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Predicting grain yield in rice using multi-temporal vegetation indices from UAV-based multispectral and digital imagery

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ABSTRACT

Timely and non-destructive assessment of crop yield is an essential part of agricultural remote sensing (RS). The development of unmanned aerial vehicles (UAVs) has provided a novel approach for RS, and makes it possible to acquire high spatio-temporal resolution imagery on a regional scale. In this study, the rice grain yield was predicted with single stage vegetation indices (VIs) and multi-temporal VIs derived from the multispectral (MS) and digital images. The results showed that the booting stage was identified as the optimal stage for grain yield prediction with VIs at a single stage for both digital image and MS image. And corresponding optimal color index was VARI with R^2 value of 0.71 (Log relationship). While the optimal vegetation index $NDVI_{[800,720]}$ based on MS images showed a linear relationship with the grain yield and gained a higher R^2 value (0.75) than color index did. The multi-temporal VIs showed a higher correlation with grain yield than the single stage VIs did. And the VIs at two random growth stage with the multiple linear regression function [MLR(VI)] performed best. The highest correlation coefficient were 0.76 with MLR($NDVI_{[800,720]}$) at the booting and heading stages (for the MS image) and 0.73 with MLR(VARI) at the jointing and booting stages (for the digital image). In addition, the VIs that showed a high correlation with LAI performed well for yield prediction, and the VIs composed of red edge band (720 nm) and near infrared band (800 nm) were found to be more effective in predicting yield and LAI at high level. In conclusion, this study has demonstrated that both MS and digital sensors mounted on the UAV are reliable platforms for rice growth and grain yield estimation, and determined the best period and optimal VIs for rice grain yield prediction.

1. Introduction

Yield in grain crops is one of the most important issues related to national food security and personal living standards (Wang et al., 2014). Timely and accurate crop yield forecasts prior to harvest enable planners to make national food policy more reasonable (Noureldin et al., 2013). Traditionally, crop yield prediction has relied on ground-based field surveys, which are costly and prone to poor crop assessment (Reynolds et al., 2000). Therefore, developing a low-cost, rapid, and accurate method for grain yield prediction at a regional scale is a vital goal for crop production (Panda et al., 2010).

Remote sensing (RS) technology is an effective means to monitor crop growth parameters such as biomass (Fu et al., 2014), leaf area index (LAI) (Haboudane et al., 2004; Verger et al., 2014; Liang et al., 2015), and chlorophyll content (Haboudane et al., 2002), which can be estimated accurately with the vegetation indices (VIs). A series of studies have addressed crop yield prediction (Moran et al., 1997). Tucker et al. (1980) showed that there is a linear relationship between the normalized difference vegetation index (NDVI) and grain yield in wheat. Wang et al. (2010) derived yield prediction models with canopy reflectance band ratios (NIR/RED, NIR/GRN) at booting stage from field measurements, and these models have successfully forecasted the large-area rice yield with the satellite images. The Becker-Reshef et al. (2010) forecasted the wheat yield in Kansas and Ukraine with time series NDVI data from the moderate resolution imaging spectroradiometer (MODIS). And multi-temple VIs were proposed to improve the yield prediction accuracy (Xue et al., 2007). Wang et al. (2014) predicted wheat yield with the accumulated VIs such as $\sum$NDVI(Nir,

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Green) and $\sum$RVI(Nir, Red) from jointing to the initial filling stage, and achieved a higher prediction accuracy than with VI at a single stage. While it is hard to acquire adequate data from the satellite, the accumulated VIs were the only form used. Another method for forecasting yield uses yield-related agronomic parameters that can be estimated from RS data. Researchers have estimated the absorbed photosynthetically active radiation (PAR) and LAI from RS data and used it to predict yield (Pradhan et al., 2014; Sibley et al., 2014).

Satellite images from Landsat, SPOT5, and Quickbird with high spatial resolution of 30 m, 10 m, and 3 m overcame the disadvantage of small survey regions and showed a high level of accuracy for crop yield prediction (Hamar et al., 1996; Yang et al., 2006, 2009). However, in the south China, the small plots, complex terrain, and cloudy cover during the rice growth stages and high cost are greatly limit the application of satellite imagery. The recent technological advancements in unmanned aerial vehicles (UAV), and the miniaturization of sensors has field the current explosion of their application to precision agriculture. Based on UAV system, high spatio-temporal resolution remotely sensed data can be acquired for crop monitoring in a low-cost and more practical way (Zhang and Kovacs, 2012; Verger et al., 2014).

