Models for estimating the leaf NDVI of japonica rice at the on a canopy scale in Northeast China by combining canopy NDVI and multisource environmental data in Northeast China

Abstract: Remote sensing of rice traits has advanced significantly in with regard to the capacity to retrieve useful plant biochemical, physiological and structural quantities across spatial scales. The rice leaf NDVI [normalized difference vegetation index] has been developed and applied in monitoring rice growth, yield prediction, diseases status to guide agricultural management practices. This study combined rice canopy NDVI and environmental data to estimate rice leaf NDVI models. The test site is was a japonica rice experiment located in the eastern city of Shenyang, Liaoning Province, China. This editorial report provides a describes (1) using the use of multiple linear regression to established four periods of rice leaf NDVI models with good accuracy ($R^2 = 0.782 - 0.903$), and (2) determined how the key point of the rice growth period based on these models was determined. This research also presents the techniques for modeling leaf NDVI at the point of canopy remote canopy sensing. The results illustrate indicate that rice leaf NDVI with canopy NDVI and multisource environmental data have a great high correlation. This research established establishes models which may be one efficient method to detect rice leaf growth at the canopy scale in the future

Keywords: Japonica rice; NDVI; Leaf Models; Canopy scale; Environmental data

1. Introduction

China has the second largest rice-planting area in the world and the largest annual rice output (204 million tons). Rice cultivation in northeast China is mainly based mainly on japonica rice, whose for which the planting area accounts for more than 30% of the total rice area and continues to increase.^[1]

The leaf of the rice plant is constitutes its rice photosynthetic vegetative organs, leaf the total nitrogen concentration is rice nitrogen with regard to nutrition being an important indicator of for diagnosis. Traditional rice nitrogen-monitoring methods for rice generally rely on plant in field-sampling of plants in the field and subsequent indoor testing. Although the results from such testing is are more reliable, but on the temporal and spatial scales are present difficulties to in meeting real-time, rapid, non-destructive diagnoses of nitrogen requirements. With the development of modern remote sensing technology, remote sensing monitoring this technology for when

applied to rice has been involved in included an estimation of the chemical composition of rice nitrogen. and In theory and practice for the evaluation of rice growth and the its physiological parameters, remote sensing provides can guarantee reliable guarantee outcomes.

Applying remote sensing technology to obtain information on rice growth had has rapidly developed in recent years because of its low cost, nondestructive testing processes, and other wide-ranging advantages^[2]. The different characteristics of rice the spectral information data on rice are constitute the theoretical basis for using remote sensing technology to obtain information on rice growth through spectral analysis analytical methods to identify and extract the corresponding phenotypic traits of rice information and spectral vegetation indices (VIs). The VIs can reduce the influence of external factors to a certain extent and thus enhance rice-growth information.^[3]

In 1999, a group of investigators funded by the NASA Earth Observations Commercialization and Applications Program (EOCAP) pooled their resources and conducted to conduct a nitrogen fertilization experiment aiming to prove the that agricultural crops are required to conduct must undergo dry-matter accumulation during photosynthesis in leaf with of chlorophyll in their leaves.^[4] Therefore, leaf leaves need requires a lot of red light and blue light to complete the process of photosynthesis. As rice in is growing, it has exhibits a strong absorption phenomenon in the visible region (VR) of sunlight radiation and weak absorption in the near infrared region (NIR) of sunlight ^[5]. The spectral bands used by most VIs are concentrated on in the VR-to-NIR (350-1700 nm) range. At present, the VIs of phenotypic traits in rice consist of more than 50 species, such as the ratio vegetation index (RVI), the normalized difference vegetation index (NDVI), the soil- regulate regulation vegetation index (SAVI), the difference vegetation index (DVI), and the enhanced vegetation index (EVI)^[6,7]. Some research has shown good NDVI data for crop production and biomass estimation ^[8-11]. However, the NDVI do does not reflect rice growth in the internal mechanism process of internal mechanism. Although many agronomists and rice NDVI parameters are present have been considered, their models are mostly based mostly on the establishment of statistical methods for remote sensing estimates, frequently with relatively strong empirical models and relatively poor versatility^[12-14]. The general remote-sensing method to obtain a rice canopy NDVI takes advantage of the natural light; and therefore, the acquired NDVI is affected by light conditions, the atmosphere, and aerosols, thereby causing all of which contribute to reduced accuracy. The plant type of japonica rice is mainly vertical leaves In Northeast China (Shendao-47, Shendao-525, etc.), the variety of rice known as japonica consists mainly of vertical leaves. A canopy NDVI also can also be affected by soil, water layers, green algae, and other surface features, and these all of which act as interfering factors that greatly influence the accuracy of the NDVI index in a rice canopy.

