Sugarcane Nitrogen and Irrigation Level Prediction Based on UAV-Captured Multispectral Image at Elongating Stage

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Abstract

Introduction

Sugarcane is the main industrial crop for sugar production; its growth status is closely related to fertilizer, water, and light input. Unmanned aerial vehicle (UAV) based multispectral imagery is widely used for high-throughput phenotyping because it can rapidly predict crop vigor. This paper mainly studied the potential of multispectral images obtained by low altitude UAV systems in predicting canopy nitrogen content and irrigation level for sugarcane.

Methods

The experiment was carried out on sugarcane filed with three irrigation levels and five nitrogen levels. A multispectral image at the height of 40 m during the elongating stage was acquired, and the canopy nitrogen content was determined as ground truth. Nitrogen prediction models, including partial least square (PLS), BP artificial neural network (BPNN), and extreme learning machine (ELM), were established based on different variables. Support vector machine was used to recognize the irrigation level.

Results

The PLS model based on band reflectance and five vegetation indices had better accuracy (R=0.7693, RMSE=0.1109) than BPNN and ELM. Some spectral information from the multispectral image had obvious different features among different irrigation levels, and the SVM algorithm was used for irrigation level classification. The classification accuracy reached 77.8%.

Conclusion

The low altitude multispectral image could provide effective information for nitrogen prediction and water irrigation level recognition.

Keywords: Sugarcane, Multispectral image, Nitrogen prediction, Irrigation classification, UAV

0 Introduction

As the most important sugar crop, sugarcane provides about 80% of the world's sugar and mainly plants in tropical and subtropical areas. The growth of sugarcane is closely related

to fertilizer, water, and radiation intensity. Evaluating the growth situation of sugarcane in time and adjusting the field management accordingly is of great significance to the yield and quality of sugarcane. In recent years, remote sensing of different scales with spectral images have been considered as an effective high-throughput phenotyping solution and have been widely used to predict the growth potential or yield of different crops.

Most of the earliest spectral images were obtained from satellite-based acquisition platforms, normally provided by governments or commercial companies, such as Sentinel [1], GF [2], Landsat [3,4], GeoEye [5], QuickBird [6], etc. Their main agriculture applications included Land Cover and Land Use, vegetation classification, yield prediction, growth prediction, etc. However, although satellite remote sensing can obtain crop population information on a huge scale, due to the limitations of low spatial resolution and fixed revisit cycle, it has formidable deficiencies for small scale applications, which usually need more subtle information or higher temporal resolution for crop growth monitoring [7].

In the early 21st century, many well-funded research institutions began to use aviation aircraft to carry multispectral or even hyperspectral cameras at an altitude of several to tens of kilometers to acquire spectral images and conducted many agricultural research and applications [8,9]. However, it was difficult to popularize due to its relatively high cost.

With the rapid development of the unmanned aerial vehicle (UAV) technology, the increasing availability and decreasing cost of spectral image sensors, there are more and more friendly opportunities for capturing high spatial resolution and high spectral resolution spectral image data. UAV-based remote sensing systems have a much higher ground resolution (centimeter-level), which means more sensitive to spatial heterogeneous information due to their lower flying altitude. In recent 10 years, UAVs, especially drones, are rapidly accepted and popularized to acquire reliable filed crop growth information as long as weather permits. It can make up for traditional crop monitoring equipment problems, such as small scope and great difficulty, and has a good application value. Multispectral imaging technology has been carried out on crop quality detection due to its advantages of fewer spectral bands, short information acquisition time, simple data structure, etc [10].

A large number of previous studies have shown that the biomass of rice 11, corn [12], barley [13], and wheat [14] could be reliably predicted by using multispectral and RGB images obtained by drones. Canopy spectral information was effective (R^2=0.7939) to estimate the grain protein content of winter wheat [15]. Ballester et al. evaluated the effectiveness of a set of spectral indicators obtained from UAV in tracking temporal and spatial variations in nitrogen (N) states and predicting commercial cotton field yields [16]. The hyperspectral techniques were used to detect crop diseases [17] and to estimate nitrogen concentration in canopy leaves [18].

Similar studies have also been conducted in recent years for sugarcane [19]. Some researchers used satellite imagery [20,21]21 and UAV hyperspectral imagery[22,23] to predict sugarcane biomass and achieved varying degrees of success. However, no reports have been published on nitrogen and irrigation level prediction based on UAV imagery for sugarcane.

Partial least square (PLS), BP neural network (BPNN), and extreme learning machine (ELM) have been widely used in nutrients predictions. For example, Mahanti et al. [24] used PLS to predict the nitrate content of spinach, and Li et al. [25] used PLS to establish

12 models of fruits and seeds for rapid analysis and quality assessment. Kira et al. [26] established a model for estimating chlorophyll and carotenoid content of three tree varieties based on BPNN. Chen et al. [27] construct a BP neural network model to invert rice pigment content with several spectral parameters as input. Pal et al. [28] proposed the ELM algorithm to fulfill the land cover classification with multispectral and hyperspectral data; it achieved better classification accuracy than BPNN and support vector machine, with far less computation complexity.

Therefore, in this study, high-resolution multispectral images of an experimental sugarcane field were obtained by low-altitude flying UAV, and prediction methods of sugarcane canopy nitrogen content were compared and evaluated by PLS, BPNN, and ELM. Also, different irrigation levels were preliminarily identified and classified by using the multispectral images.

