EXPERIMENTAL VALIDATION FOR ROBUSTNESS OF GROWTH STAGE CLASSIFICATION MODEL OF PADDY IN INDONESIA BY USING MULTI-YEAR HYPERSPECTRAL DATA

Atsushi UCHIDA[1], Keigo YOSHIDA[1], Taichi TAKAYAMA[1], Hozuma SEKINE[1], Osamu KASHIMURA[2], M. Evri[3], M. Sadly[3], Arief D.[3], Sidik Muljono[3]

[1] Mitsubishi Research Institute, Inc. JAPAN
2-10-3, Nagatacho, Chiyoda-ku, Tokyo 100-8141, JAPAN;
Tel: (+81) 3-6705-6039, Fax: (+81) 3-5157-2145,
E-mail a-uchida@mri.co.jp

[2] Japan Space Systems, JAPAN
[3] Agency for the Assessment and Application of Technology (BPPT), INDONESIA,

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ABSTRACT: The aim of this study is to validate the robustness of growth stage classification model for estimating harvest time of paddy fields in Indonesia by using multi-year hyperspectral data. Rice is one of the most important and major staple food for Asian countries, especially in Indonesia. Remote sensing techniques have the potential to provide information on agricultural crops quantitatively, instantaneously, and nondestructively over large areas. The study areas are located in Indramayu, Subang and Karawang which are well known as a major granary in West Java area. We conducted aerial observations and simultaneous ground measurement over the study area two times, 2008 and 2011. In past study, we have developed the growth stage classification model by applying a sparse linear discriminant function based on only 2008 data and showed the overall classification accuracy of that model is over 90%. In this study, we set several cases depends on ground measurement conditions (no ground measurement, part ground measurement and full ground measurement) and validate the robustness of that model for time difference by applying 2011 data to 2008 data model. A comparison of the result of each of the cases revealed that full ground measurement case is much better than other cases. This result indicates it is quite important to conduct the ground measurement for making the robust model for time differences.

INTRODUCTION

Rice is one of the principal foods in Asian countries, especially in Indonesia. For acquiring the precise information related to the production of paddy is essential for national food security. Remote sensing techniques have the potential to provide information on agricultural crops quantitatively, instantaneously, and nondestructively over large areas. Abilities to estimate harvest time within fields from remote sensing images can be quite useful for food provisions management. Hyperspectral technology is one of the advanced technologies in the field of remote sensing and its data has much power compared with other existing data such as multispectral data. Japan Space Systems have started the collaborative project with the Agency for the Assessment and Application Technology (BPPT) from 2007 to develop the hyperspectral data utilization technology for national food security, especially paddy in Indonesia and achieved several good results. (Kobayashi, et al., 2009) (Uchida, et al., 2010, 2011)
There are many studies about hypespectral data analysis such as NDSI, PLS, etc., but there is still the room to develop more effective and accurate method for analysis the hyperspectral data. Basically, multispectral data can classify land covers into small categories, and it is difficult to distinguish the growth stages of vegetation in detail. On the other hand, because hyperspectral data has more than 100 bands and ability to extract surface information more in detail, it is required to develop more effective and accurate method. We have showed the model of growth stage classification with good accuracy for estimating the harvest time (Uchida, et al., 2011) by applying a machine learning technique, Sparse Linear Discriminant Analysis (SLDA) to hyperspectral (HyMap) data. Growth stage classification information, leads to the harvest time for their Area of Interest (AOI), so this information is quite useful for the national food security in Indonesia. The aim of this study is to validate the robustness of growth stage classification model for estimating harvest time of paddy fields in Indonesia by using multi-year hyperspectral data. To validate the growth stage classification model robustness to different condition data, we apply the model generated by using one data (training data) for other data (validation data) and evaluate the capability for classification.

STUDY AREA AND DATA SET

Study Area

Java Island produces around 55 % of total national rice production, and especially, West Java areas are well known as a major grain belt. The study areas are located Indramayu, Subang and Karawang of West Java in Indonesia (Figure 1). In these areas, dual and triple cropping of rice is major trend. Furthermore, there is a time difference of water supply among paddy fields because the mountain dam supplies water to paddy fields though irrigation network from the mountain side (south) to the sea side (north). So in these areas, the mix of growth stage in same time is general trend. Figure 2 shows the various growth stage examples in observed area (Karawang).

