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Yoshio Inoue, M. Susan Moran* and Takeshi Horie**

(*National Institute of Agro-Environmental Sciences, Tsukuba, Ibaraki 305-8604, Japan ;*
**U.S. Water Conservation Laboratory, Phoenix, AZ 85040, USA ;*
***Graduate School of Agriculture, Kyoto University, Kyoto 606-8502, Japan*)

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Remote Sensing and Modeling

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(*National Institute of Agro-Environmental Sciences, Tsukuba, Ibaraki 305-8604, Japan ;*
** U.S. Water Conservation Laboratory, Phoenix, AZ 85040, USA ;*
*** Graduate School of Agriculture, Kyoto University, Kyoto 606-8502, Japan*)
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Abstract : Spectral reflectance of differentially-managed rice canopies was measured over an entire growing season and analyzed with special attention to linking remotely sensed information with a simple growth model. The fraction of absorbed photosynthetically active radiation (fAPAR), which is often used as a key variable in simple process models, was well correlated with spectral vegetation indices (VI). VIs, such as NDVI and SAVI, were derived from the ratio of reflectance at two wavelengths (R660 nm and R830 nm) and a new VI, termed the normalized difference ND [R1100 nm, R660 nm], was derived from the difference of R1100 nm and R660 nm divided by their sum. These close relations between fAPAR and VIs were expressed by exponential formulae with different parameters for the periods before and after heading. These indices became less sensitive to fAPAR when fAPAR was larger than 0.4. The use of R1100 nm and R1650 nm with R660 nm and R830 nm in multiple regression significantly improved the prediction accuracy of fAPAR. A close linear relation was found between a spectral ratio R830 nm/R550 nm and leaf nitrogen content during the ripening period although it was not the case before heading. Results suggested that R830 nm/R550 nm was effective for estimation of leaf nitrogen content when the paddy field was regarded as a big leaf. The total amount of leaf nitrogen was well correlated with ND [R1100 nm, R660 nm] ; nevertheless, the sensitivity was lost when the total amount of leaf nitrogen was greater than 3 g m^{-2}. Multiple regression analysis showed that a combination of four spectral bands R550 nm, R830 nm, R1650 nm and R2200 nm was useful for estimation of the total amount of leaf nitrogen. Remotely-sensed nitrogen variables would be a potential model parameters in a simple model. A real-time recalibration module based on a simplex algorithm was developed and proved effective in linking the remotely-sensed fAPAR with a simple model. This approach was also useful for inferring the physiological parameters such as radiation use efficiency for each rice canopy without destructive sampling. The re-parameterization and/or re-initialization with remotely-sensed information was demonstrated to be a practical and effective approach, especially for operational purposes.

Key words : Crop model, Growth simulation, Paddy field, Radiation absorptance, Remote sensing, Rice, Spectral measurement, Yield prediction.

Crop growth modeling is a potentially useful tool in agriculture for yield prediction, diagnosis and management decision making as well as environmental assessment (Whisler et al., 1986 ; Penning de Vries et al., 1989, Horie et al., 1995). A great deal of effort has been made to develop detailed and complex simulation models to describe crop and environmental dynamics from both scientific and practical viewpoints. However, it has been noted that large process models† composed of hundreds of algorithms, each containing a set of empirically determined constants, are too complex to be tested and even fail to give scientific insight to their developers (Passioura, 1996 ; Monteith, 1996). From a practical point of view as well, complicated process models usually require too many input variables and/or parameters. It is tedious or sometimes impossible to collect all the necessary data.

Corresponding author : Yoshio Inoue (yinoue@niaes.affrc.go.jp ; fax +81-298-38-8199).
Abbreviations : DM, dry matter ; DVI, developmental index ; DVR, developmental rate ; ET, evapotranspiration ; fAPAR, fraction of absorbed photosynthetically active radiation by a canopy ; LAD, leaf-angle distribution ; LAI, leaf area index ; LNC, leaf nitrogen content ; NDVI, normalized difference vegetation index ; PAR, photosynthetically active radiation ; RUE, radiation use efficiency ; SAVI, soil adjusted vegetation index ; TLN, total amount of leaf nitrogen ; VI, vegetation index.
† A "process(-based) model" is founded on some underlying biological mechanisms and is sometimes called a "mechanistic model", while a "statistical model" is based on apparent correlations between growth/development and input variables. Nevertheless, a "process model" is not always deterministic since empirical approaches are often used to express the model structure or to determine the parameters for the model. Complexity of a model is usually associated with the number of factors incorporated into the model.

Hence, especially for operational purposes, simple process models that require fewer input variables are feasible provided that they are based on sound and robust principles and are used within the range of their calibration data set (Monteith, 1996).

Several simple process models (e.g., Charles-Edwards et al., 1986 ; Horie, 1987 ; Maas, 1988 ; Kiniry et al., 1989) have been developed. Most of them are based on the proportional relationship between crop dry matter production and photosynthetically active radiation (PAR) absorbed by the crop canopy (Shibles and Weber, 1966 ; Monteith, 1977 ; Gallagher and Biscoe, 1978). They have been used to simulate crop growth and yield based on routinely available weather data such as solar radiation, mean air temperature and daylength. For example, a rice model developed by Horie (1987) has been successfully used to compare the potential rice yield in pan-Pacific countries, and to estimate rice growth under assumed climate conditions such as doubled atmospheric CO_2 and elevated air temperature (Horie, 1993 ; Horie et al., 1995). Nevertheless, such simulation models provide information on only normal growth patterns under given weather conditions with an assumption that all other conditions are optimal (such as without weed, insect, disease and water/nutrient stresses). Hence, realistic and accurate estimates for each paddy field can not be obtained by the model simulation. It is recognized that the nitrogen status of a rice canopy is a major potential parameter to be incorporated to the simple model as a next step (Horie, 1993).