1 Material and methods

1.1 Experiment design and image acquisition

The sugarcane experimental field was located in Nanning, Guangxi Autonomous Region, China (Longitude 108.33° E, Latitude 22.84° N). Two irrigation treatments and four fertilization treatments were set in the field. Urea, calcium magnesium phosphate, and potassium chloride were chosen as the N, P, K fertilizers. Eight plots with different irrigations and fertilizers and four blank plots (denoted by BL, without fertilizer, and drip irrigation) were included in the field. Concrete partitions were built between each plot, with a depth of 1.2m, to prevent water and fertilizer infiltration. The two irrigation treatments included 180 m^3/ha (denoted by W0.6) and 300 m^3/ha (denoted by W1.0). Four fertilizer treatments were: F1.0: 250 kg/ha of N, 150 kg/ha of P_2O_5, 200 kg/ha of K_2O; F0.9: 10% reduction in the amount of F1.0; F1.1: 10% increase over F1.0; F1.2: 20% increase over F1.0. The water and fertilizer were applied by drip irrigation pipes. Micronutrient fertilizer was applied for all the plots with the same amount except the blanks. The eight plots had same size of 6.6m×5.6m, with different treatments denoted by W0.6F0.9, W0.6F1.0, W0.6F1.1, W0.6F1.2, W1.0F0.9, W1.0F1.0, W1.0F1.1 and W1.0F1.2, respectively. The seed canes were planted on March 24, 2018, seedling fertilizer was applied on May 11 (48 days after planting), tillering fertilizer was applied on June 29 (97 days after planting).

The multispectral images were captured at noon on July 11, 2018 (109 days after planting), in the elongation stage. The image acquisition system was mainly composed of a drone modeled Phantom 4 Pro (DJI, China) and a multispectral image sensor modeled RedEdge-MX (MicaSense, USA), as shown in Fig 1A and 1B. RedEdge-MX has five spectral bands at 475nm, 560nm, 668nm, 717nm, and 840nm, and is equipped with a light intensity sensor and a fixed reflectivity correction panel (Group VIII, USA) for radiation correction. The optical intensity sensor could correct the change of external light's influence on the spectral image, and the fixed reflectance correction panel could perform reflectance transform. The weather was sunny and windless. The drone flew at an altitude of 40 m, with 85% forward and 85% side overlap. The time interval of image acquisition was 2 s, and the ground sample distance (GSD) was 2.667 cm. A total of 260 images were collected and mosaiced in Pix4DMapper (Pix4D, Switzerland). The false-color mosaic image was shown in Fig 2. Three to four first leaves were collected from adjacent stalks as one sample, and three random samples from each plot, 36 samples in total were collected for nitrogen

determination.

Fig 1. Image acquisition system consisted of a drone (A) and a multispectral sensor (B).

Fig 2. The false-color mosaic image of the sugarcane field and the plot distribution. BL means blank, W means water irrigation, F means fertilizer application.

1.2 Multispectral image preprocessing

The mosaic image was mainly processed in ENVI software (L3Harris Geospatial, USA). Radiation calibration was firstly implemented using the Radiometric Correction module. The atmospheric correction was conducted using the FLASH tool to eliminate the radiation errors caused by atmospheric scattering and other factors to a certain extent.

The NDVI image was calculated by simple band math. The decision tree (DT) algorithm was used to extract the sugarcane canopy from the soil, weeds, shadow, and other interfering factors. Fig 3 showed the extraction result, and the white dots in the figure represented the sample locations.

Fig 3. Sugarcane canopy extraction result based on NDVI. the white dots represent the sample locations.

1.3 Modeling algorithms

Partial Least Squares (PLS) is an algorithm that combined the advantages of multiple linear regression and canonical correlation analysis, and Principal Component Analysis, commonly used when the model input variables are large in number and multiple correlations. The model is settled at the minimum values of the sum of square error. Back Propagation Neural Network (BPNN), namely multi-layer feedforward Neural Network based on error inverse propagation algorithm, could theoretically approximate any nonlinear continuous function with arbitrary precision, which had a strong fitting ability for nonlinear functions and features of self-learning and self-adaptation. The neural network model had a strong anti-interference ability and may suitable for complex field environments. Extreme Learning Machine (ELM) algorithm allowed the random generation of the weights and threshold between the input layer and hidden layers; users only need to denote the number of hidden layer neurons in the whole training process. Compared with the traditional classification algorithms, ELM had a fast-learning speed and strong generalization capability.

2 Results and discussion

2.1 Nitrogen prediction based on multispectral image

The average spectral or vegetation index value of an area of 0.1m by 0.1m, with ground sample location as its center, was calculated as the counterpart to the ground sample to reduce random error.

2.1.1 Modeling directly from five spectral bands

The five multispectral image bands were first directly taken as the input variables, and the PLS, BPNN, and ELM algorithms were used to build canopy nitrogen content prediction models, respectively. Three-fold cross-validation was used to evaluate accuracy. The PLS model had a higher R-value and lower RMSE and SEP value in the validation set compared

to the ELM and BPNN model, indicating that it has relatively higher accuracy. ELM and BPNN model had an R-value of 1.000 and very low RMSE, showing dramatically better results than the validation set, indicating high overfitting possibility (Table 1).

Table 1. PLS, ELM, and BPNN modeling result based on the five spectral bands.

Modeling algorithms	Training			Validation		
	R	RMSE	SEP	R	RMSE	SEP
PLS	0.9092	0.0653	0.0667	0.6986	0.1166	0.1209
ELM	1.0000	0.0006	0.0026	0.5698	0.1455	0.1497
BPNN	1.0000	0.0004	0.0034	0.5706	0.1590	0.1523

2.1.2 Modeling from vegetation indices

Vegetation index (VI) has been widely used to qualitatively or quantitatively evaluate vegetation cover varieties and vigor. Normalized difference vegetation index (NDVI) is the most commonly used vegetation index, and it is also one of the important parameters close related to crop Chlorophyll and nitrogen content.

To compare the effects of different VIs on predicting canopy nutrient content and find the optimal vegetation index or their combination, 10 commonly used vegetation indices (as shown in Table 2) were selected for further study.

Table 2. Selected vegetation index and their calculation formula.