The objective of this study was to using use the rice canopy NDVI and environmental date data to modeling the rice leaf NDVI. The researchers collected different scales of NDVI data (from both canopy and leaves) from the Shenyang Agricultural University experimental rice-breeding experimental fields. The data were acquired during the rice-cultivation period of rice from transplanting to maturity period (2015.6–2015.10 June 2015-October 2015). The leaf NDVI model of northeast japonica rice was based on fusion remote fusion sensing and environmental factors such as temperature and humidity during the number of growing days, sunshine sunlight hours, and rice-growing microenvironments. ^[15]

2. Materials and methods

2.1 Testing site

The study testing site was an experimental rice-breeding experimental field at Shenyang Agricultural University (41°49' N, 123°33' E; altitude, 65 m) in Shenyang, Liaoning Province, China.

The japonica rice (Shendao-47) cultivar was transplanted on May 28, 2015. Shendao 47 has robust seedlings, strong tillering features, 350–400 m² plant, height of about 105 cm, semi-erect panicle, compact plant type, erect leaves, about 1.2 to 1.5 million per acre of panicle, ear length of 25 cm, 160 per panicle number of flowers, yellow glume and glume tips, 140 to 200 grains per panicle, and about 90% granulation.

The typical properties of Shendao-47 include the following:

- compactness;
- robust seedlings;
- strong tillering features;
- erect leaves;
- yellow glumes and tips;
- semi-erect panicles, numbering about 1.2 to 1.5 million per acre;
- 160 flowers and 140-200 grains per panicle;
- 25-cm ear lengths;
- heights of about 105 cm;
- about 90% granulation;
- 350–400 m² planting areas.

China has 10 quality indicators to meet China's its high-quality, high-palatability rice standard. Some varieties have rice resistance are resistant to blasts, lodging, low temperatures, and drought (for the medium-ripe variety). and the growth period is 155–156 days in Shenyang. Shendao-47 is widely cultivated in Shenyang, where the growth period is 155–156 days. Other areas of widespread cultivation include and Liaoyang, Anshan, Yingkou, Panjin, and North China. ^[16-18]

Data were collected from both leaf and canopy NDVI and canopy NDVI, and the in canopy was of 0.5 m^2 . The average sets have area circular had a 15 sampling points for the testing in the a paddy field, as illustrated in Figure 1. The instruments used were a Plant-Pen NDVI-300 (PSI Corporation, Czech Republic) for the leaf NDVI data collection and a SpectroSense2+ (Skye Corporation, UK) for the canopy NDVI data collection.^[19-22] Temperature and humidity data were collected by using the a wireless temperature and humidity sensor network.^[23] The sensors were distributed inside the plots (at points 1-9) and 2 m above the rice fields at each temperature. The humidity collection point heights was were divided into three sections: the bottom of rice growth (10 cm), mid-area rice growth in the middle (60 cm), and rice the canopy (110 cm). The Rice- growth data were collected at different heights, micro-environmental temperatures, and humidity levels.