A possible solution to this limitation is to recalibrate the simple model with some measured data for each field. Maas (1993) demonstrated the need for within-season calibration of a simulation model. The within-season calibration is an effective approach to reduce the model complexity, to simplify input requirements, and to make the model more operational (Maas, 1993). Since most simple models are based on biological foundations and give robust patterns of growth and development, they can be effectively tuned up with some relevant measurements such as leaf area index (LAI), dry matter (DM) and evapotranspiration (ET). Remote sensing has been proved useful for providing information on the actual status of individual canopies over a wide area (e.g., Steven and Clark, 1990 ; Asrar et al., 1989). Maas (1988) also proposed the use of remotely sensed data as calibration data for a simulation model. This approach may be the most practical and effective method to link instantaneous remote-sensing data with continuous growth simulation. It is an improvement over the direct use of remotely-sensed data as model inputs because the model can be driven only when remote sensing data are available. It is also an improvement over the use of the correlation between accumulated remotely sensed index (e.g., ΣNDVI) and productivity because this also requires frequent remote sensing observations (Wiegand et al., 1989 ; Christensen and Goudriaan, 1993).

As shown in some pioneering studies on this approach i.e., recalibration of simulation models with remotely-sensed data (Maas, 1988 ; Bouman, 1992 ; Clevers et al. 1994), there are two major methods in linking remote sensing and crop models. 1) Outputs of a crop growth model such as leaf area index (LAI) and leaf-angle distribution (LAD) are used to calculate the radiative features (e.g., spectral reflectance and microwave backscatter) of the crop canopy using some radiation transfer model such as SAIL (Verhoef, 1984). Then, simulated and measured radiative features are compared to recalibrate the crop growth model (Bouman, 1992 ; Clevers et al., 1994). 2) Remote sensing data are used to estimate a fewer number of key crop variables (e.g., LAI and ET) and they are used to recalibrate the model (Maas, 1988 ; Moran et al., 1995). The first approach would be most attractive provided that a crop model is able to output a number of geometrical and spectral variables required by radiation transfer models for a canopy, and that the spectral model is well-calibrated to give the accurate spectral feature of the canopy. However, considering the recent status of the crop modeling approach (Passioura, 1996 ; Monteith, 1996) as mentioned above, such requirements may not be feasible, especially for simple process models.

In the second approach, a wide range of vegetation indices, regression models, and model inversions can be applied to estimate crop variables such as LAI and above-ground biomass (e.g., Asrar et al., 1989 ; Steven and Clark, 1990 ; Akiyama, 1996), which may be used for recalibration of simulation models. As for a rice canopy as well, it has been shown that LAI, biomass, and nitrogen status may be estimated from spectral measurements (e.g., Shibayama and Akiyama, 1989 ; Shibayama and Akiyama, 1986). These crop variables themselves may be useful for diagnosis of crop status ; however, for the calibration purpose of a simple model, fractional absorptance of the photosynthetically active radiation (fAPAR) for the canopy may be one of the most appropriate state variables because most simple crop models calculate fAPAR as a key variable during each simulation cycle. Furthermore, it is well-known that the spectral reflectance of a canopy is more directly related to fAPAR than to other plant variables such as LAI, biomass, chlorophyll, and geometry, because both canopy reflectance and fAPAR are the components of the radiation budget of a canopy (e.g., Asrar et al., 1989 ; Baret and Guyot, 1991). Therefore, it can be assumed that the fAPAR of a canopy may be a more direct variable to be estimated from spectral measurements for recalibration of a simple model. However, these studies have been limited to the use of two-bands (red and near-infrared) VIs and such investigation for paddy rice is still limited considering the unique flooded conditions (Leblon et al., 1991).

On the other hand, it is quite useful if the nitrogen status of rice plants can be estimated and incorporated into the simple model. Since nitrogen status of rice plants is closely related to physiological activity and yield, development of new fertilizer application methods (amount, timing and positioning in a root system etc.) has been a major issue in Japanese rice cultivation (e.g., Matsuzaki et al., 1974). Because the relationship between nitrogen content and physiological activity in rice plants has been intensively studied (e.g., Ishihara et al., 1979), information on leaf nitrogen content or total leaf nitrogen of a canopy may be operationally incorporated into the model, and further used for recalibration of physiological parameters. The radiation use efficiency, for instance, may be expressed as a function of leaf nitrogen status.

Thus, the objective of this paper is to investigate the following points with special attention to linking remotely sensed information with a simple growth model; 1) the relationship between fAPAR and spectral reflectance in paddy rice for vegetative and ripening periods, 2) possible fAPAR estimation from remotely sensed visible, near- and short wave infrared spectral regions, 3) relationship between nitrogen status and spectral indices for vegetative and ripening periods, and possible estimation of nitrogen status from remotely sensed visible, near- and short wave infrared spectral regions, and 4) recalibration procedure of a rice simulation model with remotely-estimated fAPAR.

Materials and Method

1. Spectral and growth measurements for rice canopies

An experiment was conducted at the National Institute of Agro-Environmental Sciences (NIAES : Tsukuba, Japan ; 36.0 degrees North, 140.1 degrees East, and 25 m above the sea level) in 1994. Seedlings of rice (*Oryza sativa* L., cv. Nipponbare) were transplanted in four plots at two planting densities (D0 : 13.3 plant m^{-2} and D1 : 26.7 plant m^{-2}) and two levels of nitrogen application (N0 : 0-0-0-0 g m^{-2} and N1 : 5-2-2-3 g m^{-2}). The top-dressing was made on June 25, July 20, and August 20, respectively for N1 plots. Sowing and transplanting were on May 11 and June 3, respectively for all plots. The dates of heading were August 16 for plot N1D1, August 17 for plots N0D1 and N1D0, and August 18 for plot N0D0, respectively. The date of physiological maturity were September 30 for N0D1 and N0D0, and October 3 for plots N1D1 and N1D0. The size of each plot was 10 m × 10 m, respectively. Plant parameters such as fresh and dry weights, LAI, and nitrogen concentration of each plant part were determined by weekly sampling during the entire growing season. Five hills per plot were taken each time and separated into stems, green leaves, heads, roots, and dead parts. The green leaf area was measured with an area-meter (Hayashi-denkoh, AAM8). The water content of each part was determined after desiccation in an oven at 80°C for 48 hr, and used to calculate dry weights. Each dried sample was powdered with a mill (Fritsch, P-14) and the nitrogen concentration for each plant part was measured with a nitrogen-carbon analyzer (Sumigraph, NC-800).

