Using a UAV-based active canopy sensor to estimate rice nitrogen status

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Abstract. *Active canopy sensors have been widely used in the studies of crop nitrogen (N) estimation as its suitability for different environmental conditions. Unmanned aerial vehicle (UAV) is a low-cost remote sensing platform for its great flexibility compared to traditional ways of remote sensing. UAV-based active canopy sensor is expected to take the advantages of both sides. The objective of this study is to determine whether UAV-based active canopy sensor has potential for monitoring rice N status, and to identify suitable models for practical use. Two field experiments were conducted with different N rates and varieties in 2016 and 2017. Plant sampling and sensing data collection were carried out at each key growth stage. Handheld sensing was conducted using a portable active canopy sensor RapidSCAN CS-45 with red, red edge and near infrared wavebands in all experiments for building prediction models. In the experiment of 2017, the sensor was mounted on a gimbal under a multi-rotor UAV to collect UAV-based data for validation. The results showed great potential of UAV-based active canopy sensor on rice leaf N status monitoring based on linear regression models, and red edge ratio vegetation index(RERVI) has good performance for predicting leaf dry matter (R^2 = 0.76), leaf area index (R^2 = 0.77) and leaf nitrogen accumulation (R^2 = 0.79). UAV-based sensing with 1.5 m height above rice canopy is suitable for practical use. For better estimation, research on better prediction models and widely-feasible operational mode are needed in the future study.*

Keywords. *UAV, active canopy sensor, nitrogen status, rice.*

Introduction

Because of the suitability for different environmental conditions, active optical canopy sensors have been widely used in the studies of crop nitrogen estimation. Unmanned aerial vehicle(UAV) is a low-cost remote sensing platform which has great flexibility and mobility. Accordingly, the system of UAV-based active sensor is expected to take the advantages of both sides, and it also has convenience in data processing compared to image-based sensing of UAV.

Little is known about the performance of active canopy sensor mounted on UAV for estimating rice leaf N status. The objective of this study is to determine whether UAV-based active canopy sensor has potential for monitoring rice N status, and to identify suitable models for practical use.

Materials and Methods

Two experiments were conducted during rice season of 2016-2017 in two experimental stations of Nanjing Agricultural University in Jiangsu Province. Exp. 1 (2016) was conducted in Sihong (33.37°N and 118.26°E) which covered four N rates (0, 120, 240, 360kg N ha^{-1}) and three rice varieties. Exp. 2 (2017) was conducted in Lianyungang (34.56°N and 119.32°E) which covered four N rates (0, 135, 270, 405 kg N ha^{-1}), two transplanting ways and three rice varieties. All field experiments were replicated three times in a randomized complete block design.

The sensor used in this study is RapidSCAN CS-45, an active optical crop canopy sensor with red (670nm), red-edge (730nm), and near infrared (780nm) wavebands. For UAV-based sensing, the sensor was mounted on a gimbal in a fixed gesture under a multi-rotor UAV (DJI Spreading Wings S1000+ with D-RTK GNSS system); sensing data was collected according to the preconcerted flight path along the central axis in row direction of each plot with flight height of 1.5 m and 2 m above canopy respectively (**Fig 1**). For handheld sensing, data was collected along the same path of the UAV-based sensing. The average reflectance values were computed to represent each plot. Plant sampling and sensing data collection (handheld data in Exp. 1 and Exp. 2 for calibration, UAV-based data in Exp. 2 for validation) were conducted at key growth stages.

Fig 1. Overview of the UAV-based sensing system used in this study.

The vegetation indices (VIs) used in this study were NDRE, RERVI, NDVI and RVI. Linear regression models were built between VIs and leaf dry matter (LDM), leaf area index (LAI) and leaf nitrogen accumulation (LNA) across all stages. the coefficients of determination (R^2) was used to show the prediction performance of models. In addition to R^2, relative root mean square (RRMSE) and relative error (RE) were used to evaluate the validation results based on UAV-based data.

Results

Leaf N-status indicators (LDM, LAI and LNA) of rice varied greatly across different N rate treatments, management practices, rice varieties, growth stages, sites and years, and the large variability of these parameters was supposed to cover major possible situation (**Table 1**).

Table 1. Descriptive statistics of LDM, LAI, LNA across all growth stages, varieties, sites and years in this study.

Parameters	N	Min	Max	Mean	SD	CV
Calibration dataset (Handheld)						
LDM (kg ha^{-1})	624	51.93	5313.40	1991.17	1187.40	59.63%
LAI	624	0.13	10.34	3.60	2.19	60.84%
LNA (kg ha^{-1})	624	0.96	192.61	58.57	43.29	73.92%
Validation dataset (UAV-based)						
LDM (kg ha^{-1})	192	1238.73	5313.40	2906.11	895.18	30.80%
LAI	192	2.25	10.34	5.54	1.74	31.40%

LNA (kg ha^{-1})	192	41.75	187.36	97.81	35.50	36.29%

The regression models between N-status indicators and vegetation indices were built using handheld data from Exp. 1 and Exp. 2, and the relationships were showed by R^2 in **Fig 2**. RERVI performed best for these three leaf N-status indicators, and 76% of LDM (LDM = 2721.21 * RERVI - 3190.51, kg ha^{-1}), 77% of LAI (LAI = 5.05 * RERVI - 6.02) and 79% of LNA (LNA = 101.20 * RERVI - 134.13, kg ha^{-1}) could be predicted.