Vegetation index	Calculation formula	Reference
Normalized Difference Vegetation Index (NDVI)	$(NIR-R)/(NIR+R)$	Literature [29]
Modified Rededge Simple Ratio Index (MSR)	$(NIR/R-1)/\sqrt{NIR/R+1}$	Literature [30]
Optimized Soil Adjusted Vegetation Index (OSAVI)	$1.16(NIR-R)/(NIR+R+0.16)$	Literature [31]
Ratio Vegetation Index (RVI)	NIR/R	Literature [32]
Soil Adjusted Vegetation Index (SAVI)	$1.5(NIR-R)(NIR+R+0.5)$	Literature [33]
Structure Insensitive Pigment Index (SIPI)	$(NIR-B)/(NIR+B)$	Literature [34]
Simple Ratio Pigment Index (SRPI)	B/R	Literature [34]
Normalized Pigment Chlorophyll Index (NPCI)	$(R-B)/(R+B)$	Literature [35]
Ratio Vegetation Index 2(RVI2)	NIR/G	Literature [36]
Normalized Green-Blue Difference Index (NGBDI)	$(G-B)/(G+B)$	Literature [37]

Note: The spectral reflectance of B, G, R, RE and NIR is at the wavelength of 475nm (blue), 560nm (green), 668nm (red), 717nm (red edge) and 840nm (near infrared), respectively.

Grey relational analysis (GRD) is based on the developing trend, and its requirements on sample quantity and sample distribution are not strict. This process's basic idea is to find out the primary and secondary relationship between various factors by calculating the relational degree to find out the factor with the greatest influence. The higher relational degree of any two factors is considered to have a more consistent change between those two factors.

Let the reference sequence be $X_0 = \{x_0(k), k = 1,2,\cdots,n\}$, and the comparison sequence be $X_i = \{x_i(k), k = 1,2,\cdots,n\}$, GRD between X_0 and X_i is calculated by Equation 1 and Equation 2.

$$\mathrm{GRD} = \frac{1}{n}\sum_{k=1}^{n} \gamma(x_0(k), x_i(k)) \quad \text{(Equation 1)}$$

$$\gamma(x_0(k), x_i(k)) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \rho \min_i \min_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \min_i \min_k |x_0(k) - x_i(k)|} \quad \text{(Equation 2)}$$

where ρ is the grey correlation coefficient, and its value range is 0-1, here we took 0.538.

All the samples' nitrogen content was used as the reference sequence and all the selected VIs as comparison sequence. The gray relations between each vegetation index and nitrogen content are listed in Table 3.

Table 3. Grey relational analysis result between each vegetation index and nitrogen content.

VIs	Grey relational degree	Rank
NGBDI	0.8891	1
SRPI	0.8053	2
NPCI	0.6375	3
SIPI	0.6180	4
RVI	0.6049	5
NDVI	0.5798	6
RVI2	0.5797	7
MSR	0.5503	8
OSAVI	0.5400	9
SAVI	0.5154	10

NGBDI had the strongest relation with nitrogen content. The first six vegetation indices, namely NGBDI, SRPI, NPCI, SIPI, RVI, and NDVI, were selected for nitrogen prediction modeling (Table 3). Different combinations of VIs were used to build nitrogen prediction models, including single VI prediction models, multiple VIs prediction models, hybrid prediction models with raw band reflectance data, and VIs. All the results are listed in Table 4 and Table 5. It is shown that:

(1) The R values of the models built from VIs were about 0.3-0.5, showing poor accuracies; but the models from combining VIs with RAW band reflectance data had obvious higher R values (around 0.5-0.8) and lower RMSE values (around 0.1-0.2) than the models built from VIs only.

(2) The model with best performance was built from RAW band data, NGBDI, SRPI, and NPCI, with the PLS algorithm. This model had the highest R-value (0.7693), obvious lower RMSE (0.1109) and REP (0.1147) value, and most balanced accuracy between the training set and validation set, compared to other algorithms. This result is similar to many other research types on other crops based on multispectral images, such as winter wheat nitrogen prediction (R^2=0.53， RMSE=0.28) by Lu et al. [39], grapevines leaf nitrogen prediction (R^2=0.56，RMSE=0.23) by Moghimi et al. [40].

(3) For every input variable set, the PLS model had the most balanced result than the BPNN and ELM model, the same as Table 1. PLS was also demonstrated as a recommended algorithm because of its better performance. PLS was used to predict citrus canopy nitrogen and reached a prediction accuracy of 0.6398 in R-value [41]. The PLS combined with GRA was also used to estimate the accuracy of water content in winter

wheat leaves, and the model effect was better than stepwise regression [42].

Table 4. The modeling results from Vegetation Index by using different algorithms.

Input variables	Modeling algorithms	Training			Validation		
		R	RMSE	SEP	R	RMSE	SEP
NGBDI	PLS	0.4238	0.1417	0.0707	0.4104	0.1820	0.1670
	BPNN	0.9932	0.0064	0.0105	0.4105	0.5307	0.4713
	ELM	1.0000	0.0001	0.0006	0.4184	0.7167	0.5827
SRPI	PLS	0.4373	0.1470	0.1503	0.3753	0.1451	0.1483
	BPNN	1.0000	0.0005	0.0005	0.3966	0.7142	0.6713
	ELM	1.0000	0.0008	0.0006	0.3976	0.1953	0.1827
NPCI	PLS	0.4055	0.1523	0.1555	0.3890	0.1531	0.1564
	BPNN	1.0000	0.0033	0.0065	0.3976	0.1953	0.1827
	ELM	1.0000	0.0002	0.0006	0.3961	0.7573	0.6734
SIPI	PLS	0.4332	0.1670	0.1697	0.4881	0.1848	0.1893
	BPNN	0.9997	0.0153	0.0295	0.4096	0.7021	0.6483
	ELM	0.7914	0.5255	0.4703	0.4268	0.6040	0.5686
RVI	PLS	0.4632	0.1082	0.1107	0.4065	0.1220	0.1246
	BPNN	0.9896	0.0064	0.0032	0.4656	1.0161	0.9347
	ELM	0.7147	0.6107	0.5973	0.3214	0.7843	0.6902
NDVI	PLS	0.4520	0.1194	0.1227	0.4020	0.1350	0.1380
	BPNN	0.8472	0.2704	0.1290	0.4770	0.3521	0.2463
	ELM	0.7120	0.5988	0.5070	0.4300	0.4412	0.1946
NGBDI +NPCI	PLS	0.5244	0.1103	0.1127	0.4616	0.2493	0.1368
	BPNN	0.9976	0.0629	0.0768	0.4580	0.8972	0.8059
	ELM	1.0000	0.0003	0.0001	0.4162	1.4684	1.1759
NGBDI + SRPI+NPCI	PLS	0.5158	0.1073	0.1096	0.4819	0.0903	0.0832
	BPNN	0.9066	0.1628	0.1594	0.0420	0.2693	0.3568
	ELM	0.7102	0.9636	0.8724	0.3958	1.4895	1.1255
NGBDI + +NDVI	PLS	0.6229	0.1339	0.1367	0.4632	0.1256	0.1271
	BPNN	0.9475	0.2031	0.3618	0.4258	1.0339	1.0814
	ELM	0.7034	0.5736	0.9638	0.4085	1.6770	1.1515

