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Rice yield estimation using remote sensing and simulation model*

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Abstract: Remote sensing techniques have the potential to provide information on agricultural crops quantitatively，instantaneously and above all nondestructively over large areas. Crop simulation models describe the relationship between physiological processes in plants and environmental growing conditions. The integration between remote sensing data and crop growth simulation model is an important trend for yield estimation and prediction，since remote sensing can provide information on the actual status of the agricultural crop. In this study，a new model(Rice-SRS) was developed based mainly on ORYZA1 model and modified to accept remote sensing data as input from different sources. The model can accept three kinds of NDVI data: NOAA AVHRR(LAC)-NDVI，NOAA AVHRR(GAC)-NDVI and radiometric measurements-NDVI. The integration between NOAA AVHRR (LAC) data and simulation model as applied to Rice-SRS resulted in accurate estimates for rice yield in the Shaoxing area，reduced the estimating error to 1.027%，0.794% and (－0.787%) for early，single，and late season respectively. Utilizing NDVI data derived from NOAA AVHRR (GAC) as input in Rice-SRS can yield good estimation for rice yield with the average error (－7.43%). Testing the new model for radiometric measurements showed that the average estimation error for 10 varieties under early rice conditions was less than 1%.

Key words: Rice，Remote sensing，NOAA(National Oceanic and Atmospheric Adiministration) AVHRR (Advanced Very High Resolution Radiometer)，Simulation model，LACC (Local Area coverage)，GAC(Global Area Coverage)

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INTRODUCTION

Rice is the most important staple food in the world; it has fed more people over a longer period than has any other crop. Asia accounts for 90% of the world's production and consumption of rice because of its favorable hot and humid climate. In China，although the rice cropping area represents only 29.1% of the total national crop-growing area，rice production contributes 43.7% of total national grain production，representing 22.8% and 36.9% of total world cropping area and production respectively(Xiong et al.，1992). Information on crop production is of fundamental importance for the decision-makers of a country，and correct decisions are dependent on timely and accurate information.

ORYZA1 simulates crop growth under irrigated conditions，with optimum supply of nutrients(wherein N is explicit input as leaf-N content)，and without pest and disease infestation. It is based on SUCROS model and MACROS-L1D module. An important advantage of this model is that it can be used to simulate realistic yields and to assess the impact of planting date，weather，and latitude at measured leaf N contents. This is in contrast to models for potential production that have a fixed pattern of leaf photosynthesis in time(Kropff et al.，1994). The model of ORYZA1 as described above was developed to formalize and synthesize knowledge on the processes governing crop growth. When applied to operational uses such as yield estimation，this model appears to be impractical，as it is difficult to gather data on crops during the crop calendar year; and as crop vigor changes over time，

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so ideally, data should be collected several times during the growing seasons, an expensive task given the size of the areas involved. Furthermore, this model often appears to fail when growing conditions are nonoptimal (caused by stresses, e. g., fertilizer deficiency, pest and disease incidence, severe drought, frost damage). Therefore, for yield estimation, it is necessary to "check" modeling results with some sort of information on the actual status of the crop throughout the growing season. Optical remote sensing can provide such information. Remote sensing techniques with multispectral repetitive coverage have shown promise for use in estimating the agronomic parameters and monitoring the changes in these parameters during the growth cycle of the crop. An important goal of agricultural remote sensing research is to spectrally estimate crop variables related to crop conditions which can subsequently be entered into crop simulation and yield models (Ahlrichs and Bauer, 1983). To utilize the full potential of remote sensing for the assessment of crop conditions and yield prediction, it is essential to quantify the relationships between agronomic parameters and spectral properties of the crop (Patel et al., 1985). Use of satellite spectral data for estimation of crop yields is an attractive prospect since yield is related to crop vigor, which is related to the spectral response of the crop vigor, which in turn is related to the spectral response of the crop measured by satellite sensor (Barnett and Thompson, 1982). Such technology resulted from more decades long research on ways to make much better global forecasts. There are reports of various studies on the suitability of satellite data for estimating crop yields. The correlation between the spectral reflectance of crops and agronomic variables encouraged application of those data in crop yield models (Tucker et al., 1980; Richardson et al., 1982).

This study focuses on using remote sensing data in modeling of Zhejiang Province's rice yield per unit area for different seasons.