Several sensors have been installed on UAVs for crop growth monitoring and plant cover, disease detection (Córcoles et al., 2013; Garcia-Ruiz et al., 2013; Hunt et al., 2005). Multispectral (MS) and hyperspectral (HS) cameras have been widely used to monitor plant growth and biochemical indicators for many options of vegetation indices (Li et al., 2012; Zarco-Tejada et al., 2012; Verger et al., 2014). Zarco-Tejada et al. (2013) combined R_{515}/R_{570} and TCARI/OSAVI narrow-band indices for the leaf carotenoid estimation with a hyperspectral camera onboard UAV. And Stagakis et al. (2012) have successfully estimated the water stress for citrus orchard with PRI_{515} and PRI_{570} from MS image. The digital camera has also been widely used for its high spatial resolution and low price (Córcoles et al., 2013). Classification of the RGB image acquired from digital camera have been a powerful tool for plant cover detection (Córcoles et al., 2013). In addition, A large number of studies have derived the color index from digital images for crop growth monitoring (Hunt et al., 2005). Torres-Sánchez et al. (2014) used the color index such as Excess green (ExG), Vegetative (VEG) calculated from the RGB images for vegetation fraction mapping, and achieved good accuracy with the value ranging from 89.33% to 91.99%. Jannoura et al. (2015) reported that normalized Green-Red difference index (NGRDI) derived from the RGB image was positively and significantly correlated with the aboveground biomass of peas and oats with R^2 ranging from 0.58 to 0.78.

UAV platform can provide high spatio-temporal resolution images for agricultural RS, and some of exploratory researches have conducted for yield prediction. Swain et al. (2010) proved that NDVI at panicle initiation stage calculated from the UAVs was highly correlated with rice yield and Teoh et al. (2016) also successfully estimated the yield with the NDVI and band R, G. But in these studies, the limited datasets were acquired at one single stage, and the model was developed based on NDVI which easily saturated when the canopy is dense (Liang, 2004). Some studies also tried to predict crop yield with the plant height. Crop surface models (CSMs) have been developed for crop height determination based on the digital images (Bendig et al., 2014, 2015; Geipel et al., 2014). However, the crop yield–height relationship usually varies with rice cultivars under different crop growth status. In addition, fewer studies focused on estimating crop yield with the color index derived from the UAVs. VIs derived from multispectral images and digital images showed sensitivities to crop growth status and canopy structure. The performance and potential of these VIs for crop yield prediction should be further tested. LAI is an important parameter that indicates crop photosynthesis and growth status and is of significance for crop yield prediction (Noureldin et al., 2013; Verger et al., 2014). A systematic analysis for the similarity between the yield and LAI estimation is essential for the yield prediction. Therefore, in this study, MS images and digital images at critical growth stages were acquired and VIs were correlated to the grain yield and LAI to (1) determine the best period and optimal VIs for rice grain yield prediction; (2) assess the potential of multi-temporal VIs for grain yield prediction based on UAV images.

2. Material and methods

2.1. Experimental design

The study was conducted at the experiment station of the National Engineering and Technology Center for Information Agriculture (NETCIA), which is located in Rugao city, Jiangsu province, China (120°45′E, 32°16′N). The predominant soil type is loam and the organic carbon concentration in the soil is 12.95 $g \cdot kg^{-1}$. The annual average temperature, number of precipitation days, and precipitation are 14.6 °C, 121.3, and 1055.5 mm, respectively. Two field-plot experiments involving different rice (*Oryza sativa L.*) cultivars, nitrogen application rates, planting densities were designed for this study, as summarized in Table 1. And three rice cultivars with different plant types were selected in this study including two *indica* rice cultivars: Y liangyou 1 (compact plant type with erect leaf), Liangyou 728 (semi-compact plant type) and one *japonica* rice cultivar: Wuyunjing 24 (loose plant type with inclined leaf).

Experiment 1 (Exp. 1): The experiment was conducted for a single season from June 2015 to November 2015. Two rice cultivars (Wuyunjing 24 and Y liangyou 1) were sown on 16 May and transplanted on 15 June with two planting densities. The plot areas were 30 m^2 (6 m length × 5 m width). Four N fertilization rates were applied in the form of urea at the rate of 40% at preplanting, 20% at tillering, 20% at jointing, and 20% at booting. In addition, 135 $kg \cdot ha^{-1}$ P_2O_5 as a phosphate fertilizer supplement and 190 $kg \cdot ha^{-1}$ K_2O as potash fertilizer were applied in all the experimental plots. Every treatment had three replications and a total of 36 plots (12 treatments) within a randomized complete block design were grown for the whole study.

Experiment 2 (Exp. 2): The experiment was conducted for a single season from June 2015 to November 2015. Two rice cultivars were sown on 16 May and transplanted on 15 June at three planting densities. The plot areas were 30 m^2 with 6 m length and 5 m width. Two N fertilization rates were applied in the form of urea at the rate of 40% at preplanting, 20% at tillering, 20% at jointing, and 20% at booting. Every treatment had three replications with a total of 36 plots (12 treatments) within a randomized complete block design grown for the whole study. Phosphate and potassium fertilizers were applied as described for Exp. 1.

In these experiments, N levels were determined based on the growth status of rice and the weather conditions during various growth stages. Management practices during the experiment were based on local production standards.

2.2. Field data collection

Repeated destructive sampling was carried out in each plot for Exp. 1 and Exp. 2. After the UAV flight, three hills from each experimental plot were randomly selected to determine LAI. For each sample, the green leaves were separated from the stems and immediately scanned using the Laser area meter (LI-3100C; LI-COR Inc., NE, USA). The leaf area was then obtained and the LAI for each plot was calculated based on the planting densities. At maturity, 30 hills from each plot were harvested manually for