Figure 1. Test site: japonica rice experiment at Shenyang Agricultural University in 2015; points 1~15 was the designate sampling area. (Background: Shendao-47, June 17, 2015, UAV collection)

2.2 NDVI data collection

2.2.1 Leaf NDVI collection

Rice leaf NDVI data were collected by using a PlantPen NDVI-300 as an the active light source of NDVI for the measuring instrument. The center of the instrument visible-light wavelength of the instrument was 660 nm (VIS = 660 nm); the near-infrared light-source center wavelength, was 740 nm (NIR=740 nm); and the range, was 620–750nm. ^[24] The leaf NDVI measurement period was from a week after transplanting after a week (June 4) to harvesting a week before the month's end (October 1). The measuring time for measurement was every day at 10:30H–13:30H daily. On rainy days measurement will be was postponed to after until the rain ended, the latest but not more later than 16:00. Given the relatively relative slenderness leaves of north japonica rice leaves, this study on leaf NDVI measurement included pointed and three-tail leaves, as measured by three NDVI data sets averaged as rice single-leaf NDVI values. For each sample, the number of leaves was collected was

considered as an NDVI point for the entire canopy sampling area (0.5 m^2) , the area of leaves, and the resulting calculated average NDVI. The leaf NDVI in for the region was then obtained. For rice in the tillering stage of rapid growth, the sampling points in the region had included many leaves to ensure accurate data accuracy. The rice canopy leaves and rice fields within the main leaf angle blade were averaged for the entire rice sampling area to obtain the average NDVI value of the leaves (not less than 70 leaves).

2.2.2 Canopy NDVI collection

Rice canopy NDVI data were very important in this study, for which the canopy-NDVI measuring instrument used was a SpectroSense2+ (Figure 2a), which had has a passive light source. The corresponding wavelength of the incident solar radiation incident intensity was measured, and the vegetation canopy of the reflected light was set to be strong based on the basis of the measurement of the corresponding spectral characteristics. ^[25] To reduce the error caused by the different spectral bands, the selected sensor band was kept consistent with the measurement range of the Plant-Pen NDVI-300 (Figure 2b), and the detection range was being 620–750 nm. The canopy NDVI measurement time was consistent with the leaf NDVI. and Moreover, to reduce human error during the canopy NDVI measurement process, steps were taken to ensure measurement personnel back and the back of the instrument that the backs of the personnel and the instruments was were not measured in the coverage area to reduce human error (Figure 2c).



Figure 2. Testing instruments: a) SpectroSense2+ for canopy NDVI collection; b) NDVI-300, for leaf NDVI collection; c) canopy NDVI measurements: The center of the instrument visible-light wavelength of instrument, was 660 nm (R = 660 nm); near-infrared light-source center wavelength, was 740 nm (NIR=740 nm).

2.3 Measurement of field environmental parameters

The NDVI is does not represent a physical quantity of rice; thus, the models of NDVI and rice growth show an unclear growth mechanism. The Such models cannot clarify the underlying mechanism of change and its relationship with the NDVI ^[26-27]. Under the a same-soil condition of the same soil condition, the growth of rice was is mainly affected by the environmental factors.

In this study, fifteen wireless temperature and humidity sensor networks were set up in the experimental field, and each sample was being divided into three heights. For each height, temperature and humidity data were detected obtained in the experimental fields field, and the where an external space was also provided with environmental temperature-and-humidity-detection sensors. These wireless sensors network communicated through the a ZigBee network, and the networking modes of which had a star connections. Temperature Sensor data (including information such as temperature, humidity, time, and power) were collected every 10 minutes. The power consumption of the wireless sensor network was low, and the entire experimental process did not require a battery replacement. The sensor used four 3A AAA batteries; and the receiver was charged every 2 two days by using solar panels and a mobile power supply to ensure smooth operation of the entire system. Given that the experimental sites were site was located in the northeast region of China, which had has rainy days in the summer, the study researchers performed waterproof processing for the temperature and humidity tests to ensure that the wireless temperature and humidity sensor network can be is all-weather compatible for temperature and humidity data collection.

