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Prediction model of rice crude protein content, amylose content and actual yield under high temperature stress based on hyper-spectral remote sensing

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RESEARCH ARTICLE

Abstract

Crude protein and amylose constitute two main representative components of rice quality. The non-destructive, quick assessment of grain crude protein content (GCPC), grain amylose content (GAC), and actual yield (AC) are necessary for quality and yield diagnosis in rice production. The objectives of this study were to determine the effects of high temperature stress on rice GCPC, GAC and AC, to define the relationships of GCPC, GAC, and AC to ground-based canopy hyper-spectral reflectance and derivative parameters, and to establish quantitative models for real-time monitoring of rice GCPC, GAC, and AC using sensitive spectral parameters under high temperature stress. Two field warming experiments were performed in Nanjing in Jiangsu Province, China, to investigate the effects of high temperature ((treated for continuous 3 days from 9:00 am to 14:00 pm, average temperature was set at 35, 38 and 41 °C) and a control (CK)) at flowering stage in Liangyoupeijiu rice cultivar, using a free air temperature increase apparatus. Canopy hyper-spectral reflectance, GCPC, GAC, and AC were measured under high temperature treatments during different growth stages (flowering stage, grain-filling and ripening stages). The results showed that GCPC, AC (GAC) in Liangyoupeijiu were clearly reduced (increased) under high temperature stress in this study compared with the values of CK, and the reducing extent of GCPC and AC (the increasing extent of GAC) was increased with the increase of high temperature level. The hyper-spectral reflectance in different wavelength regions under high temperature stress was different. They increased in visible light region with the elevation of temperature, but reduced in near-infrared region. Among some selected spectral indices at three different growth stages used to estimate GCPC, GAC and AC, the optimum indices were difference vegetation index(810,450) and perpendicular vegetation index- Landsat multispectral scanner with high R^2 when regressed against GCPC, GAC and AC. Furthermore, GCPC, GAC and AC prediction based on flowering stages were preferred than that on grain-filling and ripening stage by much bigger correlation coefficients. The six regression models developed in this study showed the agreement between the predicted and observed values when testing independent data under high temperature stress. Thus, the selected key hyper-spectral parameters can be reliably used to estimate GCPC, GAC and AC in rice under different high temperature treatments.

Keywords: crude protein content, amylose content, actual yield, high temperature stress, spectral parameters

1. Introduction

Rice is the major grain produced in China, accounting for approximately 40% of the total grain output. As the most important rice planting zone in China, the Yangtze River Basin is a zone that suffers from serious high-temperature damage, which adversely affects worldwide rice crop production. With increasing changes in the global climate, extreme and sustained high temperatures are consistently experienced during the summer in the Yangtze River Basin, and the frequency and degree of rice damage caused by these high temperatures are increasing accordingly, which further caused increasingly damage severity for rice quality and yield. Therefore, safe rice production has commanded an extraordinary degree of attention from the Chinese government and researchers (Dong *et al.,* 2011a,b; Xie *et al.,* 2017., Yuan *et al.,* 2018).

Many previous studies had found that high temperature stress obviously affects rice pollen vitality, pollen germination, leaf physiological and biochemical characteristics, and finally reduces grain yield (Endo *et al.,* 2009; Xie *et al.,* 2016). For example, Matsui *et al.* (2001) showed the percent fertility of the typical three varieties was different under various day-temperature conditions. The temperature at which the percent fertility decreased to 50% was about 37.0 °C for 'Hinohikari' (the most susceptible of nine experimental varieties) and about 40.0 °C for 'Akitakomachi' (the most tolerant of nine experimental varieties). Iizumi *et al.* (2007) predicted that climate changes enhanced the damage to crop yield caused by heat stress in central to southwestern Japan using the general circulation model. Laza *et al.* (2015) observed rice cultivars at the early reproductive stage had the lowest number of spikelet per panicle under high night temperature treatment, presenting a 35.90% of degenerated spikelet. Shi *et al.* (2017) concluded grain number per panicle decreased with the rising temperature and prolonging duration exposed to high temperature, and the relationship between grain number per panicle and temperature could be expressed with a quadratic equation. Similarly, some researches were focused on rice quality in the past under high temperature stress. For instance, Dong *et al.* (2011a,b) found three warming treatments had no significant impact on the starch content of rice grain but tended to reduce the amylose content and increase the ratio of amylopection to amylose. Lu *et al.* (2014) concluded that the amounts of amylopection and starch accumulation in rice grains declined significantly under 37 °C heat stress after anthesis. Although there are many meaningful conclusions recently, some field experimental data still should be provided for determining the effects of high temperature on rice quality and yield in efforts to cope with potential climate warming.

Hyper-spectral remote sensing can acquire images in narrow and continuous spectral bands and provide a continuous spectrum for each pixel. Thus, their data are considered to be more sensitive to specific crop variables. Hyper-spectral remote sensing has developed strong advantages over agricultural remote sensing. At present, some crop quality and yield monitoring studies based on hyper-spectral remote sensing were reported (Nicola *et al.,* 2018; Xie *et al.,* 2012; Yang *et al.,* 2009). For instance, Hansen (2002) reported that protein content in winter wheat and spring barley could be predicted accurately using canopy hyper-spectral reflectance and partial least squares regression. Li *et al.* (2005) observed there was a significant correlation between ratio vegetation index (1,220, 710) (RVI (1,220, 710)) and protein content in different wheat cultivars. Xie *et al.* (2012) found that the correlation coefficients between difference vegetation index (810,450) (DVI (810,450)), DVI (810,680) and amylose content with values were greater than 0.78. Zhang *et al.* (2012) concluded there was a significant correlation between grain crude protein content (GCPC) and some key spectral bands with correlation values of over 0.90. Fox and Manley (2014) suggested that it would be better to analyse cereal quality using application of single kernel conventional and hyper-spectral imaging near infrared spectroscopy. Foster *et al.* (2017) reported narrowband normalise nitrogen vegetation index was more robust and useful in predicting crop N concentration. Above researches are mainly focused on crop quality and yield monitoring based on hyper-spectral remote sensing under N or other environmental stress treatments, while few rice quality monitoring results under high temperature treatments have been mentioned. Crude protein and amylose constitute two main components of rice grain. Therefore, it is a very important subject of study for the quantitative inversion of GCPC, grain amylose content (GAC), and actual yield (AC) in rice under climate warming in the future.

