the capacity to identify the distributions of paddy rice but they do not consider mixed pixels containing paddy rice and other land cover types, which is pervasive in many parts of South and Southeast Asia because of the large population and small plot sizes for planting crops.

Considering the geographical heterogeneity of crop fields, a number of methods have been developed to address the sub-pixel issue. In particular, linear mixed models (LMM) have been used widely (Settle and Drake, 1993; Roberts et al., 1998; Shimazaki, 2004), which assume that the reflectance of a pixel is a linear combination of endmember reflectance. Garcia-haro et al. (1996) used spectral mixture analysis and found a significant correlation between the vegetation fraction and spectral reflectance in a laboratory experiment. Gitelson et al. (2002) developed a novel Visible Atmospherically Resistant Index to estimate vegetation fraction effectively. Uchida (2010) employed the seasonal NDVI in a LMM for sub-pixel classification of agricultural crops. A LMM was also used to effectively estimate changes in the rice cropping intensity in the Mekong delta in Vietnam (Chen et al., 2011a). Several nonlinear mixed models (Liu and Wu, 2005) and other unmixing techniques have been proposed, including neural networks (Liu et al., 2004), fuzzy classifiers (Foody, 1996), and Gaussian mixture discriminant analysis (Ju et al., 2003). These methods predict sub-pixel