Spectral reflectance measurements over paddy fields were made using a handheld radiometer designed for field use (Shibayama et al., 1993) two to three times a week during the entire growing period. The portable spectroradiometer was equipped with seven bands from visible to short wave infrared wavelength regions. The central wavelength for each band was 560, 660, 830, 1100, 1200, 1650 and 2200 nm, respectively and the field of view was 10 degrees. Observations were made from a height of 2 m above the canopy at the nadir looking angle. Reflectance factor (designated by R ### for ### nm) was calculated as a relative value to the reflectance of a $BaSO_4$ standard panel. The panel was coated with Kodak Analytical Standard White Reflectance Coating (# 6080) to about 1.0 mm thickness. This type of reference panel has been widely used in spectral studies to ensure the comparability of measurement results. However, any artificial panel can not be a perfect reference mainly because of non-lambertian properties ; thus the bidirectional characteristics of a panel and diffuse radiance effect cause some errors (Gu and Guyot, 1993). As for the directional effect of sun elevation on the reference panel, a simple correction was made using regression equations in which the relative reflectance was expressed as a function of solar zenith angle (Jackson et al., 1987 ; Jackson et al., 1992). The looking angle of the sensor at the panel was consistently kept nadir during the entire season to reduce directional error. Care should also be taken for changes in spectral property with aging and stains as well. The panel used in this experiment was coated before the experimental season in 1994 and installed in a box to avoid dust and exposure to the sun and open air, i.e., exposure to the sun and open air was limited to a few seconds for each measurement. As for the solar directional effect on the measurements of rice canopies, no correction was made. Simulation results using a simple spectral model SAIL (Verhoef, 1984) at several LAI values showed that the influence of the sun elevation during the experiment was small (about 2% in visible and 0.2% in near-infrared at most, respectively). Weather data including solar radiation, air and soil temperatures, humidity and windspeed were collected at the weather station of NIAES.

2. A growth simulation model for rice used in this study

The model used here was a simple process model which simulated the growth and yield of irrigated rice based on weather data (Horie, 1987). It was developed from a rational simplification of the underlying physiological and physical processes of the rice plant. Phenological stages such as heading and maturity were expressed by a developmental index (DVI) which is the sum of the daily developmental rate (DVR). The DVR was calculated from the daily mean temperature and daylength. Dry matter production was expressed as a function of absorbed solar radiation by a canopy and the radiation use efficiency (RUE ; the conversion efficiency of radiation to plant dry mass). The absorbed radiation was determined by the incident solar radiation and fAPAR which was a function of LAI. Finally, the grain yield was estimated as a specific proportion (harvest index) of the total dry matter. The harvest index was consistent in a wide range of weather conditions, except extremely cool or hot conditions which affected the formation of reproductive organs. The model took into account the effect of such extreme temperatures (sterility) using the harvest index equation.

The model required five initial inputs (date of transplanting, global coordinates of the location, and initial values of dry matter DMi, leaf area index LAIi and developmental index DVIi), and two daily input variables (daily values of incident solar radiation and mean air temperature). Because of this simple input-requirement, it was easily applied where such common weather data are available (Horie, 1993). This model also required twenty five parameters such as variety-specific information (critical daylength for photoperiod-sensitivity, radiation use efficiency, extinction coefficient, asymptotic value of LAI when temperature is non-limiting, maximum harvest index, critical temperature for cooling damage, etc.) and some empirical constants for each equation. All parameters were determined for each variety and location based on a large number of field experiments and destructive sampling. The most sensitive crop parameters were found to be those related to phenology, radiation use efficiency, and two initial values (DVIi and LAIi), so that careful specification was needed for the values of those parameters. Details of the model were presented by Horie et al. (1995).

3. Real-time calibration module for recalibration of the simple model based on remotely sensed data

The model requires variety-specific parameters, initial observation data, and calendar-day information such as planting date. Three initial values at the planting date (DMi, LAIi and DVIi) strongly affect the simulation results and tedious to be properly collected for each paddy field. Values of the light use efficiency (RUE) and asymptotic leaf area index (LAIx) were strongly affected by nitrogen availability, air temperature and other stress factors. The latter two parameters were especially important in the estimation of biomass productivity. All other parameters were consistent and/or specific to each variety.

Recalibration of the model with remotely sensed data was accomplished by optimization of these five parameters. Based on the concept proposed by Maas (1988), a real-time calibration module was developed and linked with the simulation model (Fig. 1). The process of optimization was based on a simplex method (Spendley et al., 1962) which is an algorithm to determine the parameters of a non-linear formula so as to minimize the residual error between modeled and actual data. The real-time calibration module performs both re-initialization of DMi, LAIi and DVIi, and re-parameterization of RUE and LAIx by an automated iteration procedure. Upon reaching a certain minimum and stable value of residual error, the module determines a set of parameters, and thereafter they are used for subsequent growth simulation. In the present study, based on the considerations in the Introduction section, the fAPAR was used as a key variable for the recalibration procedure.

Results and Discussion

1. Experimental analysis of the relationship between fAPAR and spectral reflectance in paddy field

Time course changes in LAI, dry matter and fAPAR for the four rice plots are shown in Fig. 2. Under the same weather conditions, the rice growth showed a great variation. For example, at the middle growth stage, values of LAI and dry matter in the minimum plot were only 60% and 73% of those in the maximum plot, respectively. This great difference in the actual growth was mainly caused by the difference in fertilizer application (N0 vs. N1). Dry matter growth and yield in N0 plots was not extremely low presumably because of high soil fertility and nutritious irrigation water.

In this study, fAPAR was estimated from the measured green LAI because there is a well-established relationship between green leaf area index and fAPAR.