Two field experiments were performed in this study in Nanjing, China, to investigate the effects of high temperature stress on rice quality for the hybrid rice Liangyoupeijiu, using a free air temperature increase (FATI) apparatus. Canopy hyper-spectral reflectance during the main growth stages, GCPC, GAC, and AC based on various experiments under different high temperature stress were measured, and the relationship between canopy spectral parameters and grain quality were further discussed by the correlation analysis. Our principal objectives were: (1) to determine the effects of high temperature stress on rice quality and yield; and (2) to select sensitive spectral parameters to predict GCPC, GAC and AC in Liangyoupeijiu under high temperature stress.

2. Experimental details

Experimental set-up

Experiments were conducted in 2015 and 2016, at the agro-metrological experimental station (32.0°07'N, 118°50'E) of Nanjing University of Information Science and Technology in Jiangsu Province, China, during the rice growing seasons from May to November. This region has a warm temperature and semi-humid monsoon climate. The average yearly precipitation is 1,100 mm. The average air temperature from 2000 to 2016 was 16.7 °C, which is 1.5 °C and 0.8 °C warmer compared to the 1980s and 1990s, respectively. Average annual sunshine is over 1,900 h, with 237 frost-free days. The soil at the experimental plot is Hapli-Stagnic Gleysol, with a total organic carbon (C) content of 9.28 g/kg, total N content of 1.06 g/kg, available phosphorus (P) content of 6.89 mg/kg, and exchangeable potassium content of 125 mg/kg.

The rice cultivar used in this study was Liangyoupeijiu, which is widely cultivated in Nanjing, China. Planting was carried out on 20 May in two study years. Transplanting was carried out on 20 June using plastic buckets with a diameter of 30 cm, with one seedling being planted in each bucket. A total of 138 kg N/ha was broadcast and split-applied: 50% at seeding, 25% applied at jointing and 25% at booting. P and potassium were applied pre-planting as calcium (Ca) superphosphate and potassium chloride at a rate of 30 kg P/ha, respectively. Hand weeding before sowing was used to control weeds. Pesticides (imidacloprid) and fungicides (tebuconazole) were sprayed to control pests and diseases as needed.

Experimental design and high temperature treatments

Following the FATI apparatus design developed by Nijs *et al.* (1996) and Tian *et al.* (2010), we designed an experimental warming apparatus with far-infrared heating tubes (length, 1.5 m; power, 1000 W power; two tubes, (Technology Co. Ltd., Hangzhou, China), which were placed 1.5-1.7 m (the set temperature is different when the height of heating tubes is different.) high on steel column pipe supports, surrounded by a resin film allowing 98% light transmittance and open at the top. The experiments in 2015 (E_1) and in 2016 (E_2) involved three treatments (treated for continuous 3 days from 9:00 am to 14:00 pm, average temperature was set at 35, 38 and 41 °C, and a control (CK)) during flowering stage in FATI. Then the plants were placed back to a natural condition after high temperature stress. Each treatment included three replicate plots, which were placed in a randomised block design. The apparatus had a heating area of 4 m^2 and was capable of inducing remarkable increases in temperature. The Canopy temperature data were obtained with a temperature recorder instrument (Technology Co. Ltd.) that automatically recorded instantaneous values every 30 min. Data of E_2 was used for testing the prediction model.

Experiment measurements

All canopy spectral measurements were taken with an ASD FieldSpec Pro spectrometer (Analytical Spectral Devices, Boulder, CO, USA). This spectrometer is fitted with 25° field of view fibre optics, which operate in the 350-2,500 nm spectral region with a sampling interval of 1.4 nm between 350 and 1,050 nm, and 2 nm between 1,050 and 2,500 nm, and with a spectral resolution of 3 nm at 700 nm, 10 nm at 1,400 nm. The measurements were carried out from a height of 1.0 m above the rice canopy with a field of view diameter 0.44 m under clear sky conditions between 10:00 and 14:00 h. Vegetation radiance measurements were performed at 3 sample sites from each plot. A panel radiance measurement was taken before and after vegetation measurements by performing two scans on each occasion. In each experiment, data were obtained at the flowering, grain-filling and ripening stages.

All grain samples were harvested at maturity, then dried and pulverised before being measured, part of dried samples were kept for determining actual yield. Actual yield was determined by weighing all grains in one bucket (one seedling planted inside), there were nine replications for each treatment. Crude protein is a conventional expression of the total content of N compounds of the analysed product, calculated by multiplying the corresponding N content by a conversion factor. N content was measured according to micro-Kjeldahl method provided by Xie *et al.* (2018), and the conversion factor for rice grain is 5.95. Amylose content was measured according to the method provided by Hong *et al.* (2004).

