Rice growth vegetation index 2 for improving estimation of rice plant phenology in costal ecosystems

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Abstract

Crop growth is one of the most important parameters of a crop and its knowledge before harvest is essential to help farmers, scientists, governments and agribusiness. This paper provides a novel demonstration of the use of freely available Sentinel-2 data to estimate rice crop growth in a single year. Sentinel 2 data provides frequent and consistent information to facilitate coastal monitoring from field scales. The aims of this study were to modify the rice growth vegetation index to improve rice growth phenology in the coastal areas. The rice growth vegetation index 2 is the best vegetation index, compared with 11 vegetation indices, plant height and biomass. The results demonstrate that the coefficient of rice growth vegetation index 2 was 0.83, has the highest correlation with plant height. Rice growth vegetation index 2 is more appropriate for enhancing and obtaining rice phenology information. This study analyses the best spectral vegetation indices for estimating rice growth.

Keywords: crop growth, spectral indices, phenology, rice growth vegetation index 2.

Introduction

Rice (Oryza sativa) is a major essential food for approximately 50 % of the world's population and China around 28 % of global rice production [1]. It is most extensively consumed in Asia and Africa. Rice agriculture is deliberated as an important sector to sustain the national economy [2]. Chinese government strategy emphasizes ameliorate rice yields through techniques for evolving plant growths (using fertilization and irrigation) for food security and sustainability [3]. Effective monitoring and improved agricultural practice are important in China [4, 5], but there is a major challenge to generate and accurate local information. In particular, understanding the dynamics of specific phenological stages of rice to inform strategic and management practices is important [6, 7]. It is accredited as a dominant index for estimate phenological events of crop growth [8, 9]. Southern China has substantial light and temperature resources that are suitable for dual rice production systems [10, 11].

Vegetation Indices (VIs) access from remote sensing based canopies are effective algorithms for quantitative and qualitative estimations of vegetation cover and growth phenology [12]. Numerous, vegetation indices published but few of them are consequential for crop monitoring [13]. The cropland mapping can confer basically essential material for all crop monitoring applications [14]. The time series exploration conveys an appropriate tool to distinguish phenology on a pixel basis [15]. The main purpose of VIs is to expansion the vegetation gesture while decreasing the effects of solar radiation and soil background [16]. Subsequently, NDVI is used as the most essential algorithm for analyzing the spatial distribution of vegetation in the last two decades [17]. The NDVI is determined as the combination of $(R_{NIR} - R_{RED})/(R_{NIR} + R_{RED})$. Huang et al. (2010) [18] have demonstrated that NDVI is an exceptional appraisal of light interception by canopies since they are saturated during the season.

The Green Index (GI) can be determined by the consolidation of red and green bands, which is sensitive for plant chlorophyll [19]. The soil-adjusted vegetation index (SAVI) has conferred for soil background, it is illustrated as $SAVI = (R_{NIR} - R_{RED})(1 + L)/(R_{NIR} + R_{RED} + L)$ [20]. The enhanced vegetation index (EVI) was described to optimize of leaf area index signal. The EVI is the reflectance of the blue band in the electromagnetic radiations to assist to separate soil from vegetation.

The crop information obtaining through traditional methods, such as ground surveys and sampling are time-consuming and costly [21]. Numerous studies using time-series data, acquired from sensors such as MODIS, SPOTVGT, Rapideye have been successfully accompanied for regional monitoring of crop phenology [22, 23]. The Sentinel-2A planetarium was launched on 23 June

2015 and Sentinel-2B on 7 March 2017 advantageous to simultaneously map the rice field over a large region, due to the spatiotemporal resolution and the repetition frequency. Sentinel-2 has a 5 day revisit cycle with high resolution, which is appropriate for crop mapping at field level. The Sentinel-2 improved spatial and temporal resolution that is beneficial for farmers and academic researchers focusing on agricultural development [24, 25, 26]. The China agriculture field sizes are typically less than 1 hectare, so high spatial resolution acquaintance is essential for evaluating crop information for decision-making.

In this paper, we modify a rice growth vegetation index to improve rice plant phenology monitoring in coastal ecosystems using Sentinel-2 data time-series. The newly modified rice growth vegetation index 2 (RGVI2) uses the spectral reflectance of red, NIR, and SWIR bands to discriminate between the green vegetation and background signal. The findings in form of quantitative and spatial information on rice growth at the field level could be valuable to agronomists to timely address issues of food security. This study aims to explain RGVI2 with different VIs relationships derived from reflectance of crops and to compare with different growth parameters such as; plant height and biomass factors which are very important for crop growth monitoring.
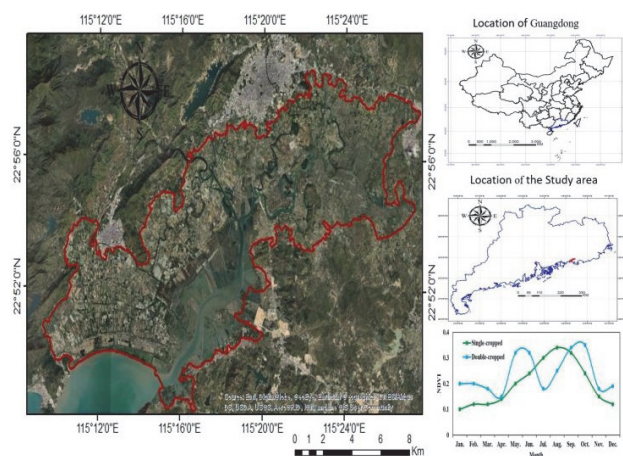
1. Study area