Table 5. The modeling results from both raw band reflectance and Vegetation Index by using different algorithms.

Input variables	Modeling algorithms	Training			Validation		
		R	RMSE	SEP	R	R	RMSE
RAW+ NGBDI	PLS	0.8528	0.0426	0.0435	0.6734	0.1525	0.1392
	BPNN	1.0000	0.0003	0.0002	0.6446	0.1521	0.1463
	ELM	1.0000	0.0001	0.0001	0.5642	0.1865	0.1913
RAW+SRPI	PLS	0.8270	0.0547	0.0558	0.7039	0.1011	0.1018
	BPNN	1.0000	0.0003	0.0002	0.6142	0.2613	0.1945
	ELM	1.0000	0.0005	0.0004	0.5213	0.1896	0.1524

RAW+NPCI	PLS	0.8979	0.0558	0.0571	0.7237	0.1293	0.1162
	BPNN	1.0000	0.0003	0.0002	0.5582	0.1479	0.1527
	ELM	1.0000	0.0001	0.0001	0.5429	0.1865	0.1913
RAW+SIPI	PLS	0.8192	0.0487	0.0498	0.7277	0.1678	0.1020
	BPNN	1.0000	0.0004	0.0002	0.6528	0.1208	0.1234
	ELM	1.0000	0.0005	0.0003	0.5900	0.1843	0.1702
RAW+RVI	PLS	0.8270	0.0547	0.0558	0.7039	0.1011	0.1018
	BPNN	1.0000	0.0003	0.0002	0.6440	0.1722	0.1445
	ELM	1.0000	0.0005	0.0004	0.5213	0.1896	0.1524
RAW+NDVI	PLS	0.8528	0.0426	0.0435	0.7140	0.1026	0.0966
	BPNN	1.0000	0.0003	0.0002	0.6446	0.1521	0.1463
	ELM	1.0000	0.0001	0.0001	0.5642	0.1865	0.1913
RAW+NGBDI+NPCI	PLS	0.8247	0.0324	0.0283	0.7023	0.0994	0.1024
	BPNN	1.0000	0.0005	0.0005	0.5162	0.1642	0.1713
	ELM	1.0000	0.0008	0.0006	0.4976	0.1953	0.1827
RAW+ NGBDI + SRPI+NPCI	PLS	0.8429	0.0376	0.0743	0.7693	0.1109	0.1147
	BPNN	1.0000	0.0036	0.0322	0.5937	0.8846	0.6814
	ELM	1.0000	0.0001	0.0001	0.5183	0.7049	0.4935
RAW+ NGBDI +NDVI	PLS	0.7852	0.0809	0.0826	0.6767	0.1290	0.1151
	BPNN	1.0000	0.0004	0.037	0.5207	0.6679	0.4961
	ELM	1.0000	0.0003	0.0001	0.4629	1.6937	1.0463

2.2 Irrigation level recognition based on multispectral image

Water is a vital input for the sugarcane plant; water deficiency could let obvious yield reduction [43]. In this research, the relations between spectral features and irrigation amounts were analyzed as well. Firstly, the scatter plots of all the band reflectance and VIs in different irrigation levels were generated. Red band, NDVI, RVI, MSR, SIPI, and RCVI2 have been found obvious difference in different irrigations, regardless of the amount of fertilizer applied, as shown in Fig 4. The red band shows a negative correlation with irrigation, while the other five VIs show a positive correlation. The average values of the same irrigation for all the spectral bands and VIs, as well as the correlations between average values and irrigation amounts, were also calculated in Table 6.

Fig 4. The scatter plots of the red band and five VIs according to different irrigation levels. 0 represents no drip irrigation but rain; 180 represents drip irrigation amount of 180 m^3/ha or W0.6; 300 represents drip irrigation amount of 300 m^3/ha, or W1.0.

For the average reflectance data of spectral bands, the mean reflectance of visible bands (Red, Green, and Blue) decreased as the irrigation amount increased, showing strong negative correlations, while the other two bands (NIR and RedEdge) showed a strong negative trend (Table 6). Normally, the plant has lower reflectance in the visible range and higher reflectance in the NIR range as it is more vigorous. This result indicated that a proper increase in irrigation amount could make sugarcane healthier. For the average VIs, most VIs had strong positive correlations with irrigation amounts except NPCI, which had a

strong negative correlation, indicating that increasing irrigation could improve the health status of sugarcane.

Table 6. Average spectral values and their correlation with irrigation amounts.