APPROVED MODEL

The main idea of developing this model was to combine the power of the simulation model (ORYZA1) with the accurate and timely information of remote sensing data for rice yield estimation. So, our approach here was to replace the simulated leaf area index (LAI) with LAI calculated by using normalized difference vegetation index (NDVI), derived from remote sensing data possibly from NOAA (National Oceanic and Atmospheric Administration) AVHRR (Advanced Very High Resolution Radiometer) LAC (Local Area Coverage), or NOAA AVHRR GAC (Global Area coverage), or radiometric measurements. This calculated LAI can be obtained in the field and entered directly into the model (Fig. 1).

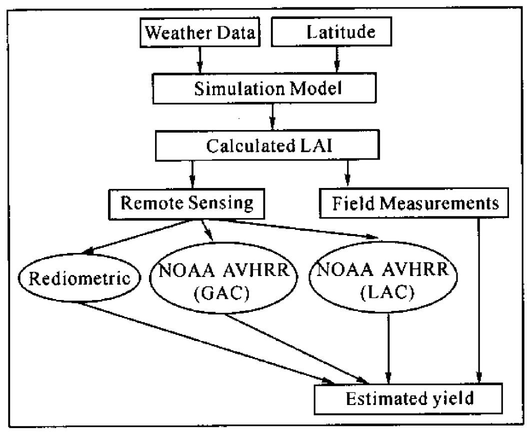

Fig. 1 Flowchart of rice yield estimation by the new model (Rice-SRS)

The main task for the new model is to estimate rice yield by using simulation and remote sensing, so the name of the new model is Rice-SRS.

1. Correction for green vegetation fraction

The same NDVI signal may result from different sub-pixel structures of a satellite pixel (Price 1992). Fig. 2 shows possible combinations of horizontal and vertical densities that may reflect the same signal.

According to statistics, each unit area (pixel for example) in rice field contains 92.669% rice, 4.006% bare-soil, and 3.29% waterbody.

Bare soil consisted of built banks, beaches, field banks and agricultural roads. Whereas the waterbody includes ponds, irrigation channels etc..

So, the obtained NDVI from each pixel is:

$$NDVI = (\%\ soil \times 0.05) + (\%\ water \times 0.01) + (\%\ rice \times NDVI_r) \quad (1)$$

Where, 0.05 and 0.01 are the NDVI values for baresoil and waterbody respectively.

$NDVI_r$ is the real NDVI for rice.

The value 0.01 was chosen for waterbody because the water here is very shallow and the background will affect this value, as well as the water cannot be pure or clean.

Finally we can calculate the real value for rice by putting in the above values as follows:

$$NDVI_r = [NDVI - (0.002003 + 0.0003294)] / 0.926999$$

$$NDVI_r = (NDVI - 0.002333)/0.926999 \quad (2)$$

So every value of NOAA AVHRR-NDVI will be corrected by the model according to the Eq.(2).

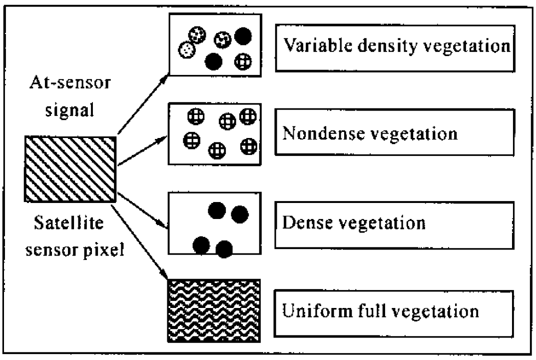

Fig. 2 Schematic representation of satellite sensor pixel models.

2. Estimating LAI from NDVI

The program uses three different approaches for calculating LAI according to the source of remote sensing data. In the case of satellite-derived data, the model simulates LAI first. Then the simulated LAI value for a specific dates (remote sensing acquisition date) is used as input in another procedure (subroutine) to calculate LAI by remote sensing data. As a result, several LAI values equal in number to the number of acquisition remote sensing data will be obtained. The last step is to use these calculated LAI values in another procedure to generate daily LAI values by using interpolation techniques, and then, to use the daily-calculated values in yield estimation procedures.

In the case of radiometric measurements, there is no need to simulate LAI, because LAI will be calculated in another way as we will see later, but the calculated LAI values will be entered into the same procedure to generate daily LAI values as mentioned above. The three approaches are explained in detail as follows:

(1) Estimating LAI from NOAA AVHRR (LAC) NDVI

Following the correction of NDVI for the green vegetation fraction, the leaf area index was calculated by the method of by Yin & Williams (1997) but with some modifications. Their LAI-NDVI model is as followings:

$$LAIi = LAI_{max} \times (NDVIi - NDVI_{min}) / (NDVI_{max} - NDVI_{min}) \quad (3)$$

Where:

$LAIi$ is leaf area index at date (A);

$NDVI_{min}$ and $NDVI_{max}$ are the minimum and maximum $NDVI$ (positive values) in the image on date i;

$NDVIi$ is $NDVI$ value for the studied area on date A.