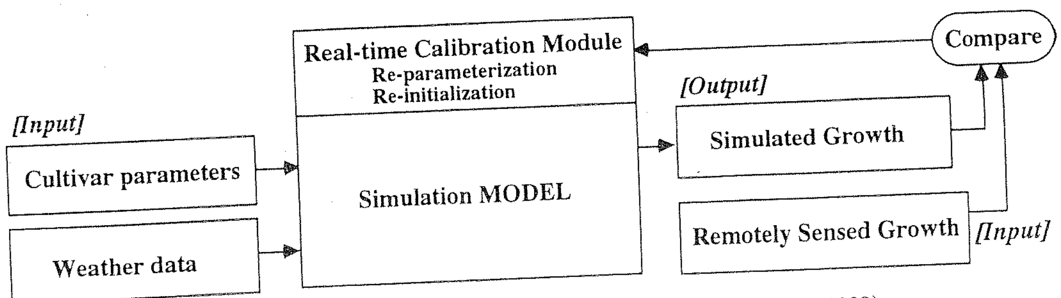

Fig. 1. Scheme of the real-time calibration system (after Maas, 1993).

Based on the radiation balance for a canopy, fAPAR was expressed as ;

$$\mathrm{fAPAR}=1-r-(1-r_0\ \exp[-(1-m)k\ \mathrm{LAI}])\quad\cdots(1)$$

where r and r_0 are the reflectance of canopy and soil background, respectively, and m is the scattering coefficient, and k is the extinction coefficient of the canopy to shortwave radiation. On the other hand, the reflectance of shortwave radiation by a rice canopy was given by the following equation (Research group of evapotranspiration, 1967) ;

$$r=r_f-(r_f-r_0)\exp(-0.5\ \mathrm{LAI})\quad\cdots\cdots(2)$$

where r_f is the reflectance when the surface is completely covered by the vegetation. The value of fAPAR shown in Fig. 2c was calculated from green LAI based on Eqs. 1 and 2.

The relationship between vegetation indices and fAPAR has been reported for various crops (e.g., Daughtry et al., 1983 ; Hatfield et al., 1984 ; Gallo et al., 1985 ; Asrar et al., 1989 ; Christensen and Goudriaan, 1993 ; Leblon et al., 1991). They all showed that vegetation indices based on reflectance at red and near-infrared wavelengths which had been developed to infer biomass or LAI had a close relation with fAPAR. Asrar et al. (1989) showed that there was a curvilinear relationship between the VI and fAPAR based on a theoretical analysis using a simple radiative transfer model by Goudriaan (1977) ; however, he reported a close linear relationship between them using experimental data for wheat canopies. To investigate these relationships for rice canopies, three spectral vegetation indices were calculated using our experimental data (Fig. 3). These indices are defined as,

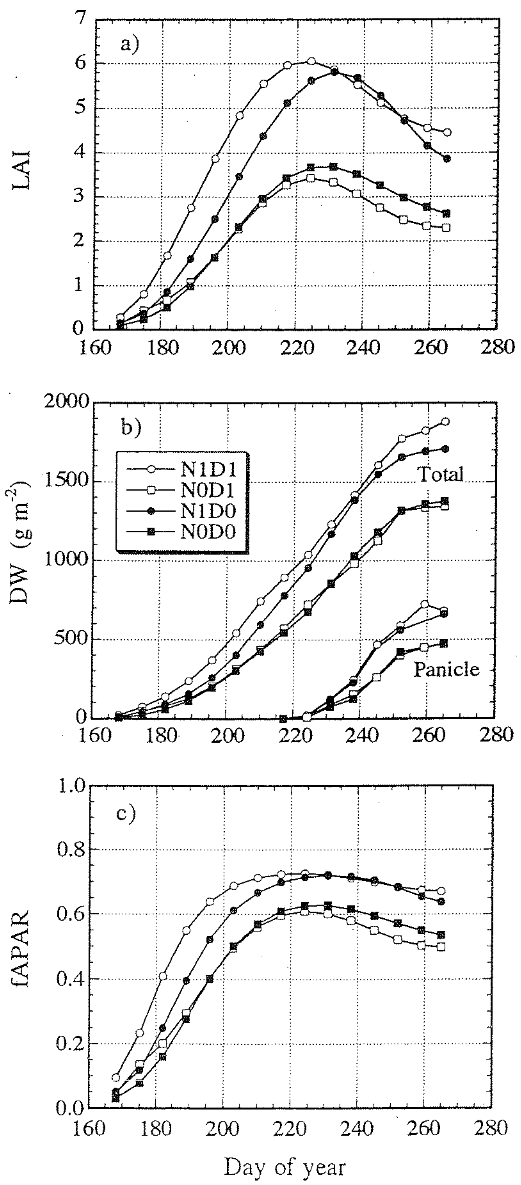

Fig. 2. Seasonal change of leaf area index, dry matter production and fAPAR in four differentially-managed rice canopies.

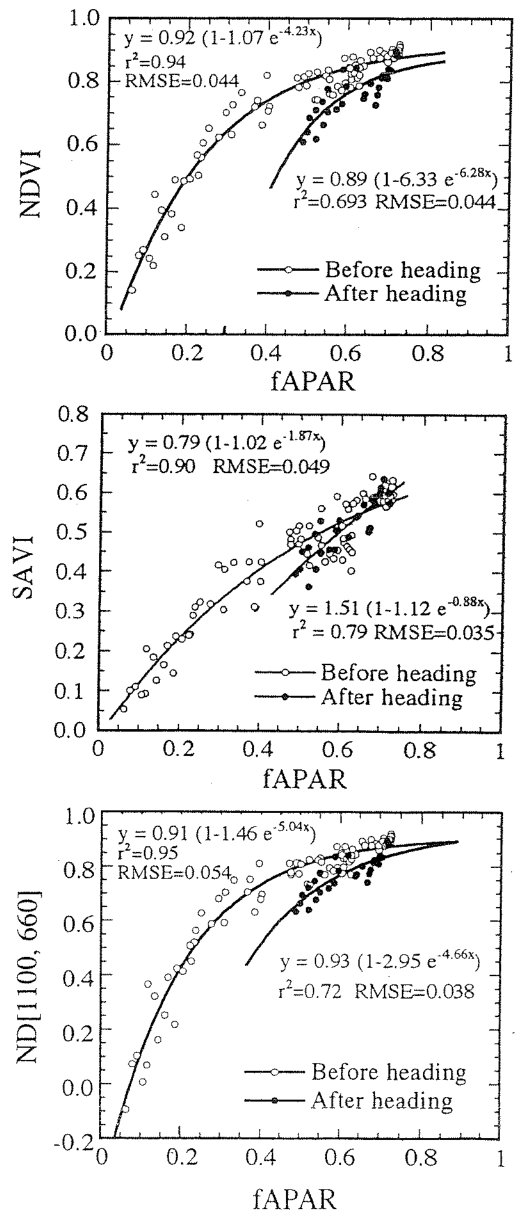

Fig. 3. Relationship between fAPAR and spectral indices in rice canopies.