2.4 Statistical analyses

Statistical analyses were executed in Microsoft[®] Excel[®] 2013 and IBM[®] SPSS[®] Statistics 22.0.0.0. Depending on In accordance with the growth stage of japonica the rice, we analyzed the correlation between the leaf NDVI, and canopy NDVIs, as well as the respective sunshine-exposure time, and growth times of the leaves throughout the entire growth period. ^[28]

We performed simple linear or exponential regression for leaf NDVI, and canopy NDVIs, environmental temperature and humidity, as well as respective temperatures and humidity levels within the rice canopy, temperature and humidity, temperature and humidity of rice in the middle, and rice bottom temperature and humidity mid-rice and bottom-rice areas. For day-length data, we used multiple linear regression (MLR).^[29-30] The following equation was used for the linear model had the following equation:

$y_{L} = \beta_{0} + \beta_{1}x_{C} + \beta_{2}x_{S} + \beta_{3}x_{D} + \beta_{4}x_{EHH} + \beta_{5}x_{ETH} + \beta_{6}x_{MTL} + \beta_{7}x_{BTL}$

where y_L and x_C represents represent the leaf NDVI and canopy NDVIs, respectively; Where x_S and x_D , represents the sunshine- and the growth-days of the rice, respectively; Where x_{EHH} and x_{ETH} , are the highest relative humidity levels

and highest temperatures of in the environment, respectively; Where x_{MTL} and x_{BTL} , are the lowest temperatures in the middle and bottom parts of japonica the rice, respectively. The model coefficients $(\beta_0, \beta_1, \beta_2, \dots, \beta_7)$ were determined for the linear-regression model based on the basis of the calibration dataset.

Japonica rice From transplanting to maturity, of the growth process of the rice underwent different growth periods (such as the tillering, jointing, heading, and filling stages), and during each period of which the changes in the rice leaves and canopy was were not the same. Therefore, the different periods of in the rice leaf NDVI model should vary. ^[31] Accordingly, the Japonica rice leaf NDVI fitting model was divided into four stages: tillering (June), jointing-booting (July), heading and milking (August), and maturity (September) stage models.

3. Results and discussion

3.1 Leaf NDVI modeling of japonica rice

The data collection period of for the NDVI fitting model was lasted 118 days, from June 4 to September 30. and the number of days was 118 days. Given that rainy days were are unsuitable for NDVI and humidity data collection, the rain to removal, the effective number of days for was 114 days. Because the respective durations of the various growth stages of rice were are not an absolute, time. Thus, to facilitate the future application of the model, we used a monthly modeling process segment, as well as the experimental varieties used in this study and planting time^[32] we therefore used a monthly modeling process segment, as well as the experimental varieties and planting time in this study, to facilitate future applications of the model. ^[32] Moreover, because many of the key growth points were at the beginning or end of the a month, so the use of segmentation modeling to improve the accuracy of the model was feasible.

We collected the canopy NDVI of japonica rice, sunshine-duration, and ricegrowth micro-environmental growth data for the rice. The linear-regression model was established created with SPSS software to obtain the tested paddy-leaf NDVI models of for Shendao-47 (Table 1).

Table I Shendao-47 leaf	NDVI models
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Stage	Regression model
Tillering stage	$y_L = -9.119 + 0.166x_C + 0.633x_S + 0.002x_{EHH}$
Jointing and booting stage	$y_L = 0.608 - 0.673x_C + 0.051x_S + 0.008x_{MTL} - 0.009x_{BTL}$
Heading to grain-filling stage	$y_L = 0.965 - 0.285 x_C - 0.003 x_D + 0.001 x_{ETH}$
Mature stage Maturity	$y_L = -0.705 - 1.056x_C + 0.176x_S - 0.009x_D$

Note: y_L =leaf NDVI, x_C =canopy NDVI, x_S = sunshine, x_D =growth days, x_{EHH} =the highest relative humidity, x_{ETH} =highest environmental temperature of the environment, x_{MTL} = the lowest temperature in the bottom part of japonica rice, x_{BTL} = the lowest temperature in the middle part of japonica rice.