Fig. 1. The Location of the study area (Shanwei) and Normalized difference vegetation index (NDVI) rice growth process

The study area selects Shanwei, the city of Guangdong province, China, which is positioned between latitudes 22°50′0″ to 23°07′55″ N and longitudes 115°10′0″ to 115°27′30″E (Fig. 1). For this research, the total area of 244 km^2 selected. The topography of the study area is comparatively flat and its mean terrain elevation is 8 m. The study area is considered by a humid subtropical monsoon climate with the warm season, plentiful precipitation, sufficient sunshine, long frost period, and maritime monsoon characteristics [27]. The mean annual precipitation is 1891 mm, with 80 % occurring during the monsoon season. Precipitation in the rainy season ranging

from May to August accounted for over 80 % of the annual total. The temperature ranges from 15.2 °C in January to 28.3°C in July, and the annual mean is 22.60º C.

The image covers most of Haifeng County and some parts of Chengqu district. The main productions have been rubber, corn, cotton, groundnut, rapeseed, rice, wheat, soybean, fruits and animal husbandry. The rice is the main production in the study region. The soil type is red, which has a low capacity for water storage. The rice growing time period comparatively: Early rice (March-July) and late rice (June-November). This research work was focused on the early rice season (March-July).

2. Materials and methods
2.1. Data and processing

To exclusive VIs for rice crop growth mapping, we selected Sentinel-2 data with an acquisition date from January to December. We choose 25 sites for phenology calculation in the study area. The Copernicus, led by the ESA, is one of the most significant Earth observation programs that is focused on the detection and assessment of vegetation. Sentinel-2 data have numerous ways to freely download; one of them is through Copernicus (https://scihub.copernicus.eu/dhus/#/home) and another United States Geological Survey (USGS) (https://earthexplorer.usgs.gov/). The ArcGIS software is applied for all analyses of work. The radiometric calibration is the most accurate processing for remote sensing data [28]. We used radiometric and geometric correction to improve the image. The Sentinel-2 has three different spatial resolution 10 m, 20 m, and 30 m, so all the images were resampled at 10 m spatial resolution. All vegetation indices were generated for tracking crop health conditions in all growth stages. The crop data (plant height and biomass) were obtained from the website of the Ministry of Agriculture of China (http://english.moa.gov.cn/datastatistics/) and http://www.ricehub.org/RT/varieties/variety-trials/module-3-data-collection/. The rice yield data obtained from (http://www.stats.gov.cn/tjsj/ndsj/). It demonstrates that as plant height increased, the reflectance of the near−infrared band steadily increased.

2.2. ECOSTRESS spectral library data

Selection of the correct wavelengths and bandwidths are important for rice phenology monitoring. In this study, Sentinel 2 spectral bands, centers and widths in the visible, near-infrared and shortwave infrared spectra were examined for rice crop phenology characteristics using ECOSTRESS library. The chlorophyll pigments present in green leaves strongly absorbs in the visible region of the spectrum, especially in the blue and red wavelengths. The near-infrared (NIR) leaves demonstrate high reflectance values, frequently related to leaf structural properties and biomass. The SWIR, from approximately 1300 to 2500 nm, has good absorption of radiation conquered by water. In agriculture circumstances where crops interrelate with any accustomed aspect of their environment

(seasonal climatic differences, meteorological events, soil properties, etc.) the interactions between plants and light reflectance translate into changes in plant signal patterns that can be interpreted using satellite data. The mostly spectral ranges used of vegetation are red and near infrared because they accommodate around 90 % of the information relating to vegetation. Thus, vegetation covers can be measuring the difference between the two spectral bands that is the basis of a VIs [29].
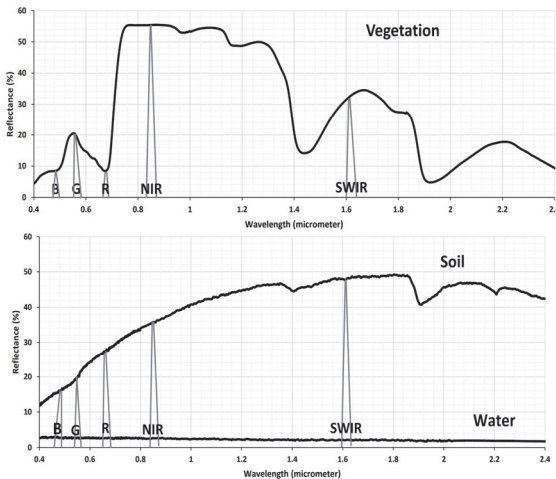

Fig. 2. Spectral reflectance curve of vegetation, soil and water obtain from the Eco-stress spectral library