Data analysis

Grain crude protein, amylose and yield statistical analyses were performed with SPSS 12.0 (SPSS Inc., Chicago, IL, USA). Statistically significant differences were identified from LSD calculations at P=0.05. The standard errors (SEs) of the means were also calculated and were presented in the graphs as error bars.

Correlation analyses were conducted between the hyper-spectral parameters, GCPC, GAC and yield under high temperature stress so that the reported sensitive spectral ranges and spectral indices related to GCPC, GAC and AC could be identified by using a self-developed computer program based on MATLAB 7.0 software (The Mathworks, Inc., Natick, MA, USA). Seven selected spectral parameters were calculated according to the equation in Table 1. The data were fitted to different linear models to determine the best crude protein, amylose and yield coefficients of determination (R^2) values for the spectral parameters.

Relationships with best-fit R^2 values were tested with data gathered from E_1 under high temperature stress. During testing, the predicted results were compared with field measurements (E_2) to evaluate the reliability and accuracy of the equation output under practical conditions. Root mean square error (RMSE), which is an indicator of the average error in the analysis, was expressed in original measurement units; relative error (RE) indicated the relative difference between predicted and observed data, and RMSE and RE were used to calculate the fit between the estimated results and observed data (Onoyama *et al.,* 2015). The prediction was considered excellent at RE<10%, good at 10-20%, fair at 20-30%, and poor at >30% (Feng *et al.,* 2008; Xie *et al.,* 2013).

Table 1. Algorithm and references for different parameters.[1,2]

Spectral parameter	Algorithm	References
DVI (λ_1,λ_2)	$R_{\lambda 1} - R_{\lambda 2}$	Richardson and Wiegang, 1977
PVI (λ_1,λ_2)	$\frac{R_{NIR} - a \times R_{RED} - b}{\sqrt{1 + a^2}}$	Richardson and Wiegang, 1977
Ri		Cropscan, 2003
FDi		Johnson *et al.*, 1994
PVI-MSS	$(Band4 - a \times Band2 - b) / (1 + a^2)^{0.5}$	Lyon *et al.*, 1998
DVI-MSS	$Band4 - a \times Band2$	Lyon *et al.*, 1998
GM-1	R_{750} / R_{550}	Gitelson and Merzlyak, 1997

[1] DVI = difference vegetation index; FD = first derivative; MSS = Landsat multispectral scanner; PVI = perpendicular vegetation index; R = reflectance.
[2] λ_1, λ_2, i = wavelength; a, b, = 0.96916, 0.084726.

3. Results and discussion

Diurnal mean temperature variation

Trends in E_1 for diurnal mean temperature variation (18 August, 2015) under different temperature treatments were similar to that for CK (Figure 1), which showed that warming systems did not change the diurnal variation feature of field temperature. The order of canopy temperature under different temperature treatments was 41 °C > 38 °C > 35 °C > CK.

GCPC, GAC and AC

High temperature stress reduced GCPC and AC, but increased GAC in Liangyoupeijiu (Figure 2). In the 35, 38 and 41 °C treatments, GCPC were reduced by 8.86,10.91 and 16.67%, AC were reduced by 11.62, 19.16 and 43.62% respectively, while GAC were increased by 3.16, 8.27 and 16.78%. GCPC (or GAC) in Liangyoupeijiu reduced (or increased) with the increase of high temperature level, but there were no significant differences for different high temperature treatments (P>0.05). However, there were significant differences for AC among 38 and 41 °C and CK treatments. Above results were similar to Xie *et al.* (2011, 2012) who observed in other rice cultivars (Yangdao 6 and Nanjing 43) under high temperature stress. However, Fan *et al.* (2005) found drought increased amylose accumulating rate and protein content, while waterlogging reduced them. Additionally, they reported N reduced amylose and amylopectin accumulating rate under drought and waterlogging, while increased protein content in wheat grain.

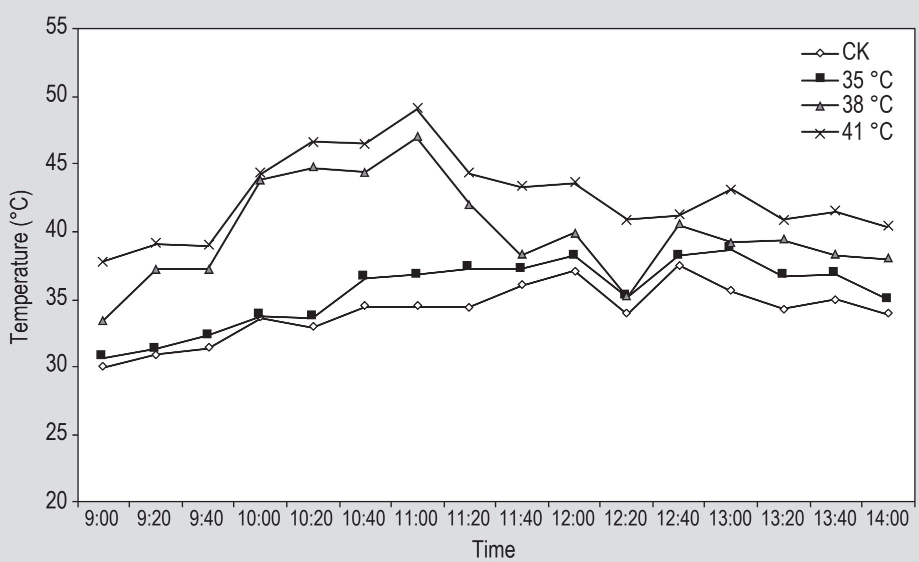

Figure 1. The trends in E1 for diurnal mean temperature variation (18 August, 2015) under different temperature treatments.