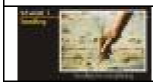
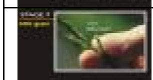
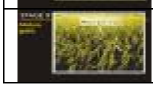
Figure 1: Study Area

Figure 2: Mix growth stage example

Data Collection

For data collection, airborne observation and simultaneous ground measurement are conducted at Subang and Indramayu in 2008 and at Karawang and Indramayu in 2011. For ground measurement, about 100 quadrats are set at each year in side of airborne observation area and by ground measurement, several kinds of data, such as spectral data by Fieldspec, LAI, growth stage information, are recorded. Growth stage data are recorded according to IRRI (International Rice Research Institute) definition, that is to say, 3 growth phases (Vegetative, Reproductive and Ripening) and 9 growth stages (Seedling, Tillering, Stem elongation, Panicle initiation to booting, Heading, Flowering, Milk grain, Dough grain and Mature grain). Table 1 shows the comparison table between IRRI definition and our definition. Data about days after transplanting of Ciherang are provided from Indonesia local government agriculture officer (Indramayu).
With regards to the airborne observation, HyMap sensor with 126 bands (450nm - 2480nm) is selected as an airborne hyperspectral sensor, and images are acquired by 5m spatial resolution. The airborne observational days are 30th June (Indramayu) and 1st July (Subang) in 2008, and 13th July (Karawang) and 14th July (Indramayu) in 2011. Both observations were conducted in dry season in Indonesia.

Table 1: Growth stage definition (Defined by IRRI)

	Growth phase name	Growth stage name	Class Name	Days after transplanting (Cultivar: Ciherang)
	IRRI		Our definition	Local gov definition
	Vegetative	Seedling	Vegetative early (Veg_early)	0-2
		Tillering	Vegetative middle (Veg_mid)	2-7
		Stem elongation	Vegetative late (Veg_late)	8-20
	Reproductive	Panicle initiation to booting	Reproductive early (Rep_early)	21-27
		Heading	Reproductive middle (Rep_mid)	28-55
		Flowering	Reproductive late (Rep_late)	56-65
	Ripening	Milk grain	Ripening early (Rip_early)	66-75
		Dough grain	Ripening middle (Rip_mid)	76-85
		Mature grain	Ripening late (Rip_late)	86-92

METHODS

The large number of spectral bands acquired by the hyperspectral sensor gives us much information for observed targets. But, as is often the case, compared to the number of spectral bands, samples of ground truth data are relatively small because of limitations of ground measurement and it often leads to overfitting problems. Regularization is one of the most promising solutions for this problem, and there are some successful studies of the hyperspectral application such as regularized discriminant analysis (RDA) (Bandos et al., 2009), Sparse Regularization (Yoshida et al., 2011). We select one statistical modeling method called sparse linear discriminant analysis (SLDA) (Clemmensen et al., 2008) for this study. SLDA is a famous machine learning technique and one of the supervised methods for classification. Generally, linear model such as Linear Discriminant Analysis (LDA) is easy to interpret and shows us the effective bands information. Additionally, it is simple implementation for Multi-class classification. But, when we make a model with small number of samples by using LDA, we sometimes face overfitting problems. "Sparse" means a model with a low number of non-zero parameters and SLDA is a simple model with smaller number of bands which causes less overfitting problems and achieves high accuracy.

Also, effective bands are selected automatically by optimization calculation. Additionally, SLDA is said to be faster than traditional feature selection methods and the results are quite better with regards to classification rates and sparseness.

EXPERIMENTAL SETUP

Data Set

Regarding the 2008 measurement data, we set up 100 samples (data sets) with 7 growth stages and with regards to the 2011 data, we set up 74 samples (data sets) with 7 growth stages. Unfortunately, we could not measure the data of Rep_mid and Rip_mid in 2008 and Veg_early and Rep_mid, so we classify these data sets into 8 growth stages except for Rep_mid.

Table 2: Number of samples for analysis

	Vegetative			Reproductive			Ripening		
	Early	Mid	Late	Early	Mid	Late	Early	Mid	Late
2008	19	21	23	23	0	4	4	0	6
2011	0	4	13	21	0	11	14	8	3

On the other hand, we use reflectance data from 450 nm to 2490 nm observed by Hymap as a explanatory variables. But, several numbers of bands are deleted from original observed HyMap data (126 bands) because of the influence of water absorption in the atmosphere, low Signal Noise ratio, etc. Totally, we use 86 bands data.