2.3. Calculation between rice spectral and rice age

All acquisition dates of the Sentinel-2 images were taken randomly in the twenty-five field observation sites. The relationship between rice age and rice spectral was completed from spectral of Sentinel-2 and vegetation index with the following equation, which is developed by Nuarsa [30]:

$$y = f(X), \tag{1}$$

$$R^2 = 1 - \frac{\sum (y - \bar{y}')^2}{\sum (y - y')^2}, \tag{2}$$

$$SE = 1 - \frac{\sum (y - y')^2}{n}. \tag{3}$$

Where y is the rice age and x is the rice spectral. The relationship between rice age and spectral was calculated using statistical parameters and standard error of estimation [30]. The water environment plays an important role in rice spectral. The blue band of Sentinel-2 has a good sensitivity with water. Hence, the development of a rice growth vegetation index (RGVI) by Nurasa (2011) used blue, red, NIR, SWIR1 and SWIR2 bands with the following equation:

$$RGVI = 1 - \frac{(R500 + R687)}{(R927 + R1662 + R2130)}. \tag{4}$$

2.4. Rice growth vegetation index 2 (RGVI2)

In agriculture conditions where crops interact with the environment (climatic differences, meteorological differ-

ences, soil properties, etc.), there is intervention between plants and light reflectance in plant signal configurations that can be estimated using satellite data. We extract VIs values after calculated reflectance values of green, red, NIR, SWIR1, and SWIR2 bands of a single-pixel comparable. This research is established on coastal area rice monitoring so due to climatic discrepancies, SWIR 2 band does not provide appropriate information about rice phenology because it is sensitive to leaf water content and unfortunately it may not capture the phenology timing in coastal ecosystems. So we modified RGVI VIs into RGVI2. The shortwave infrared 2 is a mix-up between rice and water, hence, an improvement in the index is essential and the RGVI is modified here to overcome this problem. It is essentially applied in the analysis of crop growth, desertification research, and rice yield estimation. The equation of rice growth vegetation index 2 is following:

$$RGVI2 = 1.05 - \frac{(R500 + R687)}{(R927 + R1662 + \alpha)}. \tag{5}$$

Where α is a weight factor ranges from 0.0 to 1.0, depending on the spectral configuration of satellite sensors. In practical applications, the values of α are determined according to the specific environmental conditions. After validation procedures, a coefficient value of $\alpha = 0.5$ appears to be generally effective for the RGVI2 calculations. The value of α is around 0.5 under the most common environmental conditions. The RGVI2 was proposed to obtain high contrast between rice growth and backgrounds, as well as to minimize the differences among the backgrounds. It is therefore expected to be insensitive to the effects of atmospheric effects in rice phenology monitoring. So we add 0.05 values to improve plant phenology. These values can be simply computed using the central wavelengths of satellite sensors. These results are reliable with the fact that in the visible bands, light is absorbed by leaf pigments, while radiation in the near−infrared is highly reflected by the internal cellular structure of plant leaves [31].

2.5. Vegetation indices

A significant selection of vegetation indices, derived from remote sensing data, usually characterizes the crop growth pattern. The main determination was to improve a rice crop growth vegetation index which gives quantitative results of plant growth. The RGVI vegetation index was evaluated for rice growth. The vegetation indices and spectral wavelength applied in this analysis are described in table 1. All VIs mean values and regression models are applied for different vegetation phenomena identification. The selected VIs analyses were conducted into five stages of rice plant growth. This research work used 25 sample plots that have similar vegetation structures. The higher values illustrate a broad spreading of the data points.

3.   Results

This section demonstrates the time series analysis of VIs and illuminate with different phenological stages of rice for several fields. Subsequently, Spatio-temporal im-

ages of VIs are interpreted and the relationship between | plant height and VIs with biomass is evaluated.

Table 1. Different Vegetation Indices (VIs) computed for the study

Vegetation Index	Abbreviations	Equations	Properties	References
Normalized difference vegetation index	NDVI	$(R927 - R687)/(R927 + R687)$	Green Biomass	Thenkabail et al. (2000)
Moisture stress index	MSI	$R1662/R927$	Water content	18Thenkabail et al. (2000)
Green Index	GI	$R554/R677$	Green Biomass	Zarco-Tejada et al. (1999)
Ratio Vegetation Index	RVI	$R927nm/R687\ nm$	Light use Efficiency	Thenkabail et al. (2000)
Plant senescence reflectance index	PSRI	$R(680 - 500)/R750$	Carotenoid pigments	Sims and Gamon (2002)
Leaf chlorophyll index	LCI	$(R850 - R710)/(R850 + R680)$	Chlorophyll presence	Thenkabail et al. (2000)
Enhanced vegetation index2	EVI2	$2.4(R800 - R670)/(R800 + R670 + 1)$	LAI	Huete et al. (2002)
Green Ratio vegetation Index	GRVI	$R800/R554$	Leaf pigments	Sripada et al. (2006)
Soil adjusted vegetation index	SAVI	$(R800 - R670)/(R800 + R670 + L)$ $*(1 + L)$	Vegetation Canopy / soil brightness	Huete et al. (1988)
Normalized differential greenness Index	NDGI	$0.65*R554 + 0.35*R800 - R670/0.65*R554 + 0.35*R800 + R670$	Soil brightness, snow and grass	Wei et al. (2019)
Rice Growth Vegetation Index	RGVI	$1 - (R500 + R687)/(R927 + R1662 + R2130)$	Light use Efficiency	Nuarsa et al., (2011)

R *refer to the reflectance at wavelength*

3.1. Time series analysis of spectral vegetation indices

Fig. 3 illustrates the consistency between different VIs for each class which was extracted from all the training points. Water is straightforwardly recognized in all VIs. The vegetation values in RGVI2, NDGI, EVI2, and NDVI show a perfect distinction from the crop value. For crops, rice was different from other crops in the GRVI, RVI, SAVI, EVI2 and NDVI. The RGVI2 demonstrates huge differences between rice and other crops. The MSI shows a discrepancy between vegetation and water but less discrepancy between rice and other crops. During the transplanting stage of Early rice (March to July) and Late

rice (June to November), water flooding significantly decreased backscatter, which helped to identify rice cropping intensity.