Irrigations		Average values			Correlations between Average values and irrigation amounts
		0	180	300	
Band reflectance	NIR	30.831%	35.345%	35.935%	0.954
	RedEdge	4.997%	6.175%	7.035%	1.000
	Red	4.741%	3.659%	3.421%	-0.972
	Green	6.068%	5.764%	5.391%	-0.985
	Blue	3.152%	2.803%	2.642%	-0.996
Vegetation Indices	NDVI	0.723	0.811	0.822	0.951
	MSR	2.005	2.658	2.814	0.975
	OSAVI	0.576	0.666	0.676	0.950
	RVI	6.649	9.736	10.731	0.985
	SAVI	0.343	0.426	0.440	0.964
	SIPI	0.810	0.853	0.862	0.968
	SRPI	0.673	0.766	0.777	0.952
	NPCI	0.200	0.134	0.129	-0.941
	RVI2	5.037	6.152	6.716	0.997
	NGBDI	0.316	0.346	0.341	0.850

The obvious difference shown in Fig 4 indicated that Red band, NDVI, RVI, MSR, SIPI, and RCVI2 could have great potential to classify different irrigation levels. Support Vector Machine (SVM) was used to implement this classification. Before building the classification model, all six variables were first normalized and then selected as the model inputs. The classification result was listed in a confusion matrix, as shown in Table 7. Each row represented the predicted irrigation levels; the user's accuracy (UA) was the ratio of correctly classified to the total number of classified for that class. Each column represented the actual irrigation levels; producer's accuracy (PA) meaned the ratio of correctly classified to the total number of actual exist for that class. The overall classification accuracy was 77.8%; most of the misclassified samples were misclassified to adjacent irrigation levels, only one sample was misclassified as a far different level (a sample from Irrigation_300 was misclassified as Irrigation_0), showing the great potential of irrigation recognition with multispectral images.

Table 7. Confusion matrix of the irrigation level classification.

Ground truth / Classification result	Irrigation_0	Irrigation_180	Irrigation_300	Total	User's accuracy
Irrigation_0	9	0	1	10	90%
Irrigation_180	3	11	3	17	64.7%
Irrigation_300	0	1	8	9	88.9%
Total	12	12	12	36	

Producer's accuracy	75%	91.7%	66.7%	77.8%

3 Conclusions

In this paper, an unmanned aerial vehicle was used to collect multispectral images of sugarcane filed with low altitude. Three machine learning models with band reflectance and multiple vegetation indices as input variables were used to build nitrogen prediction models, and their prediction performance was compared. In addition, an algorithm of irrigation level recognition based on the multispectral image was also proposed. The main conclusions were as follows:

(1) The combination of vegetation index and band reflectance had better prediction accuracy than vegetation index or band reflectance along.

(2) PLS algorithm showed the best performance for sugarcane nitrogen prediction. The PLS algorithm built the best model from RAW band data, NGBDI, SRPI, and NPCI, which had the highest R-value of 0.7693, obvious lower RMSE value of 0.1109, and most balanced accuracy between the training set and validation set.

(3) Sugarcane with different irrigation levels had an obvious difference in the spectral information of its multispectral image. An SVM classification model was built to classify the irrigation levels, and the classification result reached 77.8%.

Multispectral images acquired by low altitude UAV flight could provide effective information for nitrogen prediction and water irrigation level recognition. Further study should be implemented based on multi-temporal spectral images and more comprehensive ground investigation.

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References

1. Jin XL, Zarco-Tejada P, Schmidhalter U, Matthew P. R, Li SK. High-throughput estimation of crop traits: A review of ground and aerial phenotyping platforms. IEEE Geoscience and Remote Sensing Magazine, 2020:99. doi:10.1109/MGRS.2020.2998816
2. Zhang YY, Yang J, Liu XG, Du L, Shi S, Sun J, Chen BW. Estimation of multi-species leaf area index based on Chinese GF-1 satellite data using look-up table and gaussian

process regression methods. Sensors, 2020; 20(9):2460-2474. doi:10.3390/s20092460

3. Ovakoglou G, Alexandridis TK, Clevers JGPW, Cherif I, Beltran JS. Spatial enhancement of Modis leaf area index using regression analysis with Landsat vegetation index. IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium, 2018. doi:10.1109/IGARSS.2018.8519387
4. Meisam A, Mobasheri, Mohammad R. A parametric method for estimation of leaf area index using landsat ETM+ data. GIScience & Remote Sensing, 2015: 478-497. doi:10.1080/15481603.2015. 1055540
5. Qiu L, Xiong QM, Liu Y, Zhang G. GeoEye image fusion vegetation information extraction based on blue noise measurement texture. IOP Conference, 2017; 67:012007. doi:10.1088/1755-1315/67/1/012007
6. Chinsu, Lin, Sorin C, Popescu, Thomson, et al. Classification of tree species in overstorey canopy of subtropical forest using QuickBird Images. PLoS One, 2015; 10(5):e0125554. doi:10.1371/journal.pone.0125554
7. Grégory D, Pierre D. A conceptual framework to define the spatial resolution requirements for agricultural monitoring using remote sensing. Remote Sensing of Environment, 2010; 114(11):2637-2650. doi:10.1016/j.rse.2010.06.001
8. Xu R, Li CY, Paterson AH, Jung, Jinha. Multispectral imaging and unmanned aerial systems for cotton plant phenotyping. PLoS One, 2019; 14(2):e0205083. doi:10.1371/journal.pone.0205083
9. Zhang DY, Zhou X, Zhang J, Lan Y, Xu C, et al. Detection of rice sheath blight using an unmanned aerial system with high-resolution color and multispectral imaging. PLoS One, 2018; 13(5):e0187470. doi:10.1371/journal.pone.0187470
10. Martin C, Morten L, Rasmus J, et al. Designing and testing a UAV mapping system for agricultural field surveying. Sensors, 2017; 17(12):2703-2721. doi:10.3390/s17122703
11. Zhou X, Zheng HB, Xu XQ, H JY, Ge XK, et al. Predicting grain yield in rice using multi-temporal vegetation indices from UAV-based multispectral and digital imagery. ISPRS Journal of Photogrammetry and Remote Sensing, 2017; 130:246-255. doi:10.1016/j.isprsjprs.2017.05.003
12. Maresma Á, Ariza M, Martínez E, Lloveras J, Martínez-Casasnovas J. Analysis of vegetation indices to determine nitrogen application and yield prediction in maize (Zea mays L.) from a standard UAV service. Remote Sensing, 2016; 8(12):973-987. doi:10.3390/rs8120973
13. Kefauver SC, Rubén V, Omar VD, Fernández-Gallego JA, Araus JL. Comparative UAV and field phenotyping to assess yield and nitrogen use efficiency in hybrid and conventional barley. Frontiers in Plant Science, 2017; 8:1733. doi:10.3389/fpls.2017.01733
14. Michael, Schirrmann, Antje, Giebel, Franziska, et al. Monitoring agronomic parameters of winter wheat crops with low-cost UAV imagery. Remote Sensing, 2016; 8(9):706-724. doi:10.3390/rs8090706
15. XUE LH, Cao WX, Yang LZ. Predicting Grain yield and protein content in winter wheat at different N supply levels using canopy reflectance spectra. Pedosphere, 2007;