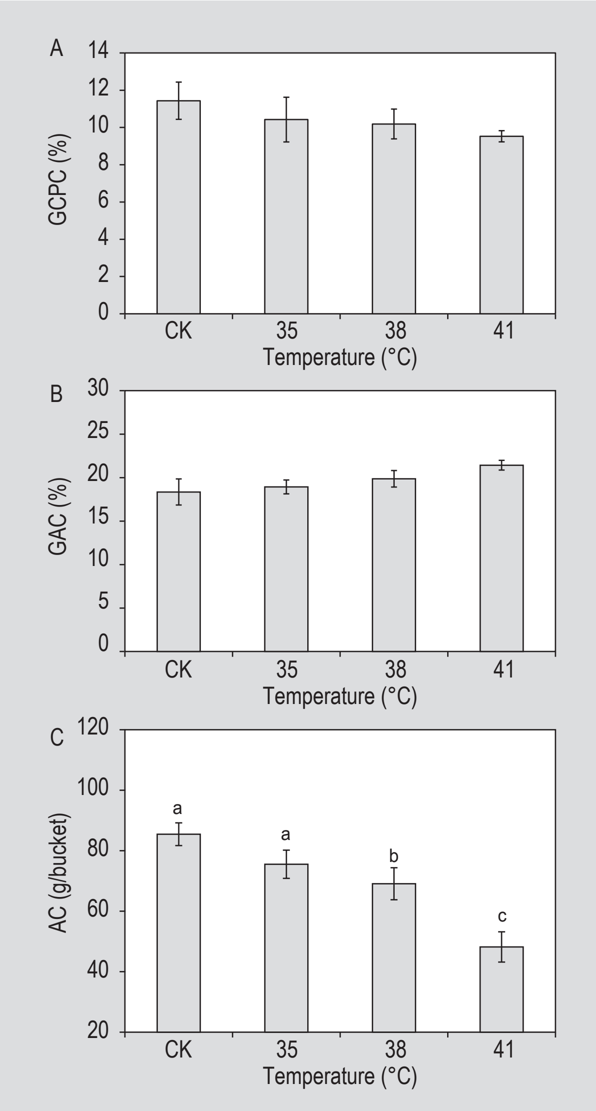

Figure 2. Change of (A) grain crude protein content (GCPC), (B) grain amylose content (GAC) and (C) actual yield (AC), of Liangyoupeijiu under different high temperature stress.

Changes in canopy hyper-spectral reflectance under high temperature stress

Taking canopy hyper-spectral reflectance characteristics of Liangyoupeijiu measured at grain-filling stage under high temperature stress as an example in 2014. Canopy hyper-spectral reflectance characteristics of Liangyoupeijiu under different high temperature stress were almost similar with those of green plants (Figure 3). Green peak of 550 nm and red light low valley of 680 nm in visible light region of 400-700 nm as well as plateau area of 780-1,100 nm in near-infrared region were observed (Liu *et al.,* 2014). Further, there are mainly water absorbing regions in 1 300-2,500 nm, wherein there are strong absorbing regions in 1,450 and 1,930 nm. But the hyper-spectral reflectance in different

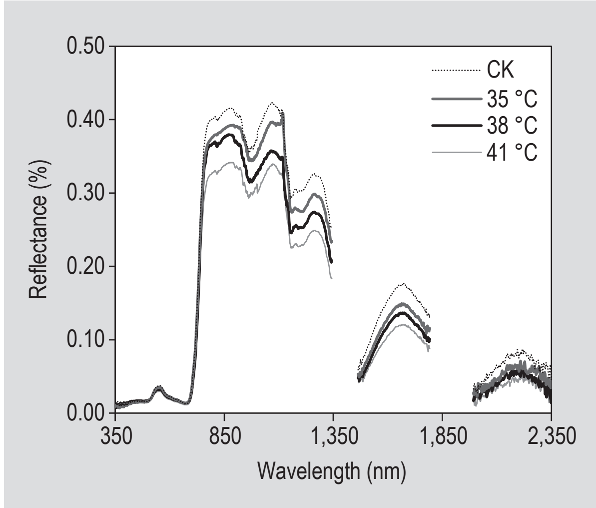

Figure 3. Change of hyper-spectra reflectance of Liangyoupeijiu at grain-filling stage under different high temperature stress.

regions under high temperature stress was slightly different, which mainly presented the increased reflectance in visible light region with the elevation of temperature. This situation may be caused by reduced leaf area and chlorophyll content resulting from high temperature stress. And reflectance in near-infrared region was reversed and reduced with the elevation of temperature (Xie *et al.,* 2011).

Relationship of GCPC, GAC and AC to canopy spectral reflectance under high temperature stress

The correlation coefficient among GCPC, GAC, AC and spectral reflectance based on different temperature treatments changed dramatically over different wavebands (Figure 4). In general, GCPC and AC had a positive correlation with reflectance at flowering and grain-filling stages over the entire wavelength range, but they had a negative correlation at the range of 350-532 nm, 575-695 nm and over 1,760 nm at ripening stage. GAC had a negative correlation with reflectance over the entire wavelength range at grain-filling stage, while they were a positive correlation at the range of 642-691 nm at flowering stage and at the range of 350-706 nm at ripening stage. Moreover, GCPC, GAC and AC had a significant or remarkably significant difference with spectral reflectance, first derivative and second derivative at some specific wavebands at three growth stages (P<0.05 or P<0.01) like 700-1,347 nm, which were shown in this study that GCPC, GAC and AC may be estimated by original canopy hyper-spectral reflectance and derivative parameters under high temperature stress. Some figures were not listed here like the correlation coefficients among GCPC, GAC, AC and first derivative and second derivative.