The early rice planted time is mid of March that time NDVI has low values due to soil contribution to the reflectance when there was no crop. The plant started developing at the end of April. So vegetation values also increase during this period. A trend demonstrates VIs rising from May to Jun because of rice plants developed in this period. Rice plant approached full development in July, that's why NDVI values decreased. In July VIs was very low because rice fields were harvested.

Table 2. Regression model (R^2) between different vegetation indices of rice crop

VIs	RGVI2	NDVI	NDGI	MSI	LCI	GRVI	GI	EVI2	PSRI	RVI	SAVI
RGVI2	1	0.89	0.82	0.22	0.01	0.86	0.27	0.91	0.32	0.90	0.88
NDVI	0.89	1	0.90	0.12	0.00	0.90	0.30	0.91	0.41	0.90	0.90
NDGI	0.82	0.90	1	0.34	0.00	0.87	0.22	0.94	0.36	0.92	0.93
MSI	0.22	0.12	0.34	1	0.00	0.25	0.01	0.29	0.06	0.31	0.30
LCI	0.01	0.00	0.00	0.00	1	0.00	0.01	0.00	0.05	0.00	0.00
GRVI	0.86	0.90	0.87	0.25	0.00	1	0.44	0.83	0.58	0.96	0.81
GI	0.27	0.30	0.22	0.01	0.01	0.44	1	0.17	0.27	0.39	0.13
EVI2	0.91	0.91	0.94	0.29	0.00	0.83	0.17	1	0.26	0.90	0.96
PSRI	0.32	0.41	0.36	0.06	0.05	0.58	0.27	0.26	1	0.46	0.27
RVI	0.90	0.90	0.92	0.31	0.00	0.96	0.39	0.90	0.46	1	0.87
SAVI	0.88	0.90	0.93	0.30	0.00	0.81	0.13	0.96	0.27	0.87	1

The consequences of selecting VIs are based on the mean value and linear regression hypostasis of the 11 vegetation indices such as NDVI, RGVI2, NDGI, MSI, LCI, GRVI, GI, EVI2, PSRI, RVI, and SAVI (Table 2). The regression analysis (R^2) showed that strong correla-

tion VIs are RGVI2, EVI2, SAVI, and NDVI, such as RGVI2 correlated with SAVI (0.89), EVI2 (0.91); EVI2 correlated with SAVI (0.96), NDGI (0.94); SAVI correlated with EVI2 (0.96), RGVI2 (0.90) and NDVI correlated with EVI2 (0.91), SAVI (0.90), RGVI2 (0.89),

NDGI (0.90). The GRVI, GI and RVI moderate correlate with other vegetation indices. PSRI and MSI are not well correlated with other VIs. Also, LCI is not correlated with other VIs. Plant senescence reflectance index and Moisture stress index as reflectance was diminished due to wa-