17(5):646-653. doi:10.1016/S1002-0160(07)60077-0
16. Ballester C, Hornbuckle J, Brinkhoff J, Smith J, Quayle W. Assessment of in-season cotton nitrogen status and lint yield prediction from unmanned aerial system imagery. Remote Sensing, 2017; 9(11):1149-1166. doi:10.3390/rs9111149
17. Thomas S, Kuska MT, Bohnenkamp D, Anna B, Elias A. et al. Benefits of hyperspectral imaging for plant disease detection and plant protection:a technical perspective. Journal of Plant Diseases and Protection, 2018; 125(3):5-20. doi:10.1007/s41348-017-0124-6
18. Tian YC, Gu KJ, Chu X, Yao X, Cao WX, Zhu Y. Comparison of different hyperspectral vegetation indices for canopy leaf nitrogen concentration estimation in rice. Plant and Soil, 2014; 376(1-2):193-209. doi:10.1007/s11104-013-1937-0
19. Zhou Z, Huang J, Wang J, Zhang K, Kuang Z, Zhong S, et al. (2015) Object-oriented classification of sugarcane using time-series middle-resolution remote sensing data based on AdaBoost. PLoS One 10(11):e0142069. doi:10.1371/journal.pone. 0142069
20. Felix R, Clement A, Igor S, Oscar R. Using low resolution satellite imagery for yield prediction and yield anomaly detection. Remote Sensing, 2013; 5(4):1704-1733. doi:10.3390/rs5041704
21. Morel J, Todoroff P, Bégué A, Bury A, Martiné JF, Petit M. Toward a satellite-based system of sugarcane yield estimation and forecasting in smallholder farming conditions:a case study on Reunion Island. Remote Sensing, 2014; 6(7):6620-6635. doi:10.3390/rs6076620
22. Miphokasap P, Wannasiri W. Estimations of nitrogen concentration in sugarcane using hyperspectral imagery. Sustainability, 2018; 10(4):1266-1281. doi:10.3390/ su10041266
23. Martins JA, Fiorio PR, Barrors S, Dematte M, Molin JP, Cantarella H, et al. Potential use of hyperspectral data to monitor sugarcane nitrogen status. Acta Scientiarum, 2020; 43:1807-8621. doi; 10.4025/actasciagron.v43i1.47632
24. Mahanti NK, Chakraborty SK, Kotwaliwale N, Vishwakarma AK. Chemometric strategies for nondestructive and rapid assessment of nitrate content in harvested spinach using Vis-NIR spectroscopy, 2020; 85(10):3653-3662. doi:10.1111/1750-3841.15420
25. Li R, Zeng C, Li J, Zhu K, Lin XX, Wen JF, et al. Characterization of the fruits and seeds of Alpinia Oxyphylla Miq by high-performance liquid chromatography (HPLC) and near-Infrared spectroscopy (NIRS) with partial least-squares (PLS) regression. Analytical Letters, 2020; 53(11):1667-1682. doi:info:doi/10.1080/00032719.2020.1715996
26. Kira O, Linker R, Gitelson A. Non-destructive estimation of foliar chlorophyll and carotenoid contents: Focus on informative spectral bands. International Journal of Applied Earth Observations and Geoinformation, 2015; 38:251-260. doi:10.1016/j.jag.2015.01.003
27. L. Chen, Huang JF, Wang FM, Tang LY. Comparison between back propagation neural network and regression models for the estimation of pigment content in rice leaves and panicles using hyperspectral data. International Journal of Remote Sensing, 2007; 28(16):3457-3478. doi:10.1080/01431160601024242