$$NDVI = (R830 - R660)/(R830 + R660) \quad \cdots\cdots (3)$$
$$SAVI = 1.5(R830 - R660)/(R830 + R660 + 0.5) \quad \cdots (4)$$
$$ND[1100, 660] = (R1100 - R660)/(R1100 + R660) \quad \cdots\cdots (5)$$

The SAVI was proposed by Huete (1988) to reduce the effect of soil background. We confirmed that these three indices resulted in the least scatter of all similar combinations of two different spectral bands. The use of R1100 was comparable to or better than that of R830 while R1200 was not. The relationship between spectral indices and fAPAR could not be approximated with a linear fit, and rather, fit an exponential curve which was suggested by the simulation analysis (Asrar et al., 1989 ; Christensen and Goudriaan, 1993). Although an exponential formula could be applied to the entire season, the function parameters differed before and after heading. The higher fAPAR during the maturity stage may be attributed to the absorption by the dead parts and heads. The two-band spectral indices (Eqs. 3-5) became less sensitive to fAPAR when fAPAR was larger than 0.4. As has been indicated (e.g., Baret and Guyot, 1991) it is clear that there is a limitation for two-band vegetation indices because they are strongly affected by the background while the vegetation cover is low and become saturated when the vegetation cover is high.

Hence, we attempted to derive a better correlation model which could be applied both before and after heading. As a result of multiple regression analysis using more than three spectral wavelengths, we obtained the most significant regression equation using four spectral bands, i.e., R660, R830, R1100 and R1650. The relative significance of R660 and R1100 as a predictor variable was especially high as suggested by the results presented in Fig. 3. To test the statistical stability, all data were divided into two data sets each of which consisted of data from different days and conditions, and then an equation derived from a data set was applied to the other data set. Figure 4 shows the results of statistical validation of an equation derived from one data set and applied to the other data set. The predictability was much improved by using these four wavelengths than the simple vegetation indices based on two spectral wavelengths. This close and linear relation between predicted and measured data suggests that the usefulness of these four wavelengths was robust, although this particular regression equation may not be applied beyond the range of calibration data, as is the case for all empirical indices and models. Since the present attempt is based on multiple regression analysis the underlying mechanism of the contribution of these wavelengths is not clear. More systematic use of these wavelengths such as a multiple-band vegetation index awaits further investigations.

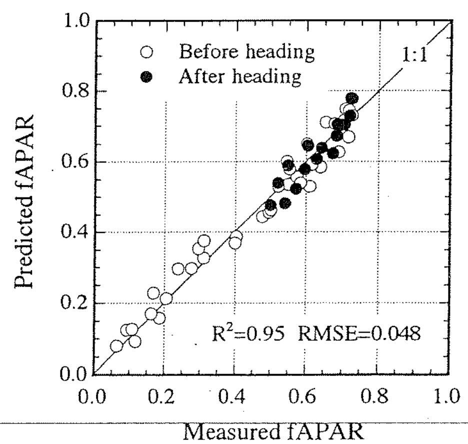

Fig. 4. Spectral estimation of fAPAR in rice canopies for entire growing season based on multiple regression analysis. An equation ; $fAPAR = 0.479 - 0.0451R660 - 0.0343R830 + 0.05R1100 - 0.0187R1650$ derived from a data set is validated with a different data set.

2. Relationship between nitrogen status of a rice canopy and spectral measurements for a simple growth model

A close correlation has been found between chlorophyll or nitrogen content and spectral transmittance of plant leaves (Inada, 1965). A handheld chlorophyll meter (SPAD502, Minolta or its former models) was developed based on these findings. On the basis of detailed laboratory analysis, Inada (1985) concluded that the spectral reflectance ratio R800/R550 was the most effective index in estimation of leaf chlorophyll content. An attempt to apply a similar relation to a rice canopy was made by Takebe et al. (1990). Their results showed a linear correlation between leaf nitrogen content and R800/R550 for the vegetative stage of rice ; however, it worked only when measurements were made at an oblique viewing angle so that the field of view was completely covered with rice leaves, and only under cloudy (scattered light) conditions.

Figure 5 shows the relationship between the spectral ratio R830/R550 and leaf nitrogen content (LNC) in our experiment. There was a poor correlation between them during the period before heading, but on the other hand, a very close correlation was found for post-heading period. It appeared that the relation was negative before heading and positive after heading. The close relation for the ripening stage agrees well with that found for single leaves by Inada (1985). This relation for the ripening period may be due to the fact that rice canopies lose greenness while maintaining a consistent amount of biomass during the senescence stage. These results indicated that the spectral ratio R830/R550 was effective for estimation of leaf nitrogen content when a paddy field was regarded as a big leaf. No other spectral indices performed as well for the entire growing season. An attempt at multiple regression of several spectral bands also resulted in a poor solution (R^2=0.68 using all seven wavelengths). Results imply that the close relation on a single leaf basis is not applicable to a field scale except at

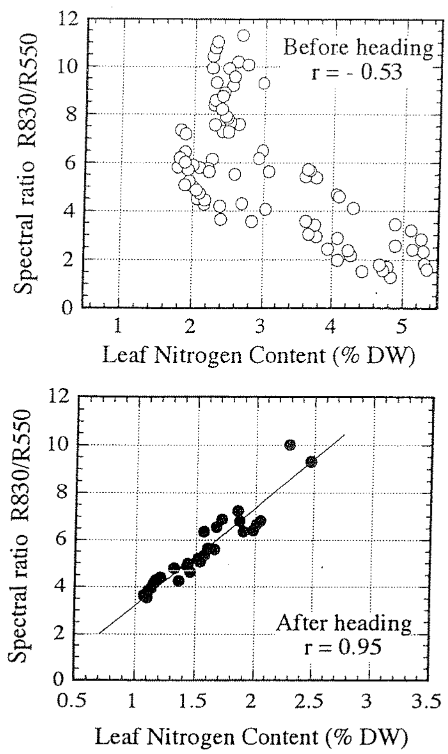

Fig. 5. Relationship between spectral ratio R830/R550 and leaf nitrogen content in rice canopies. Open and closed circles indicate data before and after heading, respectively.