3.2 Model analysis

In this study, the leaf model was included the whole rice leaf of rice. The idea objective of this study is was to investigate the effects of environmental factors on the NDVI of the leaves. The experimental area is not being very large, the difference of the soil is being relatively small, and in order to reduce the complexity of the modeling, it is considered that the soil condition is was considered consistent. In the process of model building to the canopy NDVI model as one of the input data, NDVI received the canopy leaf angle, the soil effect of water on the soil and so on other data were input, was resulting in a mixed NDVI value. Because the removal of interference factors of removal were was a complex process, and in order to facilitate the modeling, did not consider the their effects of these interference factors data were not considered. but However, the in the canopy NDVI data acquisition, through the design of experiment was designed as possible ensures to ensure as much consistency as possible the canopy NDVI with regard to the relative error of consistency.^[33] This study established The japonica leaf NDVI model established in this study was to try using resulted from an attempt to use canopy NDVI and environmental factors to formulate a quantitative description of the trend in the changes observed in the leaf NDVI change trend.] WHAT are you actually trying to say in this paragraph—especially within your English editor's green brackets? It was a big mess! Hence, these revisions are merely (grammatically correct) educated guesses.

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Stage	R^2	RMSE	RE (%)
Tillering stage	0.845	0.511	48.61
Jointing and booting stage	0.782	0.131	47.29
Heading to grain-filling stage	0.877	0.092	38.36
Mature stage Maturity	0.903	0.235	59.67

Table 2 Coefficient of determination (R^2) and root mean square error (RMSE) for regression betweenobserved and predicted leaf NDVI. (RE = relative error).

Based On the basis of the results from listed in Table 2, different-stage leaf models were selected for model application in the model. The dataset was divided into a calibration and validation dataset subsets. The validation dataset data consisted of the randomly selected sampling points 1, 5, 9 and 13; while whereas, the remaining sampling points served for the calibration. The calibration models (Table 1) were then applied to the validation dataset data and evaluated by the relationship between the

observed and the predicted leaf NDVI. The heading-to-grain-filling stage model had a high fit with $R^2 = 0.845$ and the lowest error (RMSE=0.092, RE=38.36%).

3.2.1 Tillering stage of leaf NDVI model analysis

In June, the Shendao-47 was in its tillering stage. The growth of rice the leaves was related to the maximum relative humidity of the environment and the sunshine duration of sunshine. The coefficient of determination R^2 showed indicated that the maximum relative humidity of the environment for Shendao-47 leaf growth had the most obvious effect. and This time, the rice plant height and the leaf area index (LAI) were relatively small ^[34]; therefore, the relative humidity at different heights was not obvious. and Moreover, the results showed demonstrated that no significant difference existed between the different models (Table 3).

Table 3 Leaf NDVI modeling and analysis of different environmental parameters in tillering stage. y_L —leaf NDVI ' x_C — canopy NDVI, x_S — sunshine, x_{EHH} — The highest relative humidity of in the environment, x_{CHH} — The highest humidity of canopy rice, x_{MHH} — The highest humidity of rice in the middle height, x_{BHH} — The highest humidity of rice in the bottom height

Regression model	R^2
$y_L = -9.119 + 0.166x_C + 0.633x_S + 0.002x_{EHH}$	0.845
$y_L = -7.032 + 0.158x_C + 0.492x_S + 0.002x_{CHH}$	0.839
$y_L = -7.152 + 0.154 x_C + 0.5 x_S + 0.002 x_{MHH}$	0.840
$y_L = -6.461 + 0.179 x_C + 0.449 x_S + 0.003 x_{BHH}$	0.836

Note: y_L —leaf NDVI , x_C — canopy NDVI, x_S — sunshine, x_{EHH} — The highest relative humidity of in the environment, x_{CHH} — The highest humidity of canopy rice, x_{MHH} — The highest humidity of rice in the middle height, x_{BHH} — The highest humidity of rice in the bottom height [WHY is this same information repeated from the Table 3 caption (above)? It is redundant. It would be better to leave this Note intact and delete from the caption.]