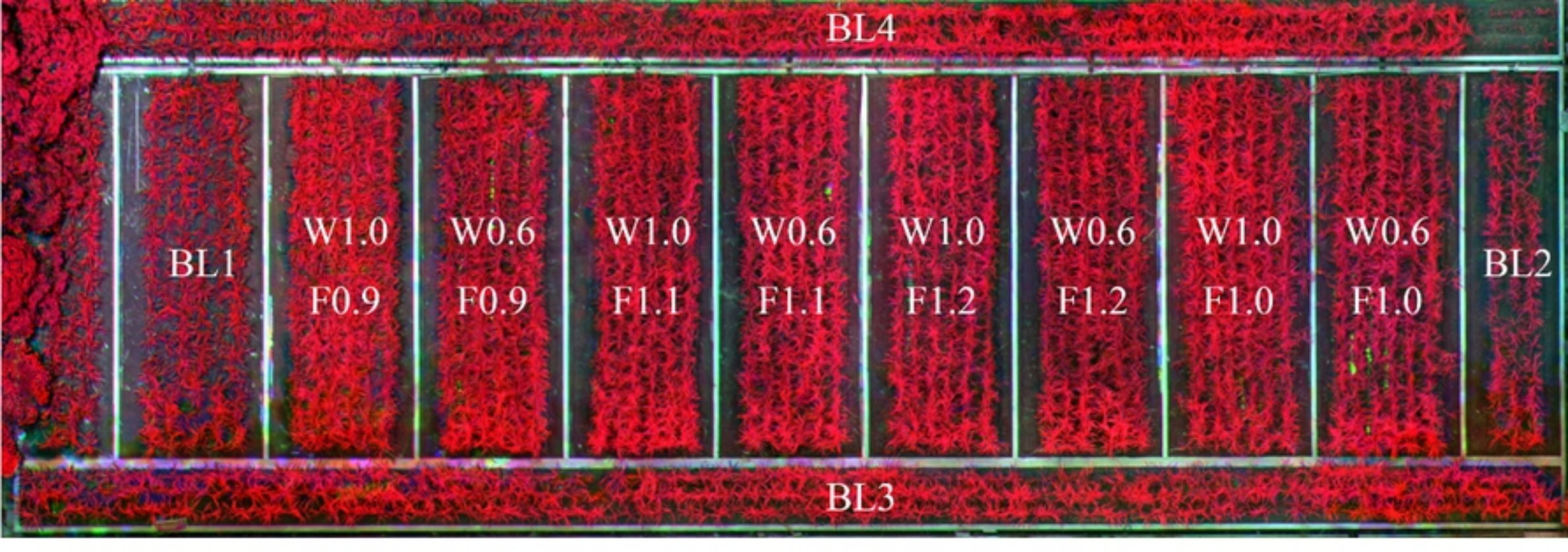
28. Pal M, Maxwell AE, Warner TA. Kernel-based extreme learning machine for remote-sensing image classification. Remote Sensing Letters, 2013; 4(7-9):853-862. doi:10.1080/2150704X.2013. 805279
29. Rouse JW, Hass RW, Schell JA, et al. Monitoring the vernal advancement and retrogradation (Green wave effect) of natural vegetation. NASA/GSFCT Type III Final Report, Greenbelt, MD, USA, 1974.
30. Chen JM. Evaluation of vegetation indices and a modified simple ratio for boreal applications. Canadian Journal of Remote Sensing, 1996; 22(3):229-242. doi:10.1080/07038992.1996.10855178
31. Rondeaux G, Steven M, Baret F. Optimization of soil-adjusted vegetation indices. Remote Sensing of Environment, 1996; 55(2):95-107. doi:10.1016/0034-4257(95)00186-7
32. Mishra S, Mishra DR. Normalized difference chlorophyll index: A novel model for remote estimation of chlorophyll-a concentration in turbid productive waters. Remote Sensing of Environment, 2012; 117:394-406. doi:10.1016/j.rse.2011.10.016
33. Huete AR. A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, 1988; 25(3):295-309. doi:10.1016/0034-4257(88)90106-X
34. Penuelas J, Baret F, Filella I. Semiempirical indexes to assess carotenoids chlorophyll-a ratio from leaf spectral reflectance. Photosynthetica, 1995; 31:221-230. doi:10.1007/BF00029464
35. Ranjan R, Chopra UK, Sahoo RN, Singh AK, Pradhan S. Assessment of plant nitrogen stress in wheat (*Triticum aestivum L.*) through hyperspectral indices. International Journal of Remote Sensing, 2012; 33(20):6342-6360. doi:10.1080/01431161.2012.687473
36. Xue LH, Cao WX, Luo WH, Dai TB, Zhu Y. Monitoring leaf nitrogen status in rice with canopy spectral reflectance. Agronomy Journal, 2004; 96(1):135-142. doi:10.2134/agronj2004.0135
37. Verrelst J, Schaepman ME, Koetz B, Kneubühler M. Angular sensitivity analysis of vegetation indices derived from CHRIS/PROBA data. Remote Sensing of Environment, 2008; 112(5):2341-2353. doi:10.1016/j.rse.2007.11.001
38. Xu QW, Xu KL. Mine safety assessment using gray relational analysis and bow tie model. PLoS One, 2018; 13(3):e0193576. doi:10.1371/journal.pone.0193576
39. Lu N, Wang WH, Zhang QF, Li D, Tao C. Estimation of nitrogen nutrition status in winter wheat from unmanned aerial vehicle based multi-angular multispectral imagery. Frontiers in Plant Science, 2019; 10:1601-1638. doi:10.3389/fpls.2019.01601
40. Moghimi A, Pourreza A, Zuniga-Ramirez G, Williams LE, Fidelibus MW. A novel machine learning approach to estimate grapevine leaf nitrogen concentration using aerial multispectral imagery. Remote Sensing, 2020; 12(21):3515-3534. doi:10.3390/rs12213515
41. Liu XF, Liu Q, He SL, Yi SL. Estimation of carbon and nitrogen contents in citrus canopy by low-altitude remote sensing. International Journal of Agricultural and Biological Engineering, 2016; 9(5):149-157. doi:10.3965/j.ijabe.20160905.2246
42. Jin XL, Xu XG, Wang JH, Li XC, Wang Y, et al. Hyperspectral Estimation of Leaf Water Content for Winter Wheat Based on Grey Relational Analysis (GRA). Spectroscopy

and Spectral Analysis, 2012; 105:1385-1392. doi:10.2134/agronj2013.0088
43. LUO WG, Chu JY, Huang ZH, Liao T, Sang XF, et al. Water requirement of sugarcane and its correlation with meteorological factors. Journal of Southern Agriculture, 2016; 47(01):74-82. doi:10.3969/j:issn.2095-1191.2016.01.74