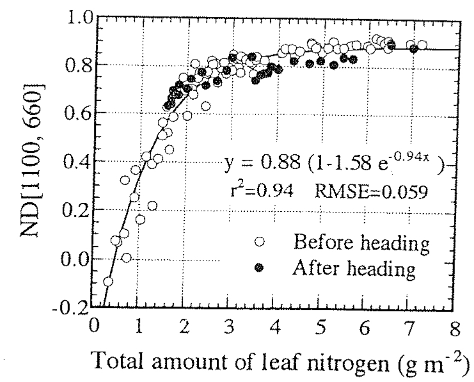

Fig. 6. Relationship between total leaf nitrogen for a canopy and a spectral index ND[1100, 660] in rice canopies.

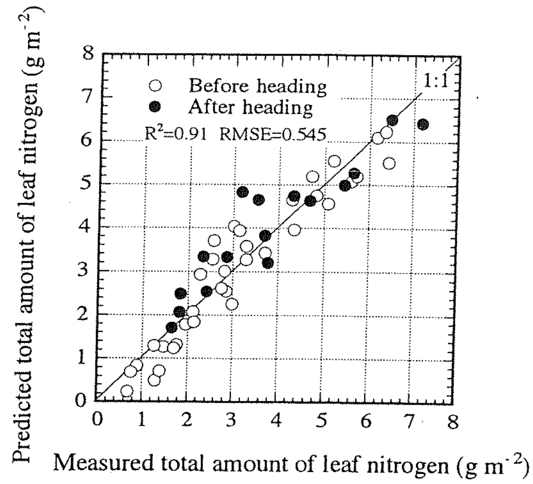

Fig. 7. Spectral estimation of leaf nitrogen content for a canopy based on multiple regression analysis. An equation; LNC $= 3.96 - 0.679R550 + 0.193R830 - 0.341R1650 + 0.361R2200$ derived from a data set is validated with another data set.

the mature stage.

Estimation of the total amount of leaf nitrogen (TLN) from remotely sensed data, instead, may be useful for the growth model since TLN can be combined with some physiological state-variables in the model such as LAI, DM and RUE, and further used for recalibration of physiological parameters. An attempt to estimate the total nitrogen of a rice canopy (Shibayama and Akiyama, 1986) suggested that the best-correlated single band to TLN was around 620–660 nm ($r=0.68$), and that the TLN might be estimated by a multiple regression of R480, R620 and R840 ($R^2=0.53$). Since the range of wavelengths for their study was limited to 400–980 nm, we re-examined the relationship between TLN and spectral indices of two different wavelengths such as SAVI for our data set. The fit with least scatter was obtained between ND [1100, 660] and TLN (Fig. 6); nevertheless, the sensitivity was lost when TLN was greater than 3 g m^{-2}. Hence, we attempted to use all visible, near- and short wave infrared wavelength bands based on a regression approach. A combination of four spectral bands R550, R830, R1650 and R2200 was selected by the multiple regression analysis. The equation derived from one data set was statistically validated with the other data set (Fig. 5). The R550 and R2200 were selectively included presumably because R550 was related to chlorophyll content and R2200 to content of lignin, cellulose and protein (enzyme), respectively (Elvidge, 1990). This enzyme is the most abundant nitrogen-bearing compound in green leaves and has a critical role in photosynthesis (Elvidge, 1990). Yoder et al. (1995) reported a significant contribution of R2132 nm in the estimation of nitrogen of maple seedlings, and suggested that the spectral region between 2000 nm and 2200 nm would be useful for this purpose though the reason remains unclear especially on a canopy scale. The contribution of this region is probably attributed to the fact that synthesis and decomposition of the enzyme and/or relative increase in lignin and cellulose are coupled with plant growth, nitrogen supply and senescence, but further detailed analyses based on hyperspectral measurements are be needed.

As shown in Fig. 4, these two wavelengths were not used for the estimation of fAPAR. The coefficient of determination was $R^2=0.91$ (RMSE=0.55) for the equa-

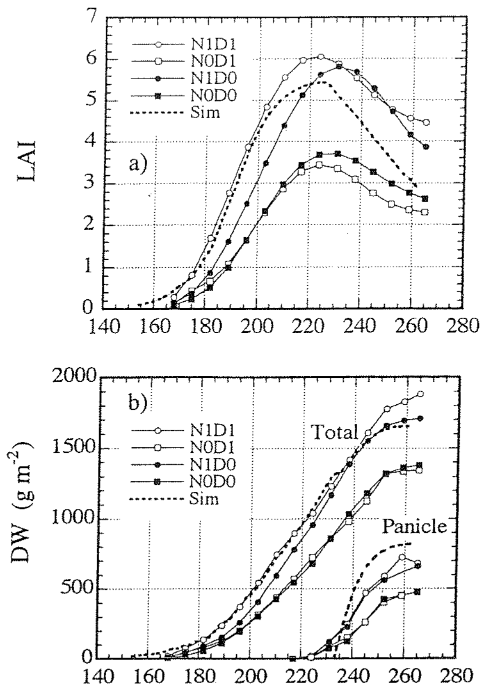

Fig. 8. Time course of leaf area index and dry matter production simulated by the growth model (dotted line) under normal conditions. Actual data in four differentially-managed rice canopies are also indicated.

tion of R550, R830, R1650 and R2200 while $R^2=0.84$ (RMSE=0.70) for that of R550, R660 and R830. Although a direct comparison with the previous results is difficult since the range of each data set are different ; for example, the maximum TLN in the present study was 7.2 g m^{-2} while 9.6 g m^{-2} in the study by Shibayama and Akiyama (1986), the use of short wave infrared wavelengths may contribute to improving the accuracy. Although results presented in Fig. 7 show a high statistical significance and this information may be used to incorporate the nitrogen status to radiation use efficiency, still more accurate estimation would be required for operational use. Hence, exploratory studies based on hyperspectral measurements over visible, near- and shortwave-infrared spectral regions would be needed for better accuracy. New statistical approaches such as PCR (principal component regression) and PLSR (partial least squares regression) that utilize all hyperspectral data may also be useful for better estimation of chemical components (Brown, 1993 ; Cloutis, 1996).

