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Hyperspectral canopy sensing of paddy rice aboveground biomass at different growth stages

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ABSTRACT

Normalized Difference Vegetation Index and Ratio Vegetation Index obtained with the fixed band GreenSeeker active multispectral canopy sensor (GS-NDVI and GS-RVI) have been commonly used to non-destructively estimate crop growth parameters and support precision crop management, but their performance has been influenced by soil and/or water backgrounds at early crop growth stages and saturation effects at moderate to high biomass conditions. Our objective is to improve estimation of rice (*Oryza sativa* L.) aboveground biomass (AGB) with hyperspectral canopy sensing by identifying more optimal measurements using one or more strategies: (a) soil adjusted Vegetation Indices (VIs); (b) optimized narrow band RVI and NDVI; and (c) Optimum Multiple Narrow Band Reflectance (OMNBR) models based on raw reflectance, and its first and second derivatives (FDR and SDR).

Six rice nitrogen (N) rate experiments were conducted in Jiansanjiang, Heilongjiang province of Northeast China from 2007 to 2009 to create different biomass conditions. Hyperspectral field data and AGB samples were collected at four growth stages from tillering through heading from both experimental and farmers' fields. The results indicate that six-band OMNBR models (R^2 = 0.44–0.73) explained 21–35% more AGB variability relative to the best performing fixed band RVI or NDVI at different growth stages. The FDR-based 6-band OMNBR models explained 4%, 6% and 8% more variability of AGB than raw reflectance-based 6-band OMNBR models at the stem elongation (R^2 = 0.77), booting (R^2 = 0.50), and heading stages (R^2 = 0.57), respectively. The SDR-based 6-band OMNBR models made no further improvements, except for the stem elongation stage. Optimized RVI and NDVI for each growth stage (R^2 = 0.34–0.69) explained 18–26% more variability in AGB than the best performing fixed band RVI or NDVI. The FDR- and SDR-based optimized VIs made no further improvements. These results were consistent across different sites and years. It is concluded that with suitable band combinations, optimized narrow band RVI or NDVI could significantly improve estimation of rice AGB at different growth stages, without the need of derivative analysis. Six-band OMNBR models can further improve the estimation of AGB over optimized 2-band VIs, with the best performance using SDR at the stem elongation stage and FDR at other growth stages.

1. Introduction

Rice (*Oryza sativa* L.) is a major staple cereal crop, providing food for more than half of the world's population (Cantrell and Reeves, 2002; Normile, 2008). Precision management of rice for high yield and high resource use efficiency is crucially important for global food security and sustainable development (Zhao et al., 2013). Information on aboveground biomass (AGB) is needed for calculating critical nitrogen (N) concentrations, which are important for in-season assessment of crop N status (Lemaire et al., 2008). It is also an important indicator of crop population, growth and gross primary production (Patel et al., 1985; Harrell et al., 2011; Peng and Gitelson, 2011). Traditional sampling methods are based on taking physical samples from the paddy fields, an approach that is time consuming, labor intensive, and results in destroying parts of the crop. Non-destructive or non-intrusive methods using digital technologies can avoid these issues and provide more representative measurements, thus avoiding sampling bias.

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Crop canopy sensors have been commonly used in precision agriculture to non-destructively estimate agronomic parameters, including AGB (Heege et al., 2008; Samborski et al., 2009; Peng and Gitelson, 2011; Cao et al., 2012, 2013; Yao et al., 2012; Diacono et al., 2013). The GreenSeeker handheld sensor (Trimble Navigation Limited, Sunnyvale, CA, USA) is a widely adopted active crop canopy sensor with two fixed wavebands (660 ± 10 nm and 770 ± 15 nm) and produces two vegetation indices, Normalized Difference Vegetation Index (NDVI) and Ratio Vegetation Index (RVI). Li et al. (2010a) found GreenSeeker NDVI (GS-NDVI) correlated with biomass of winter wheat (*Triticum aestivum*) at Feekes stages 4–10, although correlations decreased with maturity because measurements became saturated when biomass reached 3746 kg ha^{-1}, while the GreenSeeker RVI (GS-RVI) did not show such saturation effect. For irrigated rice, the influence of a water background on crop canopy reflectance poses a unique challenge for estimating rice biophysical parameters using canopy remote sensing, especially at early growth stages when the vegetation cover is low (Martin and Heilman, 1986; Shikada and Miyakita, 1992; Van Niel and McVicar, 2004; Tubaña et al., 2011).

To reduce the influence of soil backgrounds on plant canopy reflectance, scientists have developed many soil-adjusted vegetation indices. The most widely used index is the Soil-Adjusted Vegetation Index (SAVI) by including a background adjustment factor L (Huete, 1988). Qi et al. (1994) developed a Modified SAVI (MSAVI) to account for soil background differences. Haboudane et al. (2004) proposed Modified Chlorophyll Absorption Ratio Index 2 (MCARI2) and Modified Triangular Vegetation Index 2 (MTVI2) to minimize the sensitivity of the indices to chlorophyll effects, maximize their responsiveness to green LAI variations, and make them more resistant to soil and atmosphere effects. Their results indicated that these two indices performed better than the existing VIs. Little has been reported on whether these VIs can: (a) reduce soil and water background influences on rice canopy reflectance at early growth stages, and (b) improve the performance of VIs for estimating rice AGB.