ter content of the plant. There was a clear difference in the Moisture stress index at different stages for rice crops. It indicated that the index is not able to differentiate the effect of water stress. The results of the regression correlation based on the coefficient of determination are as follows:
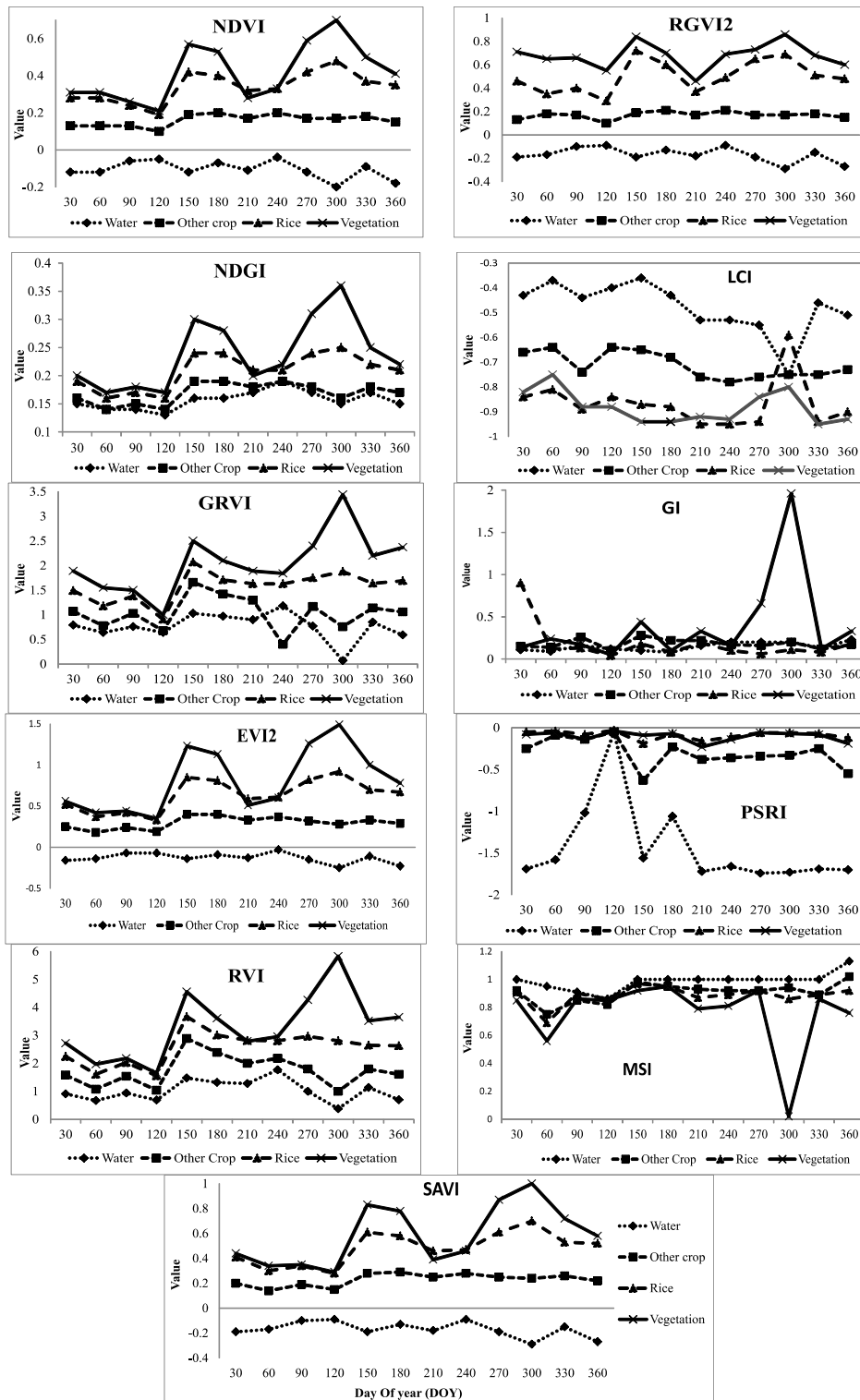

Fig. 3. Time series analysis of spectral vegetation indices for four classes

The results demonstrate that SAVI, RGVI2, NDVI, NDGI and EVI2 provide additional evidence approximately rice crop growth. The RGVI2 values are amazing where the vegetation shield is exposed and the soil surface is low. The MSI values

are a reflection measurement that is slight to increasing the leaf's water content. The Enhanced vegetation index (EVI2) results illustrate that it has been developed to optimize vegeta-tion signals with better sensitivity in high vegetation areas. NDVI is chlorophyll sensitive, with the EVI2 canopy being more responsible for structural changes (32, 33).
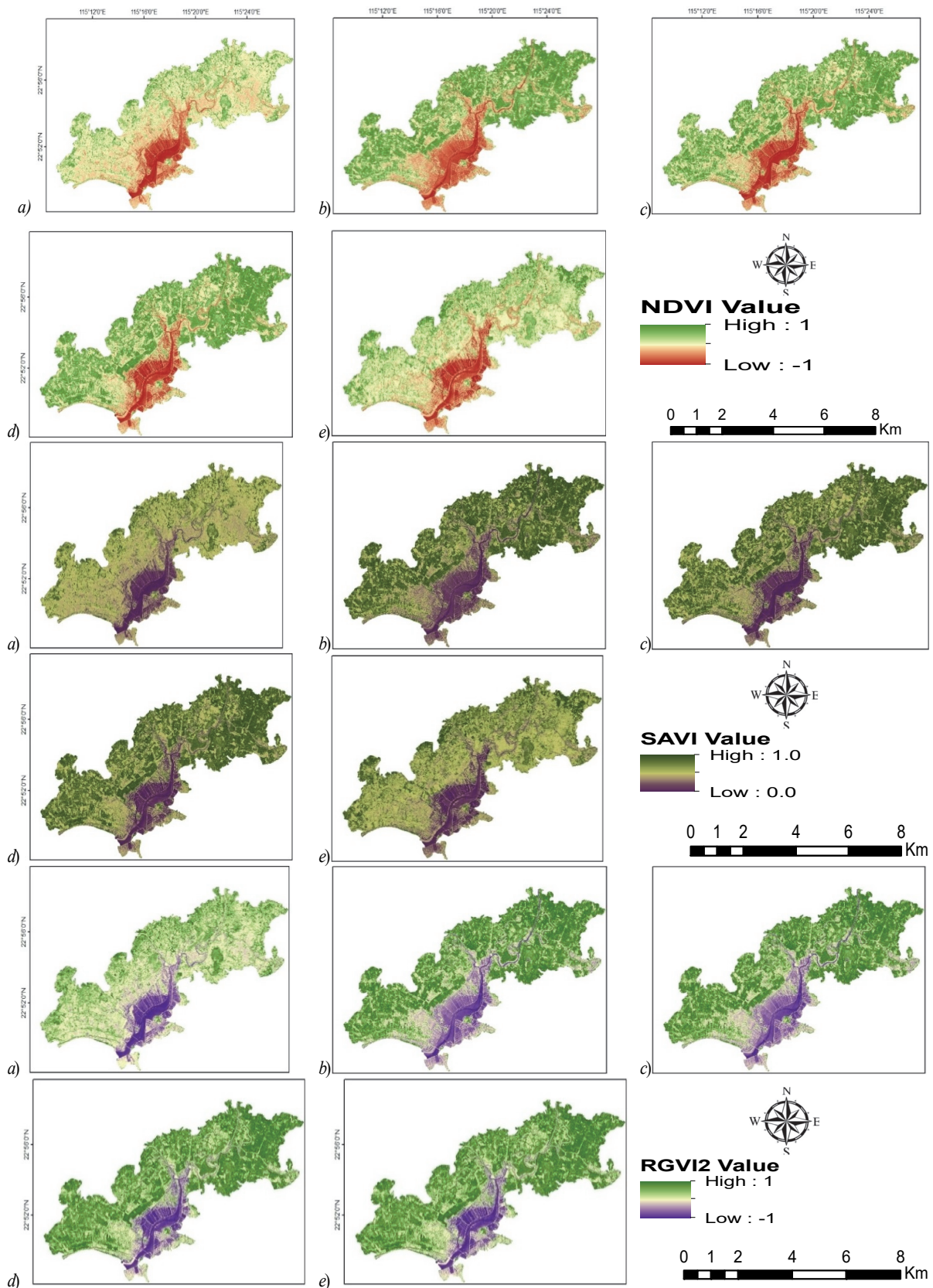