In the original model was the biweekly date, but in this model is the date of remote sensing measurements regardless of the period.

For estimating maximum and minimum NDVI, they can be estimated as NDVI for fully vegetated pixels and bare-soil pixel in each image. Seller et al. (1996), for example, defined them as the lower and upper 2% − 5% NDVI for each biome. In the new model the values 0.05, and 0.64 were selected to be the minimum and maximum NDVI, agreeing with Malingreau (1986) because of its suitability to our data as shown in Fig. 3.

For LAI_{max} it will be simulated by the model itself and then will be used to calculate LAIi, because the simulation model (ORYZA1) gives the rice yield under optimum condition, so the simulated LAI should be the maximum LAI for the date i.

(2) Estimating LAI from NOAA AVHRR (GAC) NDVI

Because of its low resolution (4km), NOAA AVHRR (GAC) must undergo two stages of corrections. First, the correction for green vegetation fraction by Eq. (2), and then calculation of the tangent of this corrected value, so that:

$$NDVI = Tan(NDVI_r) \quad (4)$$

The last value will be used to derive LAI in similar approach for NOAA AVHRR (LAC) according to the Eq. (3).

(3) Estimating LAI from radiometric measurements

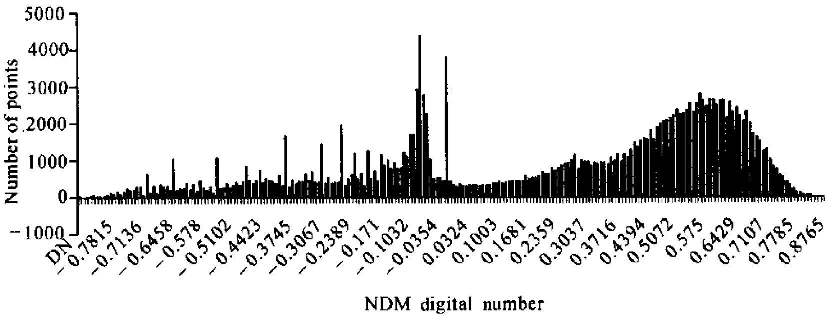

Fig.3 Histogram of NDVI digital numbers of NOAA image on June 26 1998

According to the NDVI value, the program will choose the way for calculating LAI. So, if the value is less than 0.86, LAI will be calculated according to Richardson et al. (1992)'s equation:

$$LAI = 0.139\exp[4.26(NDVI)] \quad (5)$$

If the NDVI value equals or is higher than 0.86 the model will calculate LAI according to Ramakrishna et al. (1989)'s equation as follows:

$$NDVI = \ln(LAI/0.65) \times 0.34 \quad (6)$$

Or in another mathematical form:

$$LAI = \exp((NDVI/0.34) - 0.431) \quad (7)$$

RESULTS AND DISCUSSION

1. Case of NOAA AVHRR (LAC) data

The main objective of this study is to estimate rice grain yield for different growing seasons and different areas by combining simulation model with remote sensing data. To achieve our objective, we used NDVI values as input in our new model (Rice-SRS). Table 1 summarizes the obtained results for single rice cropping area in Jiaxing, and double rice cropping area Yin County.

Table 1 Rice yield estimation results for Jiaxing and Yin County

	Simulation for	Rice-SRS	Simulation for	Rice-SRS	Simulation for	Rice-SRS
Year		1998		1998		1998
Site		Jiaxing		Yin County		Yin County
Season		Single		Early		Late
Reported Yield(kg/ha)		7845		6240		6990
Estimated Yield(kg/ha)	9129.97	8113.10	8632.67	5892.51	9302.36	7398.59
Est. error (%)	16.38	3.42	38.34	−5.57	49.08	5.85
Latitude		30.78		29.87		29.87
DOYS		143		89		175
DOYTR		172		119		207
DOYF		258		172		267
DOYM		301		192		308
DGS		158		103		133
DVRJ		0.0003266		0.001668		0.000531
DVRI		0.0007576		0.0007576		0.0007576
DVRP		0.0007955		0.0007955		0.0007955
DVRR		0.0017659		0.0023214		0.0019861
DVS at Maturity		2.004		2.044		2.005
TSTR		407.34		324.63		627.84
TSF		2157.80		1139.65		1774.44
TSM		2728.14		1570.44		2277.94

Note: DOYS, DOYTR, DOYF, DOYM are day of year for seeding, transplanting, flowering and maturity, respectively. DGS is the number of days in growing season. DVRJ, DVRI, DVRP, DVRR are constants for development rates during basic vegetative phase, photoperiod-sensitive phase, panicle formation phase, and Grain filling phase, respectively. DVS is development stage. TSTR, TSF TSM are temperature sum for transplanting, flowering and maturity.