Figure 3 was graphs the time series of the canopy NDVI and leaf NDVIs in June. The NDVI of canopy rice and Both NDVIs leaves increased in the tillering stage, but the canopy NDVI the increase was more obvious in the canopy NDVI. After June 26, the canopy NDVI was greater than the leaf NDVI after June 26, and this time covered covering the tillering stage of japonica rice growth.



Figure 3 Time-series curves in tillering stage of canopy NDVI and leaf NDVIs of Shendao-47 time-series curve intillering stage (NDVI_L_Avg—rice leaf NDVI , NDVI_C_Avg— rice canopy NDVI.)

3.2.2 Jointing and booting stages of leaf NDVI model analysis

In July, the Shendao-47 was in its jointing and booting stage. The process of achieving accuracy in the NDVI leaf-fitting model accuracy were was lower than that in other periods mainly because, at this stage in the growth of japonica, rice vegetative and reproductive growth ensued. Thus, the process was more complex from the point of view perspective on of the model elements. Conversely, by for the canopy NDVI, the long-time illumination, the rice-growing environments, and as well as the accuracy of the middle- and lower-minimum temperatures accuracy of the model were higher than the lowest temperature accuracy of the other model only when actually within the canopy NDVI and in the long-light modeling. Explained at this stage, the rice vertical-middle and lower-ambient temperatures of the rice had important implications for rice growth (Table 4).

Table 4 Leaf NDVI modeling and analysis of different environmental parameters in jointing and booting stage

Regression model	R^2
$y_L = 0.542 - 0.664 x_C + 0.052 x_S$	0.713
$y_L = 0.608 - 0.673 x_C + 0.051 x_S + 0.008 x_{MTL} - 0.009 x_{BTL}$	0.782

Note: y_L —leaf NDVI x_C — canopy NDVI, x_S — sunshine, x_{MTL} — The lowest temperature of in rice middle part of rice, x_{BTL} — The lowest temperature of in rice bottom part of rice



Figure 4 Canopy NDVI and leaf NDVI of Shendao-47 time-series curve in jointing and booting stage (NDVI_L_Avg—rice leaf NDVI , NDVI_C_Avg— rice canopy NDVI.)

Figure 4 shows graphs the time series of the canopy and leaf NDVIs in July. Both eanopy and leaf NDVI increased in the tillering stage, whereas but the increase in the canopy NDVI increase was more obvious. After June 26, the tillering stage, the canopy NDVI was greater than the leaf NDVI after June 26, which is the tillering stage of Japonica rice growth. Canopy NDVI Having relatively stable data, the canopy NDVI was higher than the leaf NDVI; and canopy NDVI data were relatively stable, whereas, the leaf NDVI data of leaves decreased because japonica rice growth is complete at tillering was complete. The LAI increased to the maximum value for the entire growth cycle and after jointing stage it entered the booting and heading process after the jointing stage. Ineffective tillers in During this period, the ineffective tillers gradually died and at the same time, while, concurrently, some nutritional leaf spikes were gradually transferred. ^[35]

3.2.3 Analysis of Grain-filling stage of leaf NDVI model

In August, the Shendao-47 was heading into entering the grain-filling reproductive stage. The rice-growth period entered the reproductive stage. Shendao-47 Its growth was affected by the duration of sunshine, duration and the number of growth days, and the changes in temperature within this period affected rice growth. Based On the basis of the fitting accuracy of the model analysis, the height environmental temperature of the height was found to affect rice the growth (Table 5).

Regression model	R^2
$y_L = 0.965 - 0.285 x_c - 0.003 x_D + 0.001 x_{ETH}$	0.877
$y_L = 0.942 - 0.262x_c - 0.002x_D + 0.001x_{CTH}$	0.866
$y_L = 0.935 - 0.25x_C - 0.002x_D + 0.001x_{MTH}$	0.861

Table 5 Leaf NDVI modeling and analysis of different environmental parameters in grain-filling stage.