Fig. 4. Spatio-Temporal changes of NDVI, SAVI, and RGVI2 at different phenological stage;
(a) Seeding; (b) Tillering; (c) Jointing (d) Booting; (e) Maturity

3.2. Crop monitoring in phenological stage

Based on literature [34, 35, 36] the growth of rice crops have been categorized into five stages; seedling, tillering, jointing, booting and maturity (Fig. 4). The seedling and tillering stage (around 65 days) contains the vegetation phase.

The jointing and booting stage (around 30 days) contains the reproductive phase. The maturity stage (around 30 days) contains of ripening phase. Meanwhile the vegetation stage rice elevation increase constantly, later small changes are seen during the reproductive stage. In the ini-

tial stage of crop growth soil visibility is the main reason for a low values, that's why all vegetation indices have low values. During the seedling stage, it increased and reached a peak around the jointing and booting stage formerly it declined towards the maturity of the crop. All these vegetation indices are related to the greenness content of the crops.

These indices recorded at the booting stage were better correlated with crop parameters as compared to other phenological stages. According to Kaur et al. (2015) [37], the correlation between different crop parameters and vegetation indices were best at $75-105$ days (booting).
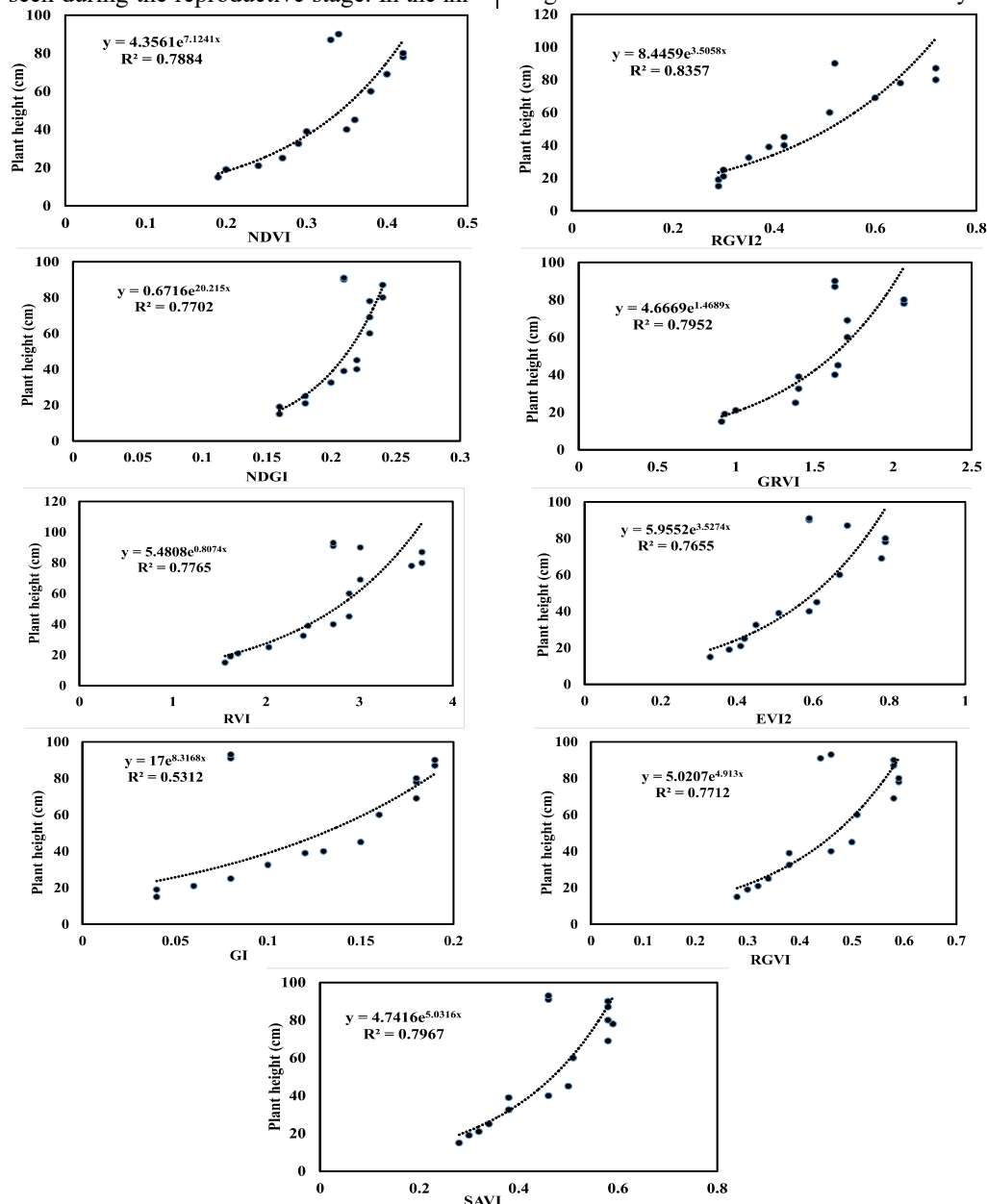
Fig. 5. Statistical analysis of vegetation indices with plant height