3. Recalibration of the growth simulation model using the real-time calibration module

The time courses of LAI and DM simulated by the model are shown with the actual ones for four experimental plots (Fig. 8). Since the model simulation

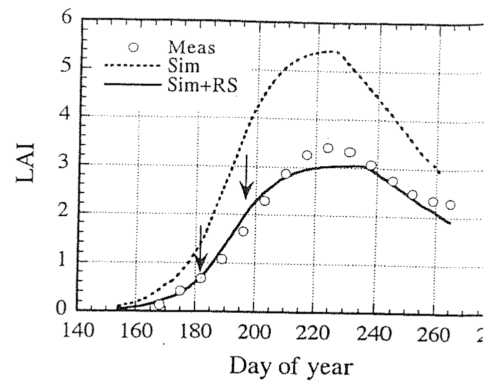

Fig. 9. Prediction of LAI based on the real-time cal system with remotely sensed fAPAR. Abbreviation: Sim, and Sim+RS mean measured data, simulation o simulation with remotely sensed data, respectively. indicate the timing of the data acquisition of remote data.

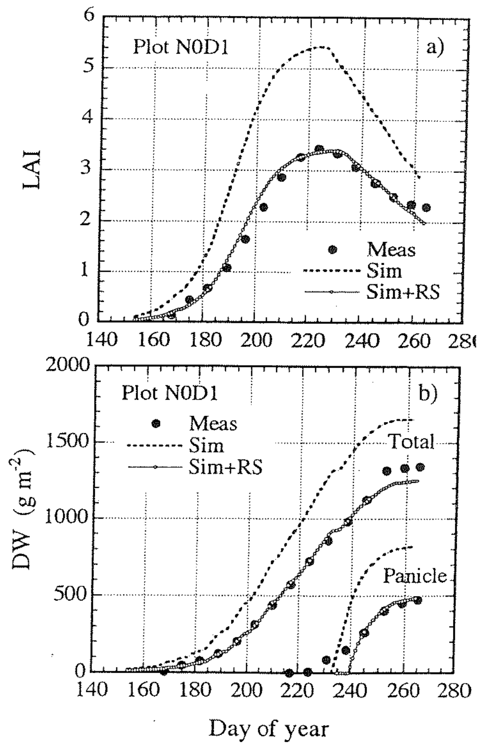

Fig. 10. Prediction and parameterization based on the re calibration system with all available (ten) remote s data. Abbreviations are the same as in Fig. 9. Estimated of initial and state variables are as follows ;

	DVIi	LAIi	DWi	LAIx	RU
Sim :	0.250,	0.100,	20.00,	5.50,	1.9
Sim+RS :	0.133,	0.039,	13.54,	3.42,	1.7

assumes standard management practices, the simul results (dotted lines) are unable to predict these variations in the actual growth patterns without r bration. The model responded to a wide range of initial inputs and crop-specific parameters; however, this implied that very careful and accurate estimates of those values were required.

The performance of the real-time calibration module was tested using remotely-sensed fAPAR values. Prediction results by the simulation model with and without remote sensing inputs are shown in Fig. 9. In this example, remotely-sensed data on two dates were used for recalibration. The approach of within-season calibration was undoubtedly effective since a model can be modified to fit reality with the data from the real object no matter what kind of data are used (e.g., estimated by destructive sampling or from remote sensing). However, errors in the estimation of fAPAR are to propagate to the calibration results. Hence, the major problems may be the accuracy and stability of estimation and the efficient use of such data. The timing and number of applied data also affect the error in simulation. Nevertheless, the greater number of remotely sensed measurements will more closely simulate reality, as shown by the example in Figs. 9 and 10. With an increasing number of remote sensing measurements, the simulation curve approached to the results in Fig. 10, where all ten available data were used for recalibration. The use of fAPAR may be rather unique for remote sensing because fAPAR is more closely linked with remotely sensed spectral reflectance than such as LAI and biomass, and a direct measurement of fAPAR is not easy, especially during the ripening period (Inoue and Iwasaki, 1991). Another useful aspect of the within-season calibration of a model with remotely-sensed data is that it can provide realistic estimates of physiological parameters incorporated in the model without any direct measurements. For instance, recalibration can be performed with all available remotely-sensed data to give physiological state-variables such as maximum LAI and radiation use efficiency for each canopy. Figure 10 shows the modified simulation pattern and subsequently determined physiological variables based on recalibration with ten remotely-sensed values. The asymptotic LAI and radiation use efficiency were lowered from 5.50 and 1.95 under optimal conditions to 3.42 and 1.79, respectively, for the particular canopy. These physiological parameters may be used for field-to-field comparison of productivity or variety-screening. Basically, a large number of field experiments and destructive measurements have been required to determine those model parameters under normal conditions for each variety and/or region. However, some of those parameters such as RUE may be determined by applying the present approach to such canopies. The combination of remotely-sensed data and a simple growth model may be useful in improving the accuracy of model prediction and in providing physiological parameters without tedious sampling.

Concluding Remarks

The fAPAR for a canopy may be a useful and unique variable for linking remote sensing to simple crop models because it is a key variable in most simple crop models and because the spectral measurements by remote sensing can be directly related to fAPAR in principle. The fAPAR was well correlated with vegetation indices derived from two wavelengths such as NDVI, SAVI and ND [1100, 660]. The relationship between them was not linear but exponential, which was inferred from a theoretical consideration (Goudriaan, 1977). This exponential relation was also applied to the ripening stage but with different function parameters. The results suggested that the use of R1100 and R1650 significantly improved the prediction accuracy of fAPAR.

The real-time recalibration module developed in the present study proved effective in linking the remotely-sensed data with a simple crop model. This approach was also useful in inferring physiological parameters such as light use efficiency for each rice canopy without any destructive sampling. This module may be applicable to various types of optimization of a crop growth models with actual data.