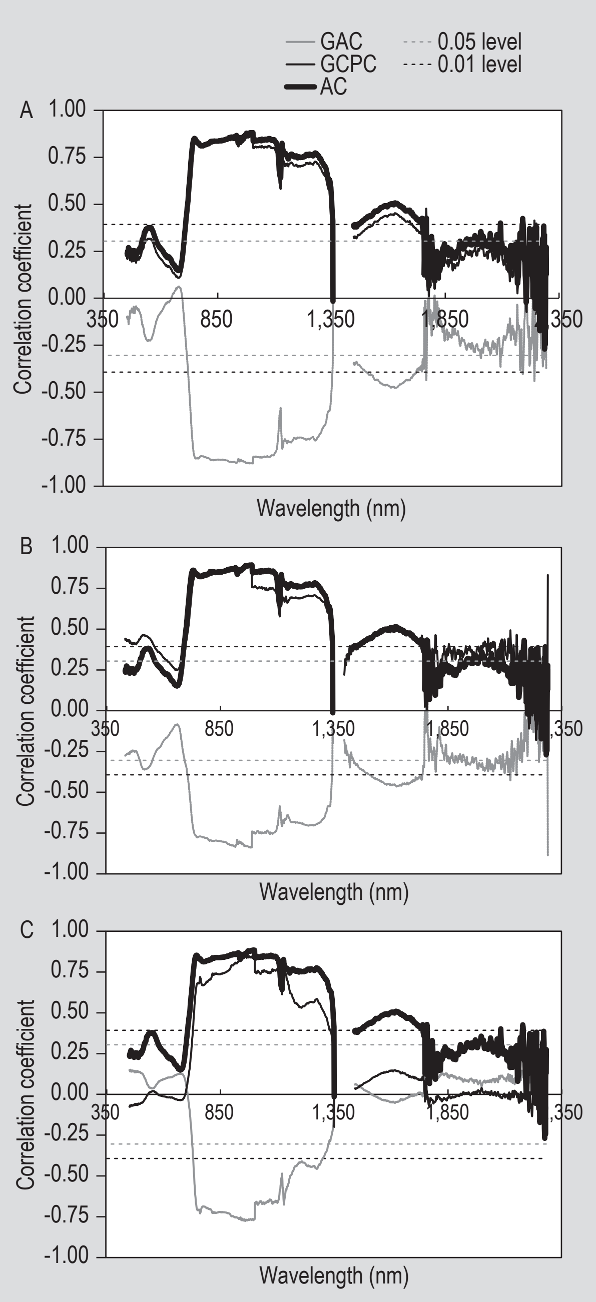

Figure 4. Correlation coefficients among grain crude protein content (GCPC), grain amylose content (GAC) and actual yield (AC) and canopy spectral reflectance during different growth stages under high temperature stress. (A) flowering stage; (B) grain-filling stage; (C) ripening stage.

Relationship between GCPC, GAC and AC and hyper-spectral parameters under high temperature stress

Rice hyper-spectral reflectance was extremely different under short-time high temperature treatments at different growth stages (Xie *et al.,* 2010). So hyper-spectral data in the study were measured after high temperature treatments for continuous 3 days at flowering, grain-filling and ripening stages individually. Comprehensive analyses were conducted to determine the relationships among GCPC, GAC, AC, hyper-spectral reflectance and derived vegetation indices under different high temperature treatments at three growth stages. Key hyper-spectral parameters based on higher correlation coefficients were selected and evaluated for the quantitative estimation of GCPC, GAC and AC under different high temperature treatments. Table 2 lists some selected spectral parameters, with the highest correlations from the data collected from the E_1 under high temperature stress. All spectral parameters and vegetation indices, including those gathered from several bands such as DVI (810,450), perpendicular vegetation index- Landsat multispectral scanner (PVI-MSS), PVI (810, 680), DVI-MSS, and reflectance 743(R743) at flowering stage, DVI (810,450), DVI (810,680) and first derivative 723 (FD723) at grain-filling stage, and DVI(810,450), PVI-MSS and FD715 at ripening stage exhibited greater correlations with GCPC (the correlation coefficients are over 0.47). Among all selected spectral indices at three different growth stages under high temperature stress used to estimate GCPC, the optimum indices were DVI (810,450) and PVI-MSS, both of which exhibited high R^2 when regressed against GCPC.

DVI(810,450), PVI(810,680), PVI-MSS and R800 at flowering stage, DVI(810,450), PVI(810,680) and PVI-MSS at grain-filling stage, and DVI(810,450), R1077, and PVI-MSS at ripening stage under different high temperature treatments exhibited greater correlations with GAC (the correlation coefficients are over 0.67). Among all selected spectral indices at three different growth stages under high temperature stress used to estimate GAC, the optimum indices were DVI (810,450) and PVI-MSS with high R^2 when regressed against GAC.

DVI(810,450), PVI-MSS, DVI-MSS and R745 at flowering stag, DVI(810,450) PVI-MSS, DVI-MSS and R759 at grain-filling stage, DVI(810,450) and PVI(810,680) at ripening stage under different high temperature treatments exhibited better correlations with AC (the correlation coefficients are over 0.36). Among all selected spectral indices at three different growth stages under high temperature stress used to estimate AC, the optimum indices were DVI (810,450) and PVI-MSS with high R^2 when regressed against AC. Figures 5 showed the linear relationship of DVI (810,450) and PVI-MSS at flowering stage to GCPC, GAC and AC.