A

B

Fig 1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BL2
BL3

Fig 2

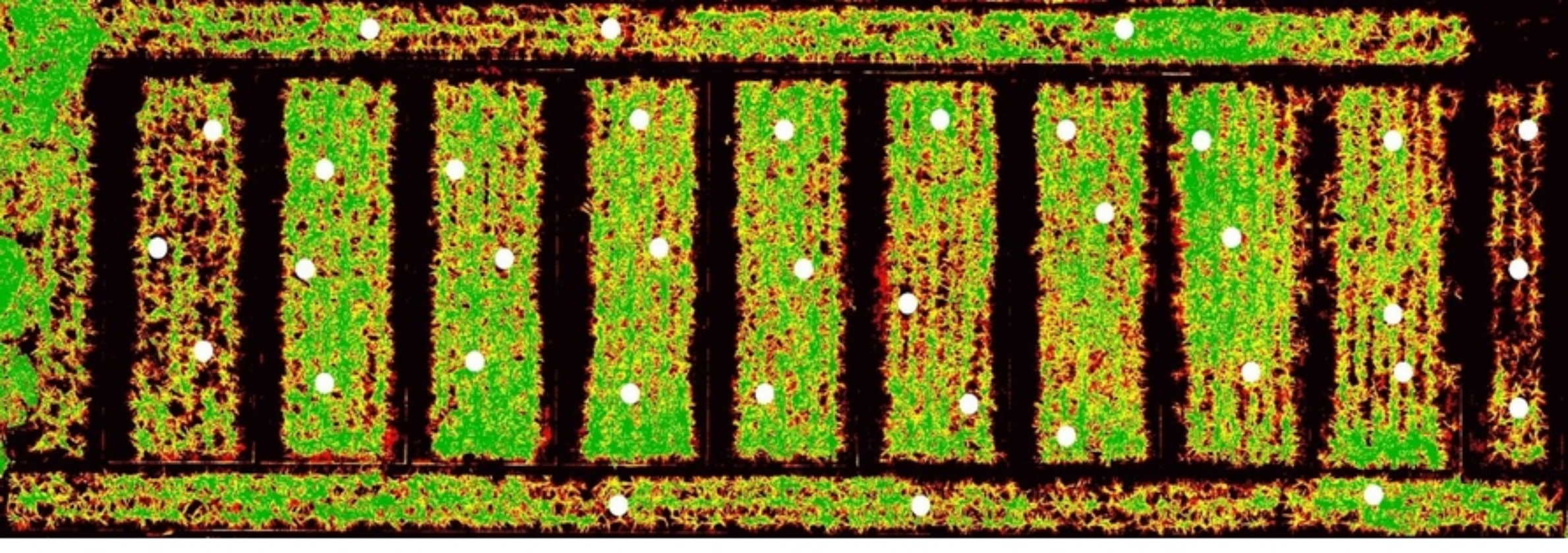

Fig 3

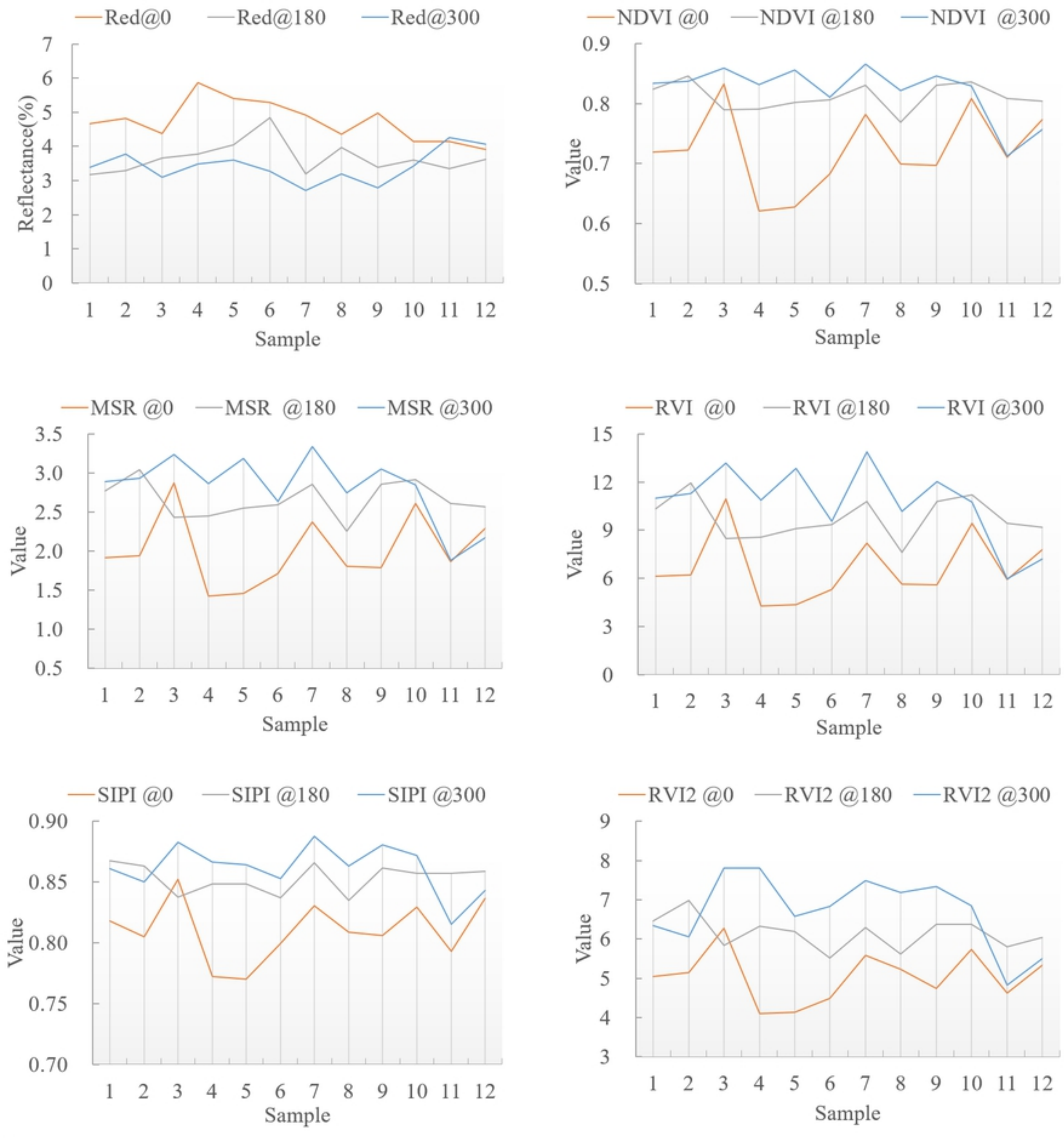
Red@0
Red@180
Red@300
Reflectance(%)
Sample
NDVI @0
NDVI @180
NDVI @300
Value
Sample
MSR @0
MSR @180
MSR @300
Value
Sample
RVI @0
RVI @180
RVI @300
Value
Sample
SIPI @0
SIPI @180
SIPI @300
Value
Sample
RVI2 @0
RVI2 @180
RVI2 @300
Value
Sample

Fig 4