Derivative spectral analysis is another technique that can be used to reduce background signals (Demetriades-Shah et al., 1990; Becker et al., 2005). Seeing the spectral reflectance as a polynomial function of degree *d*, the first-derivative of reflectance (FDR) expresses the slope of this function in dependence on the wavelength. Thereby, the FDR eliminates the influence of all constant terms ($d = 0$) on that function. The spectral signal of soil or water surfaces can be considered as a linear function of wavelength. The FDR cannot completely remove background signals. With the second-derivative of reflectance (SDR), all linear influences ($d = 1$) are removed, if the second derivative was equal to zero (Demetriades-Shah et al., 1990). Hence, in theory the SDR should be useful in reducing the water and soil background influences. Additional advantage of derivative spectra is that the SDR is relatively insensitive to variation in illumination intensity caused by changes in cloud cover or sun angle (Tsai and Philpot, 1998). This is important for rice farming because clouds are common in rice growing regions, which limits the application of remote sensing technology in rice management. Derivative analyses of hyperspectral data have been found to be more useful in estimating plant N or pest information in rice than raw reflectance (Kobayashi et al., 2001; Liu et al., 2010; Zhang et al., 2011; Huang et al., 2012). Liu et al. (2010) demonstrated that FDR and SDR explained 5% and 9% more variability than raw reflectance in detecting rice disease, respectively. Derivative analyses appeared to be very effective for retrieving attributes of vegetation at canopy level (Imanishi et al., 2004).

One common approach to overcome the limitations of the fixed band VIs like NDVI is to identify the best narrow band combinations for different crop species or growth stages using correlograms (Thenkabail et al., 2000; Hansen and Schjoerring, 2003; Li et al., 2010b; Gnyp et al., 2013; Yu et al., 2013). Yu et al. (2013) found that RVI combinations (R_{730}, R_{808}; R_{752}, R_{840}; R_{774}, R_{780}) or NDVI (R_{774}, R_{780}; R_{750}, R_{840}) could explain more than 66% of rice plant N uptake variability. Gnyp et al. (2013) found that the optimized narrow band RVI or NDVI indices also explained similar percentages of rice AGB variability. Compared with multispectral crop sensors with limited fixed bands like GreenSeeker, hyperspectral canopy sensors capture much richer information about crop canopy characteristics with the continuous acquisition of reflectance at narrow wavelengths; therefore, they may improve crop growth parameter estimation results.

Most VIs use two or three bands, which unnecessarily constrains regression analysis (Lawrence and Ripple, 1998). Thenkabail et al. (2000) proposed Optimum Multiple Narrow Band Reflectance (OMNBR) model to use stepwise multiple linear regression (SMLR) to identify sensitive band combinations to estimate crop wet biomass and LAI. They found that 4-band OMNBR models could explain up to 92% of the crop biophysical parameter variability, but they were only marginally better than optimized narrow band NDVI type models. Yu et al. (2013) found that 6-band OMNBR models could significantly improve the accuracy of estimating rice leaf N concentration and plant N concentration relative to optimized narrow band NDVI or RVI. For such models, 4–6 bands are generally used, because when the ratio (M/N) of the number of independent variables or narrow bands (M) to that of total number of field samples (N) is higher than 0.15–0.20, over-fitting can become a serious problem.

So far, little research has been conducted to evaluate how much soil adjusted vegetation indices, optimized narrow band vegetation indices, OMNBR and derivative spectral analyses can improve the estimation of rice AGB at different growth stages compared to the fixed band NDVI and RVI. Therefore, the objectives of this study were to determine: (1) if and how much published soil adjusted VIs, optimized narrow band VIs (RVI and NDVI) and OMNBR models can improve rice AGB estimation using canopy hyperspectral reflectance data as compared with the fixed band VIs at different growth stages, and (2) if derivative spectra (FDR and SDR) can further improve the above-mentioned methods for estimating rice AGB. Achieving both these objectives meets our goal of improving the fixed band RVI and NDVI approaches for estimating rice AGB.

2. Materials and methods

2.1. Study site

The study was conducted in the Sanjiang Plain (47.2 N, 132.8 E), Heilongjiang Province, Northeast China. It is an alluvial plain derived from three rivers (Heilong, Songhua, and Wusuli) and covers about 109,000 km^2. Bordered by Siberia in the north and east, it is characterized by a sub-humid continental monsoon climate with a warm summer and cold winter. The mean annual temperature is about 2 °C and the mean precipitation amounts to 550 mm per year (Wang and Yang, 2001). About 70% of the precipitation occurs from June through September. The dominant soil type in this area is Albic soil, which is classified in the FAO-UNESCO system as mollic planosols and Typical Argialbolls in Soil Taxonomy (Xing et al., 1994). The upper layer of this soil is generally thin (10–25 cm) and low in soil nutrients. An albic layer below the surface layer is compact and impermeable (Yuan et al., 2006). We selected two sites for this study in Jiansanjiang. Site 1 has been planted in rice since 1992, and Site 2 was first planted in rice in 2002 (Fig. 1).