Two spectral indices like DVI (810,450) and PVI-MSS at three growth stages under high temperature stress could be used for estimating GCPC, GAC and AC, with high R^2. Additionally, GCPC, GAC and AC prediction based on flowering stage and was preferred than that on grain-filling and ripening stage by much bigger correlation coefficients (the correlation coefficients on flowering stage are over 0.79). It meant it was better to choose the time before grain-filling stage when predicting GCPC,

Table 2. Correlation between grain crude protein content (GCPC) and grain amylose content (GAC) and actual yield (AC) and canopy spectral parameters at different growth stages under different high temperature treatments (n=40).

	Flowering stage		Grain-filling stage		Ripening stage	
	Spectral parameter[1]	Correlation coefficients[2]	Spectral parameter	Correlation coefficients	Spectral parameter	Correlation coefficients
GCPC	DVI(810,450)	0.81**	DVI(810,450)	0.75**	DVI(810,450)	0.57**
	PVI-MSS	0.83**	PVI-MSS	0.82**	PVI-MSS	0.69**
	PVI(810,680)	0.80**	DVI(810,680)	0.73**	DVI(810,560)	0.46**
	DVI-MSS	0.78**	DVI(810,560)	0.66**	GM-1	0.56**
	R743	0.84**	DVI(560,680)	0.47**	PVI(810,680)	0.38*
	FD722	0.72**	FD723	0.62**	FD715	0.47**
GAC	DVI(810,450)	-0.85**	DVI(810,450)	-0.77**	DVI(810,450)	-0.60**
	PVI-MSS	-0.88**	PVI-MSS	-0.81**	PVI-MSS	-0.67**
	PVI(810,680)	-0.82**	DVI(810,560)	-0.66**	GM-1	-0.55**
	DVI-MSS	-0.85**	PVI(810,680)	-0.69**	DVI(810,680)	-0.46**
	R800	-0.85**	DVI(560,680)	-0.49**	R1077	-0.67**
	FD722	-0.80**	FD723	-0.66**	FD715	-0.52**
AC	DVI(810,450)	0.79**	DVI(810,450)	0.77**	DVI(810,450)	0.64**
	PVI-MSS	0.81**	PVI-MSS	0.80**	PVI-MSS	0.61**
	PVI(810,680)	0.76**	PVI(810,680)	0.72**	PVI(810,680)	0.36*
	DVI-MSS	0.79**	DVI-MSS	0.81**	DVI-MSS	0.54**
	R745	0.85**	R759	0.79**	R760	0.60**
	FD716	0.75**	FD719	0.67**	FD724	0.40**

[1] DVI = difference vegetation index; FD = first derivative; MSS = Landsat multispectral scanner; PVI = perpendicular vegetation index; R = reflectance.
[2] *P=0.05, **P=0.01, r(0.05,40)=0.30, r(0.01,40)=0.39.

GAC and AC. The main reason may be most of rice grain nutrients came from the transference of leaves, stems and even roots before flowering stage. But some of rice leaves and fringes became yellow, and leaf area and chlorophyll content became obviously reduced, which caused relatively reduced contribution of whole canopy spectra from leaf chlorophyll with positive correlation of grain quality and weight (Xie *et al.,* 2011). Therefore, the prediction precision of GCPC, GAC and AC depended on grain-filling and ripening stage were worse than that on flowering stage.

It is known that GCPC, GAC and AC can be estimated with the canopy spectral parameters collected at different development stages of cereals. For instance, Zhang *et al.* (2012) found rice GCPC can be predicted with canopy spectral reflectance under five nitrogen rates. Liu *et al.* (2014) concluded that the hyperspectral reflectance of grain crude protein was different from that of crude starch and amylose. Furthermore, the contents (%) of crude protein, crude starch, and amylose in rice flour were significantly correlated to the absorbing area from 2,020 to 2,235 nm. The canopy temperature (CT) and normalised difference vegetation index (NDVI) indices have been applied to estimate yield, taking advantage of the correlation between yield and these two Vis (Bahar *et al.,* 2008; Labus *et al.,* 2002). Mason and Singh (2014) also concluded that the NDVI has also been used successfully to estimate wheat yield before harvest at the regional and farm scale.

Validation of the developed models

To test whether the above regression models were reliable and applicable to the estimation of GCPC, GAC and AC under high temperature stress, the independent data set from E_2 was used to test the performance of the proposed model. RMSE and RE were employed to compare reliability and accuracy between estimated and observed values. By comparing RMSE and RE calculated from the above models with key spectral parameters, the best indices and regression equations for estimating GCPC, GAC and AC were selected to invert rice grain quality under high temperature stress, as shown in Figure 6.

For the two monitoring models with DVI (810,450) and PVI-MSS as predictors (Figure 6A, B), the R^2 between the observed and predicted GCPC were 0.73 and 0.76, the RMSE values were 4.03 and 5.62, and the RE values were 9.00 and 18.00%, respectively. The model with DVI