The nitrogen status of rice plants is expected to be incorporated in a simple process model of rice since the fertilizer application method is still one of the major issues in Japanese rice cultivation. There was a close linear relation between a spectral ratio R830/R550 and leaf nitrogen content in the ripening period although it was not the case before heading. The results suggested that R830/R550 is effective for estimation of leaf nitrogen content when a paddy field can be regarded as a big leaf. However, no spectral indices were found applicable to a canopy for the entire growing season. Hyperspectral measurements are expected to provide more accurate information on leaf nitrogen content. The total amount of leaf nitrogen, instead, was well correlated with ND [1100, 660]; nevertheless, the sensitivity was lost when the total amount of leaf nitrogen was greater than 3 g m^{-2}. The results of multiple regression analysis showed that a combination of four spectral bands R550, R830, R1650 and R2200 was most effective. This relation was statistically significant ($R^2=0.91$), and the use of R550 and R2200 was effective for improving accuracy; nevertheless, still more accurate estimation may be needed for operational predictability.

Both remote sensing and crop simulation modeling have great potential for information-based precision agriculture; however, each method has limitations. The remote sensing can provide spectral information on wide-area and non-destructive bases, but measurements are usually instantaneous and intermittent. Crop models can simulate robust growth patterns and final yields, but can account for only limited factors and thus can simulate only normal growth under given conditions. Hence, the combination of a crop simulation model and remote sensing data is a promising, complementary approach. Among several methods in assimilation of remotely-sensed data in crop models, the re-parameterization and/or re-initialization method with remotely-sensed data is the most practical and effective approach, especially for operational purposes. The major challenge in future studies will be to improve the accuracy and consistency of remotely sensed information with an insight into the accuracy requirements for operational purposes.

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Genetic Resources and Evaluation

Selection of Rice Lines Using SPGP Seedling Method for Direct Seeding

Jong Gun Won, Yuuiti Hirahara, Tomohiko Yoshida and Souichirou Imabayashi*

(*Faculty of Agriculture, Kyushu University, Fukuoka 812-8581, Japan ;*
**Fukuoka Agricultural Research Center, Chikushino 818-8549, Japan*)

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stract : Lodging is a major cause of yield loss in the rice production systems using direct seeding. In this study, eral characteristics of 80 F_4 breeding lines and 10 check cultivars were examined in connection with lodging stance to establish a technique suitable for screening a large number of lines efficiently for breeding rice for direct ling. Experiments were conducted over a 2-year period in puddled wet-fields and in seed pack growth pouches GP). Among the root parameters of SPGP seedlings, only root thickness had a significant positive correlation (r .495**) with pushing resistance, which is the force to bend rice culm to a designated angle and is correlated with ging resistance. The root thickness of SPGP seedlings was also positively correlated with root thickness in the field 18 (r=0.346**) and 30 (r=0.512**) days after seeding. For selected lines and check cultivars, positive correlations re found between pushing resistance and culm thickness in the field (r=0.809**), between pushing resistance and ot thickness in SPGP (r=0.694**). Culm length and panicle number were negatively correlated with pushing istance (r=−0.454**, r=−0.563**, respectively). Among the characteristics related to lodging, root and culm ckness were higher in selected breeding lines than in check cultivars. Grain yield was positively correlated with anicle weight (r=0.601**) and harvest index (r=0.586**) but not with panicle number (r=−0.007ns). Thus the w-tillering, panicle-weight type plants with thick roots and culms seem to be suitable for direct seeding. Some omising lines and candidate parental lines for the next crossing cycle for direct seeding were identified.

ey words : Direct seeding, Rice, Root thickness, Seed pack growth pouch, Selection.

lging has received considerable attention in water -seeded rice (*Oryza sativa* L.) (Seko, 1962 ; Lim et 991 ; Ogata, 1996a). Because rice seeds are sown tly onto the surface of paddy soil and some roots of e plant are exposed to the air, the incidence of lodging increased. Lee et al. (1991) reported that lodging of e plants at the milky stage decreased grain yield by 3 % in Korea. The development of rice cultivars with high lodging resistance and high yield capacity is urgent d essential for direct seeding. The establishment of ethods to select promising lines quickly and efficiently early stages of development in the laboratory would be eficial. Studies on lodging of rice plants have revealed elationship between lodging and root system (Seko, ; Ogata, 1996a). Resistance to lodging of direct se ed rice is affected by thickness, distribution and dry t of roots (Miyasaka, 1970 ; Ogata and Matsue, b ; Terashima et al., 1995). Ogata and Matsue (1996a) reported that highly lodging-resistant cultivars ad ted to direct seeding can be selected by accurate me surement of pushing resistance, which is the pushing for e at 10 cm above the soil surface to bend the culm to an ngle of 45 degrees in transplanting culture.

ravois and McNew (1993) reported a positive genetic correlation between panicle weight and rice yield, and negative correlation between panicle number and yield, in long-grain rice from southern U.S. Kim and Vegara (1990) reported that close-spacing adaptability was higher in low-tillering cultivars than in high-tillering cultivars. Excessive plant stands or tillers can lead to taller plants and weaker culms, increasing the potential for crop losses due to lodging and more severe disease pressure (Gravois and Helms, 1996). Therefore, a low-tillering cultivar with large panicles may be an ideotype for the direct-seeded rice plant.

The objectives of this study are ; (1) to clarify the relationship between root size in SPGP and pushing resistance in the field, (2) to develop a selection method for improving lodging resistance using seedlings in SPGP and (3) to select promising lines or candidates for parental lines for use in direct-seeded rice improvement programs.

Materials and Methods

Eighty F_4 breeding lines, which were developed from crossings aimed at direct seeding by Fukuoka Agr. Res. Center, and six check cultivars were used in both the seed pack growth pouch (SPGP) and field experiments in 1996. Lines No. 1~50 were derived from the cross of Aoinokaze//Lemont/ Hinohikari. Lines No. 51~80

Corresponding author : T. Yoshida (yoshidat@agr.kyushu-u.ac.jp, Fax 092-642-2819).