Spatial-temporal alterations were occupied in disparate vegetation indices. These indices were derivative visible-near infrared and red bands such as NDVI, GI, RVI, SAVI, RGVI2, EVI2, etc. All maps are beneficial to evaluating variability in crop growth with the pheno-

logical stage. This field is dominated by rice and other crops. Though, this research is individually dedicated to rice. The rice growth study is incomplete without the VIs time series. We scrutinized all 11 VIs for crop health monitoring but the best consequences are given

by RGVI2. The SAVI, NDVI is intermediate VIs. These maps are increased in Plant height as the plant was growing. The vegetation indices designated the con- sistency in plant growth. These delineations exhibited that VIs can provide a good delegate for tracking vegetation health status.
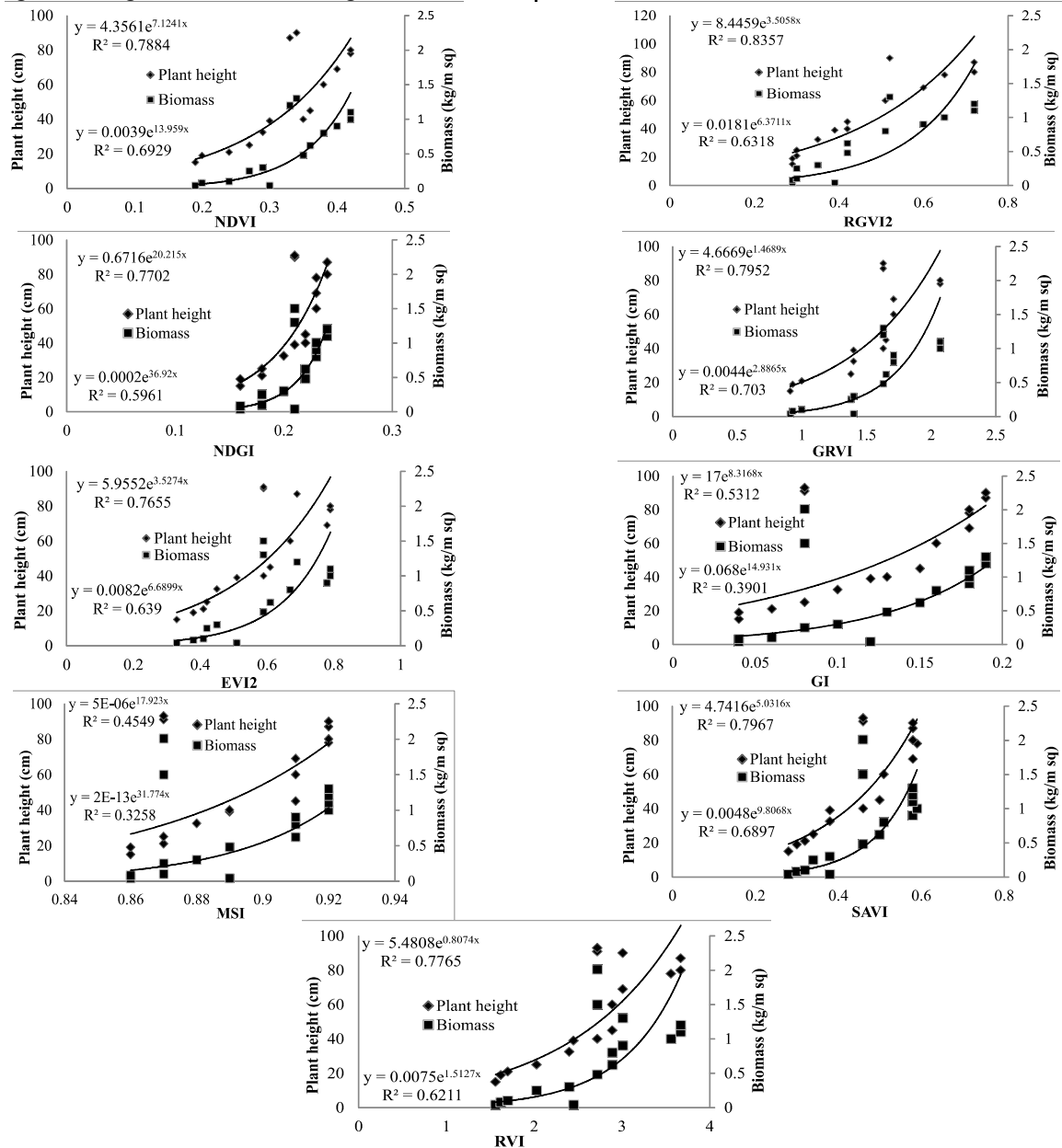