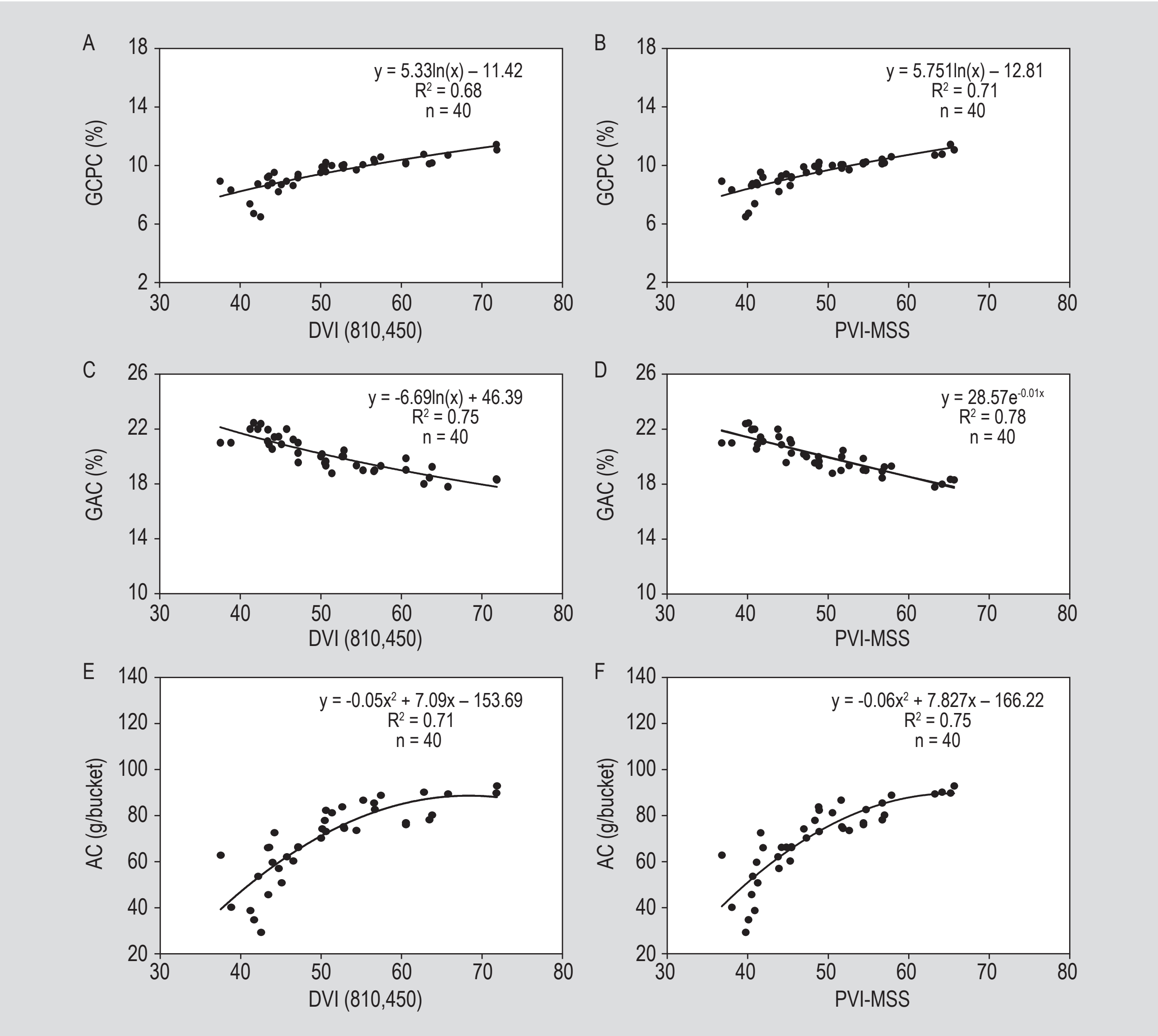

Figure 5. Linear relationships of (A) grain crude protein content (GCPC) to DVI (810,450), (B) PVI-MSS, (C) grain amylose content (GAC) to DVI (810,450), (D) PVI-MSS, (E) actual yield (AC) to DVI (810,450), and (F) PVI-MSS in Liangyoupeijiu in E1.

(810,450) as a spectral parameter exhibited a higher R^2 and lower RMSE and RE than the model with PVI-MSS as a predictor. For the two monitoring models with DVI (810,450) and PVI-MSS as predictors (Figure 6C and D), the R^2 between the observed and predicted GAC were 0.69 and 0.83, the RMSE values were 5.22 and 3.71, and the RE values were 14.00 and 6.00%, respectively. For the two monitoring models with DVI (810,450) and PVI-MSS as predictors (Figure 6E and F), the R^2 between the observed and predicted AC were 0.68 and 0.82, the RMSE values were 7.81and 6.43, and the RE values were 18.00% and 19.00%, respectively

Overall, the validation results with the monitoring models indicated a good agreement between estimated and observed values in rice under high temperature stress. Thus, the selected key hyper-spectral parameters could be reliably used for accurate estimation of rice GCPC, GAC and AC under high temperature treatments.

Although above results were obtained from field bucket experiments, impact factors were still few. The fertility condition, mature time and management technology in different regions in the world were also different in actual large-scale field production, which would further affect hyper-spectral characteristics on rice GCPC, GAC and AC. Therefore, it is necessary to use many experiments with different biological points, productivity levels and cultivation conditions for comprehensive test and improvement in order to realise the available unification between estimated-model accuracy and universality. These can promote direct application on rice GCPC, GAC and AC, and supply theoretical and technical references for high-temperature damage monitoring on rice, as well as