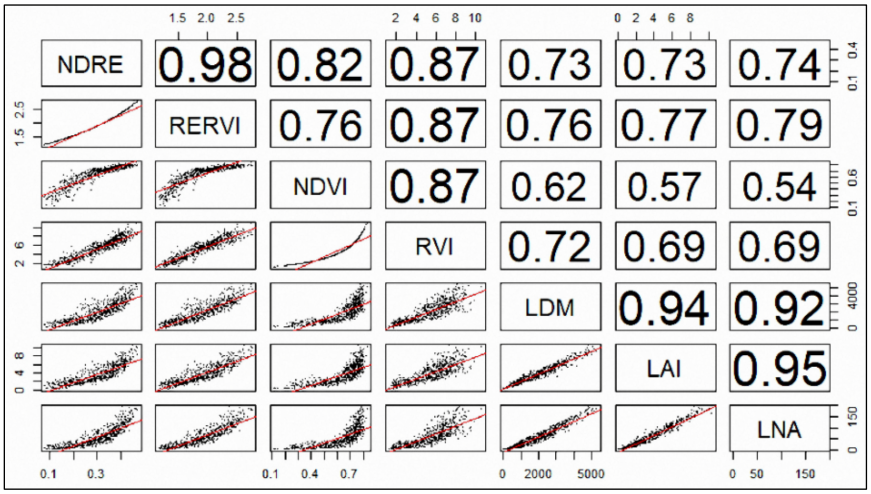

Fig 2. Coefficients of determination (R^2) and scatter diagrams for the relationship between each VI (NDRE, RERVI, NDVI and RVI from handheld sensing data) and rice LDM, LAI and LNA across all stages of rice growth.

As the validation results based on UAV-based data shown in **Table 2**, VIs calculated from 1.5 m UAV-based data perform better than the VIs from 2 m sensing data, and this showed more stability of UAV-based sensing with height of 1.5 m. Considering RRMSE and RE of each model, RERVI performed best in validation for LDM, LAI and LNA (**Fig 3**).

Table 2. Validation results of the regression models for estimating LDM, LAI and LNA based on UAV-based sensing data.

VI	LDM			LAI			LNA		
	R^2	RRMSE	RE	R^2	RRMSE	RE	R^2	RRMSE	RE
Validation data: UAV-1.5 m									
NDRE	0.71	19.6%	22.3%	0.64	21.8%	22.9%	0.67	25.1%	25.3%
RERVI	0.73	17.1%	20.1%	0.66	19.2%	20.8%	0.69	21.6%	23.1%
NDVI	0.42	25.7%	24.9%	0.39	28.9%	26.2%	0.4	34.1%	29.3%
RVI	0.51	23.9%	25.1%	0.48	24.7%	25.4%	0.48	28.3%	29.4%
Validation data: UAV-2 m									
NDRE	0.44	24.1%	28.8%	0.35	25.8%	30.6%	0.37	29.6%	34.0%
RERVI	0.45	23.8%	28.7%	0.35	25.3%	30.9%	0.38	28.6%	34.9%
NDVI	0.3	28.1%	25.9%	0.24	31.5%	28.8%	0.29	36.5%	29.8%
RVI	0.31	26.7%	26.6%	0.25	29.4%	29.8%	0.3	32.7%	30.0%

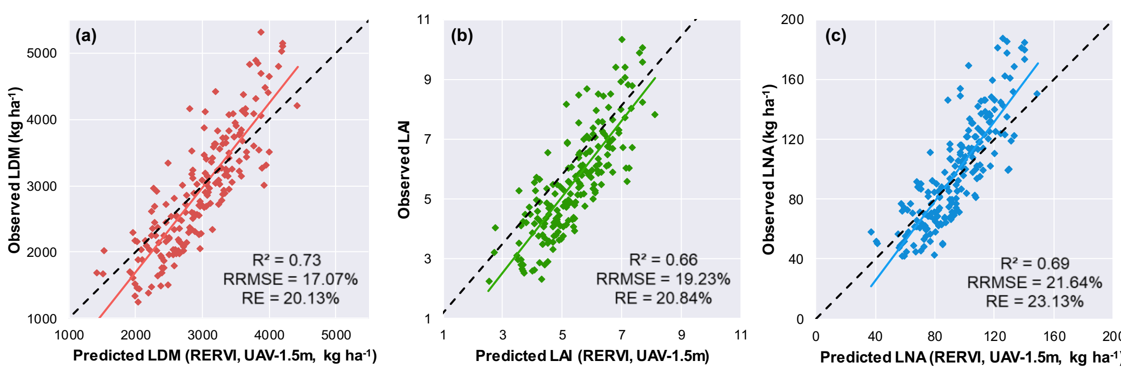

Fig 3. Validation results of LDM (a), LAI (b) and LNA (c) for best predictions (using linear regression models derived from handheld data and determined by the lowest RE) based on UAV-based (1.5 m flight height above canopy) sensing data.

Conclusion

UAV-based active canopy sensor has great potential for monitoring N status of rice. RERVI and 1.5 m-height sensing showed great applicability for practical use. Research on better prediction models and widely-feasible operating mode for this system are needed in the future studies.