Fig. 6. Regression models between plant growth parameters and spectral vegetation indices

3.3. Relationship between spectral indices and crop parameters

The exponential regression analysis was the best estimation to demonstrate the relationship amongst rice plant spectral and rice plant height. All vegetation indices estimated in this study indicated a substantial relationship with rice plant height and biomass. The Rice Growth Vegetation Index 2 (RGVI2) modified in this study gives a better relationship, with $R^2 = 0.83$, followed by NDVI, SAVI, GRVI, and RVI, with R^2 values of 0.78, 0.79, 0.79, and 0.77, scientifically. Figure 5 demonstrates that rice plant height and rice spectral have a very good rela-

tion with RGVI2 indices. Using multiple bands of Sentinel-2 gave an enhanced relationship between rice plant height and rice spectral than was applying a single band.

Exponential regression analysis between different plant growth parameters and spectral vegetation indices are presented in figure 6. The GRVI has the highest correlation with biomass. The correlation coefficient of SAVI for biomass was 2.5 % higher as compared to that of EVI2. The high correlation GRVI have the effect of replacing the green band with a red band, as the red band activation of the green band is due to leaf structure. SAVI, RGVI2, and EVI2 have well correlated with biomass. The correlation analysis of plant height and biomass of

rice was performed to the capability of VIs for rice crop growth. Most of the vegetation indices were positively correlated with both biophysical parameters.
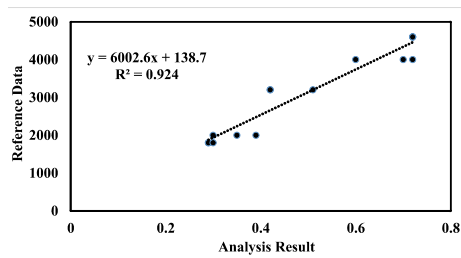
4. Accuracy

Fig. 7. Linear regression model between RGVI2 and reference data

The sentinel-2 was quantitatively evaluated for rice plant growth by analysis amongst different vegetation indices. The Google Earth Engine was very useful for identifing features during accuracy estimation. The Low estimates for almost all vegetation indices values were compared to the local government data. The mixed pixel can reduce the accuracy of the calculation. Xiao et al. 2019 [38] has approved the same phenomena using MODIS data and results in a demonstration that the estimation of the rice spectral in Southern China was lower than the reference data. The Linear regression model established between RGVI2 spectral indices and reference data (grain yield) of the rice crop is accessible in Fig. 7. The accuracy of the vegetation extraction based on RGVI2 is higher than other visible band-based VIs and G band. Furthermore, the accuracy of RGVI2 has been described to be over 92 %. So RGVI2 vegetation indices can be applied in decision support systems for yield forecasting models.

Conclusion

The RGVI2 index has a mathematical expression based on the reflectance spectra of different components (vegetation, water, soil, etc.). Furthermore, it is simply parameterized by an obvious calculation applying the wavelengths of remote sensing data. The analysis results demonstrated that RGVI2 could eliminate the effects of water on estimates of rice phenology. The RGVI2 is more suitable for the amplification of rice phenology because it can efficiently reduce the water effect. The accuracy of RGVI2 has been reported around 92 %. Different environments have their individual sophisticated characteristics, which requirements to be assumed when using different VIs. All VIs have their specific expression of green vegetation, its own suitability for specific uses. For practical applications, the RGVI indices needs to be modified with attention by comprehensively considering and analyzing the advantages then combine them to be applied in a specific environment. Among training sites, the RGVI2 was superior over the other VIs in estimating rice phenology on coastal areas. The results indicated that time series analysis and the correlation between biophysical parame-

ters provide better information for crop growth monitoring. The use of different vegetation indices is required for improved management decisions (39, Shen et al. 2019,). It can help farmers in accurately locating the problem area in their field and run necessary field operations to reduce losses in crop yield. Usually, appropriate climatic circumstances throughout the particular growth stage are critical for rice plant growth and grain yield. Hence, further study to analyze the climate character during specific growth stages related to grain yield in long term experiments is needed. The grain yield will significantly and positively be correlated with the plant height. In future studies, additional evaluations for rice yield will be carried out.

Authorship contribution statement

Komal Choudhary: Conceptualization, Formal analysis, Methodology, data curation, Writing – original draft. **Wenzhong Shi**: Supervision, Writing – review & editing. **Yanni Dong**: Data curation, Writing – review & editing.

Declaration of conflicts interest

We declare that our paper has no conflict of interest among authors and other journals.

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