The estimated errors for early, single and late rice seasons were (−5.57, 3.42 and 5.85) respectively. It is good to obtain such results since, the weather data used for the two areas was that over Shaoxing in 1998. Of course the three areas are similar geographically, very close to each other. The elevation for the three areas ranges form 4.8 to 7.0 m.

2. Case of NOAA AVHRR (GAC) data

Table 2 and Table 3 summarize the main dataset used as input in the model Rice-SRS to estimate rice yield using NDVI derived from NOAA AVHRR (GAC) Data.

Table 2 Summary of the relevant dates in three single rice seasons in Jiaxing

Year	Seeding	Transplanting	Flowering	Maturity
1982	May 11	May 31	Aug 27	Oct 22
1983	May 6	Jun 15	Aug 16	Oct 26
1984	May 13	Jun 2	Aug 20	Oct 28

Table 3 Single rice NDVI values on three dates for each season (Jiaxing)

1982		1983		1984	
NDVI	Date	NDVI	Date	NDVI	Date
0.2	Jul 6	0.2	Jun 8	0.2	Jun 10
0.37	Aug 11	0.35	Aug 1	0.38	Aug 4
0.3	Sep 26	0.3	Aug 30	0.3	Aug 15

Although the dataset was very simple, as it contains three dates only, the results obtained by the model were well reasonable as it shown in Table 4.

Table 4 The main results for yield estimation using NOAA AVHRR (GAC) data as input in Rice-SRS for Jiaxing County over three years

Year	Reported Yield(kg/ha)	Estimated Yield(kg/ha)	Error(%)
1982	11790	10951.12	−7.1
1983	11040	10842.17	−1.79
1984	12705	11005.30	−13.38

Best estimate was obtained for the year 1983 with −1.79% estimating error, followed by the year 1982 and then 1984. The average error for three years was (−7.43%).

The main reason for such good results using only three dates is that, the second NDVI value for each year was given as the highest NDVI-peak throughout the season, which means heading stage. These results assure the importance of selecting NDVI measurements-date suitable for rice yield estimation.

3. Case of radiometric measurements

Use of the Table 5 data as input in Rice-SRS and monthly average weather data, yielded the results shown in Table 6.

Table 5 NDVI values derived from radiometric measurements for 10 varieties during early season at certain for phenological stage

	Jun 2	Jun 10	Jun 9	June 18
Variety	NDVI	NDVI	NDVI	NDVI
A	0.7593	0.8439	0.8485	0.8626
B	0.7344	0.8804	0.8917	0.8640
C	0.7306	0.8484	0.8943	0.8947
D	0.7861	0.8453	0.8774	0.8593
E	0.7237	0.8517	0.8947	0.8615
F	0.7566	0.8409	0.8591	0.8590
G	0.7096	0.8552	0.8594	0.8593
H	0.7279	0.8703	0.8712	0.8547
I	0.7492	0.8216	0.8781	0.8684
J	0.7187	0.8538	0.8700	0.8358

Table 6 Estimated yield and estimating error for 10 varieties during early rice using radiometric measurements as input in Rice-SRS

Variety	Observed yield(kg/ha)	Estimated yield(kg/ha)	Estimating error (%)
A	9218	9171	−0.509
B	9473	9071	−4.241
C	8093	8454	4.473
D	8160	8027	−1.629
E	8220	9078	10.433
F	8370	8136	−2.791
G	8475	8159	−3.725
H	8783	7926	−9.747
I	8093	9138	12.919
J	7905	7808	−1.228

Best estimate was for variety (A) with an estimating error of -0.509 and worst result was for (I) with overestimate of up to 12.919. The average error for all varieties was 0.396.

We have to mention that the four acquisition dates for radiometric measurements corresponded to tillering, booting, heading and milking stages respectively. This suitable distribution of dates high qualify reliable estimates.

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