Note: y_L —leaf NDVI $\cdot x_C$ — canopy NDVI, x_D — Rice growing days, x_{ETH} — The highest temperature of in environment, x_{CTH} — The highest temperature of canopy rice, x_{MTH} — The highest temperature of rice in middle part

Figure 5 shows graphs the time series of the leaf and canopy NDVIs in August. For rice in During the filling stage, the canopy NDVI data in August 20 reached the the highest level on August 20. After the beginning of the rapid decline, the leaf NDVI decreased, resulting in the mainly due to the filling stage, during which leaf nutrients of leaves are continuously transferred to the panicle.



Figure 5 Canopy NDVI and leaf NDVI of Shendao-47 time-series curve in-heading to entering grain-filling stage (NDVI_L_Avg—rice leaf NDVI, NDVI_C_Avg— rice canopy NDVI)

3.2.4 Mature stage of leaf NDVI model analysis

In September, the Shendao-47 was at the mature stage reached maturity, This period was the last stage of rice growth, in during which rice gradually matured and the leaves turned turn yellow, the canopy NDVI and leaf NDVIs were being really very low and the yield of rice was basically formed. Based On the basis of the established model, this stage of the leaf NDVI fitting model was composed of the canopy NDVI, the duration of sunshine duration, and the number of days. The leaf NDVI is not related to the changes in temperature and humidity, which also meant means that changes in the environmental temperature and humidity did not influence the japonica rice final output (Table 6).

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Regression model	R^2
$y_L = -0.705 - 1.056x_C - 0.009x_D + 0.176x_S$	0.903
$y_L = 1.227 + 0.424 x_C + 0.011 x_{CTA} + 0.176 x_{MTH}$	0.612
$y_L = 0.215 + 0.043 x_C - 0.094 x_{MTL} + 0.116 x_{BTL}$	0.553

Table 6 Leaf NDVI modeling and analysis of different environmental parameters in mature stage

Note: y_L —leaf NDVI, x_C — canopy NDVI, x_D — Rice growing days, x_{CTA} — The average temperature of canopy rice, x_{MTH} — The highest temperature of rice in middle part, x_{MTL} — The lowest temperature of rice in middle part, x_{BTL} —The lowest temperature of rice in bottom part

Figure 6 shows graphs the time series of the leaf and canopy NDVIs in September. For rice In the mature stage, both leaf and canopy NDVIs decreased, and the canopy NDVI significantly decreased decreasing. In During this stage, leaf both NDVIs twice intersected twice with canopy NDVI. After the second intersection, the leaf NDVI rapidly declined, which indicated thus indicating that the rice was ripe.



Figure 6 Canopy NDVI and leaf NDVI of Shendao-47 time-series curve in mature stage (NDVI_L_Avg—rice leaf NDVI , NDVI_C_Avg— rice canopy NDVI.)

3.3 Time-series analysis of japonica rice NDVI

We collected canopy NDVI and leaf NDVI of japonica rice growing in northeast China. Figure 7 shows the time-series curves with for the leaf and canopy NDVIs of Shendao-47 from transplanting to maturity period.



Three intersection points existed exist on the time-series curves of the leaf and canopy NDVIs, and the first intersection point was being on June 27, 2015. Before this period, the leaf NDVI was higher than the canopy NDVI because the LAI was small. The canopy NDVI also contained most of the water layer. At this time, the leaves rapidly grew rapidly; so therefore, in this period the canopy NDVI was smaller than the leaf NDVI during this period. After this period of growing LAI growth, the canopy NDVI was greater than the leaf NDVI; so hence the two curves at the first

intersection were represent a sign of rice growth and the tillering stage. ^[36] The second intersection of the two curves was occurred on September 8, 2015. Before this date, the canopy NDVI was greater than the leaf NDVI. The leaf NDVI was greater than canopy the NDVI after this date because of the continuous growth of rice with the leaves and the stem energy being transferred to the panicle. This phenomenon caused the leaves to turn yellow, this time for the dough-stage node. The third point of the two curves of intersection was occurred on September 27, 2015. Beyond this point, the leaf NDVI rapidly decreased because the rice was basically essentially mature, and Over more than 90% of the leaves became had become yellow. ^[37] Therefore, predicting the key growth process of japonica the rice was became possible by using the time-series curves of to graph the canopy and leaf NDVIs (Table 7).