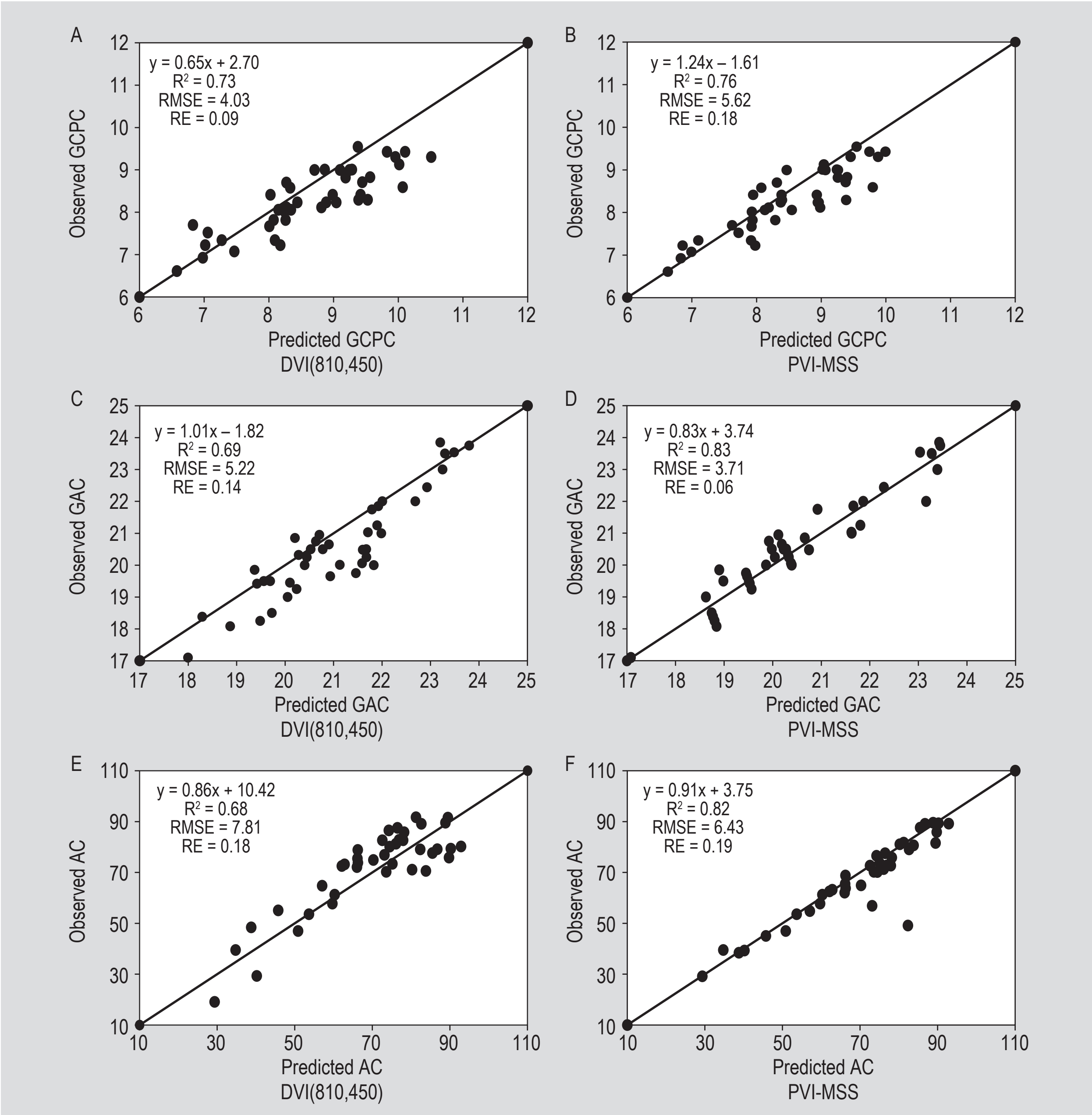

Figure 6. Comparison between observed and predicted grain crude protein content (GCPC), grain amylose content (GAC), and actual yield (AC) with linear equations based on DVI (810,450) (A,C,E), PVI-MSS (B,D,F) and in rice from E2 (n=40).

make an extensive application expectation for improving development of information agriculture in the future.

Further, compared with general estimation methods, such as statistical, agronomical and meteorological methods, the remote sensing estimation method with instantaneous and universal properties was attached to widely attention from agriculturalists around the world. However when there had a lot of changes for certain climate conditions in the experiments, such as light illumination, soil nitrogen level and soil moisture, the estimated rice GCPC, GAC and AC by remote sensing may have a big deviation, and the crop growth model with continuity and dynamic properties just offset this drawback (Li *et al.,* 2008). If the rice quality, yield-estimated model was performed for coupling computation using remote sensing inversion in practice, the accuracy can be highly improved, which will just be the next objective and target in this research.

4. Conclusions

GCPC and AC (GAC) in Liangyoupeijiu were clearly reduced (increased) under high temperature stress in this study compared with the values of CK, and the reducing extent of GCPC and AC (the increasing extent of GAC) was increased with the increase of high temperature level. However, there were no significant differences for GCPC and GAC under different high temperature treatments (P>0.05), but there were significant differences for AC among high temperature treatments (P<0.05). In order to accurately assess the response of rice GCPC, GAC and AC to potential climate change, a more complex study is currently under way.

The hyper-spectral reflectance in different wavelength regions under high temperature stress was different. They increased in visible light region with the elevation of temperature, but reduced in near-infrared region. In general, the correlation coefficient among GCPC, GAC, AC and spectral reflectance changed dramatically over different wavebands under high temperature stress, which showed that GCPC, GAC and AC could be estimated by original canopy hyper-spectral reflectance and their derivative parameters under high temperature treatments.

Among some selected spectral indices at three different growth stages under high temperature stress used to estimate GCPC, GAC and AC, the optimum indices were DVI (810,450) and PVI-MSS with high R^2 when regressed against GCPC, GAC and AC. Moreover, GCPC, GAC and AC prediction based on flowering stages were preferred than that on grain-filling and ripening stage by much bigger correlation coefficients. The six regression models developed in this study based on different temperature treatments showed the agreements between the predicted and observed values when testing independent data. Thus, the selected key hyper-spectral parameters can be reliably used to estimate GCPC, GAC and AC in rice under high temperature stress.

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