Prediction time	Canopy NDVI and Leaf NDVIs	Period	Traditional time
2015/6/26	Canopy NDVI was greater than leaf NDVI	Tillering stage	2015/6/25
2015/7/1	Leaf NDVI maximum	Jointing stage	2015/7/1-2015/07/05
2015/7/21	The Maximum difference between canopy	Booting stage	2015/7/25
	NDVI and leaf NDVIs in July		
2015/8/2	The Minimum difference between canopy	Initial heading	2015/8/5
	NDVI and leaf NDVIs in August	stage	
2015/8/22	The Maximum difference between canopy	Milk stage	2015/8/24
	NDVI and leaf NDVIs		
2015/9/8	Leaf NDVI was greater than NDVI	Dough stage	2015/9/3
2015/9/27	Canopy NDVI was greater than leaf NDVI in	Mature-	2015/10/1
	September	Maturity	

Table 7 Using Use of canopy and leaf NDVIs of canopy	rand leaf to predict key	growth period	of japonica ric	e.
(Traditional time is the approximate time range)				

3.4 Discussion

This study analyzes analyzed the relationship of between the canopy and leaf NDVI scales of japonica rice NDVI between canopy scales and leaf scales. USDA In a 2013 study the USDA suggested that the crop canopy and leaf canopies of the same vegetation index have different sensitivity sensitivities, and this kind of different difference that affects the accuracy of crop information inversions. ^[38] The results of this study show indicate that the respective scales of the NDVIs in for different growth periods of rice canopy canopies and leaf leaves of the change of the scale is are different, this is in line with the predecessors' thereby corroborating research the results of previous research. The changes in the leaf NDVI during the growth cycle is were far much less than in the growth cycle the changes in the canopy NDVI; changes, but however, after the filling stage, the changes in both leaf and canopy NDVIs change is were relatively small. while Although the a rapid change in the leaf NDVI

of rapid change is was caused by the transfer of leaf energy transfer to the grain, a phenomenon that could reflect the a change in the final stage of rice the crop, it is has been the focus on of fewer problems in the previous research of previous on rice NDVI. This research focused mainly in on the process of the establishment establishing of the a model while takes taking into account the environmental factors and canopy NDVI. From The results indicate that the influence of different parts of rice on the NDVI is different, through by means of the canopy NDVI and environmental date data detection to get obtain the rice leaf NDVI value. But However, this study does did not take into account the influence of soil conditions on the model. and Furthermore, some previous experience is a prerequisite for get obtaining the such a model. of this study need to have some previous experience, Moreover, additional research is needed in the future for the further promotion of the model still needs further research. in future studies, especially from the perspective of a mechanism to further explain the rice relationship between the leaf NDVI and canopy NDVIs.

4. Conclusions

Our studies conducted in Northeast China indicated have demonstrated that the leaf NDVI of japonica rice was able to can be simulated by the canopy NDVI and environmental data in Northeast China. The main contributions of this work research are as follows: (1) establishing, with good accuracy (R2= 0.782–0.903), four periods of leaf NDVI models with good accuracy (R2= 0.782 0.903). These models that can predict the key stages of in the rice growth period; (2) By collecting the rice canopy NDVI data and environmental data that can more quickly get efficiently obtain the leaf NDVI information, which is the traditional canopy remote sensing cannot get do; (3) demonstrating that rice leaf NDVIs can be estimated by canopy NDVIs and multisource environmental data that may be used for rice growth management.

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[CJR stopped editing at this point.]

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