Case Setup

To validate the growth stage classification model robustness to different condition data, the model generated by using one data (training data) is applied for other data (validation data) and evaluated the capability for classification. For this purpose, we set several case scenarios for training data based on the differences of availability for ground measurement data. As described previously, there are big growth stages trend from mountain side to sea side in these area. So, we set 4 cases based on the ground truth data, no ground truth data; part (only sea side area) ground truth data; part (only mountain side area) ground truth data; and full (all area) ground truth data. Regarding to validation data, we use same data set, half of 2011 data (all stage data) to evaluate accuracies of each models under the same condition. Table 3 and 4 show the case scenarios in detail, data set definitions and number of data of each scenario.
Training data and validation data are generated from a spectral average value from four pixels corresponding to each quadrat. Then, growth stage classification model is generated by SLDA. A hyper parameter is optimized in order to increase a percentage of correct answers in growth stage classification by 5-fold cross-validation.

Table 3: Case scenarios and definitions

Case No.	Ground measurement condition	Training data	Validation data
1	No ground truth data	2008 (IN, SB)	Half of 2011 (KW) (all stage data)
2	Part ground truth data (Only early-stage samples of different time are available) *(sea side area data)*	2008 (IN, SB) 2008 , Half of 2011 (KW) (veg_mid – rep_early data)	
3	Part ground truth data (Only late-stage samples of different time are available) *(mountain side area data)*	2008 (IN, SB) 2008 , Half of 2011 (KW) (rep_late – rip_late data)	
4	Full ground truth data (All stage samples of different time are available)	2008 (IN, SB) 2008 , Half of 2011 (KW) (all stage data)	

(IN:Indaramayu, SB:Subang, KW:Karawang)

Table 4: Case scenarios and samples

Case No.	Number of Data	Year	Vegetative			Reproductive		Ripening		
			Early	Mid	Late	Early	Late	Early	Mid	Late
1	100	2008	19	21	23	23	4	4	0	6
		2011	-	-	-	-	-	-	-	-
		Total	19	21	23	23	4	4	0	6
2	120	2008	19	21	23	23	4	4	0	6
		2011	0	2	7	11	-	-	-	-
		Total	19	23	30	34	4	4	0	6
3	123	2008	19	21	23	23	4	4	0	6
		2011	-	-	-	-	6	5	5	2
		Total	19	21	23	23	10	14	5	8
4	143	2008	19	21	23	23	4	4	0	6
		2011	0	2	7	11	6	5	5	2
		Total	19	23	30	34	10	14	5	8
Val	36	2011	0	2	6	10	5	9	3	1

RESULTS AND DISCUSSION

As described previously, classification performance of model is assessed by using validation data which are not used for model training. We checked the accuracy by comparing the result of HyMap data classification to ground measurement recorded data during field campaign in each quadrat. Table 5 shows the result of each case. We check two case, one is normal case (8 growth stage case) and the other is 5 growth stage case (Veg_late and Rep_early are merged into one stage, Rep_late and Rip_early are also merged into another stage). In normal case, 8 stage case, Case 4 shows the best accuracy performance, overall accuracy is 63.9% and Case 3 show the second one (47.2%). It is indicated that if some ground truth data in the same image of different time are available, classifier provides better prediction performance for similar growth stage. Additionally, it is pointed out that most of misclassifications are occurred between Veg_late & Rep_early and Rep_late & Rip_early. It is supposed that the short growth term (only 7days) is the reason of misclassification about former one (Veg_late & Rep_early) and small number of samples is the reason about latter one (Rep_late & Rip_early). In 5 stage case, Case 4 also shows the best performance and achieved about 80%.

Table 5: Accuracy result of each case

	Case 1	Case 2	Case 3	Case 4
8 stage case (Normal)	36.1%	27.8%	47.2%	63.9%
5 stage case (Veg_late & Rep_early merged, Rep_late & rip_early also merged)	58.3%	44.4%	47.2%	77.8%

Based on these results, two things are suggested. The first is that the classification capability level which is achieved by using another data because ground measurement at the targeted season was not enough and samples are not obtained at all is not enough level. In the case 1, accuracy of growth stage classification remains at less than 40% (36.1%). However, in the case where Veg_late and Rep_early, which are difficult to identify because of short period, as well as Rep_late and Rip_early are classified the same category, it is identified with 60% of correct answers rate. Second, even if there are a few data of ground measurement, the classification performance of growth stage is much improved by utilizing it. Compared with the case 1, correct answers percentage of Veg_late and Rep_early in the case 2 as well as Rep_late and Rip_early in the case 3 are improved. In the case 4 where Veg_late and Rep_early as well as Rep_late and Rip_early are classified the same category, 77.8% is achieved.

The growth stage classification map, which is applied case 4 model to HyMap image of three study areas, Karawang in 2011, Indramayu in 2008 and Subang in 2008, are shown in the figure 3.
These images show the large growth stage trend from mountain side (south) to the sea side (north). They also show not only the big trend but also the detail of it. Additionally, overall growth stage conditions are in consistency with the record of ground measurement.

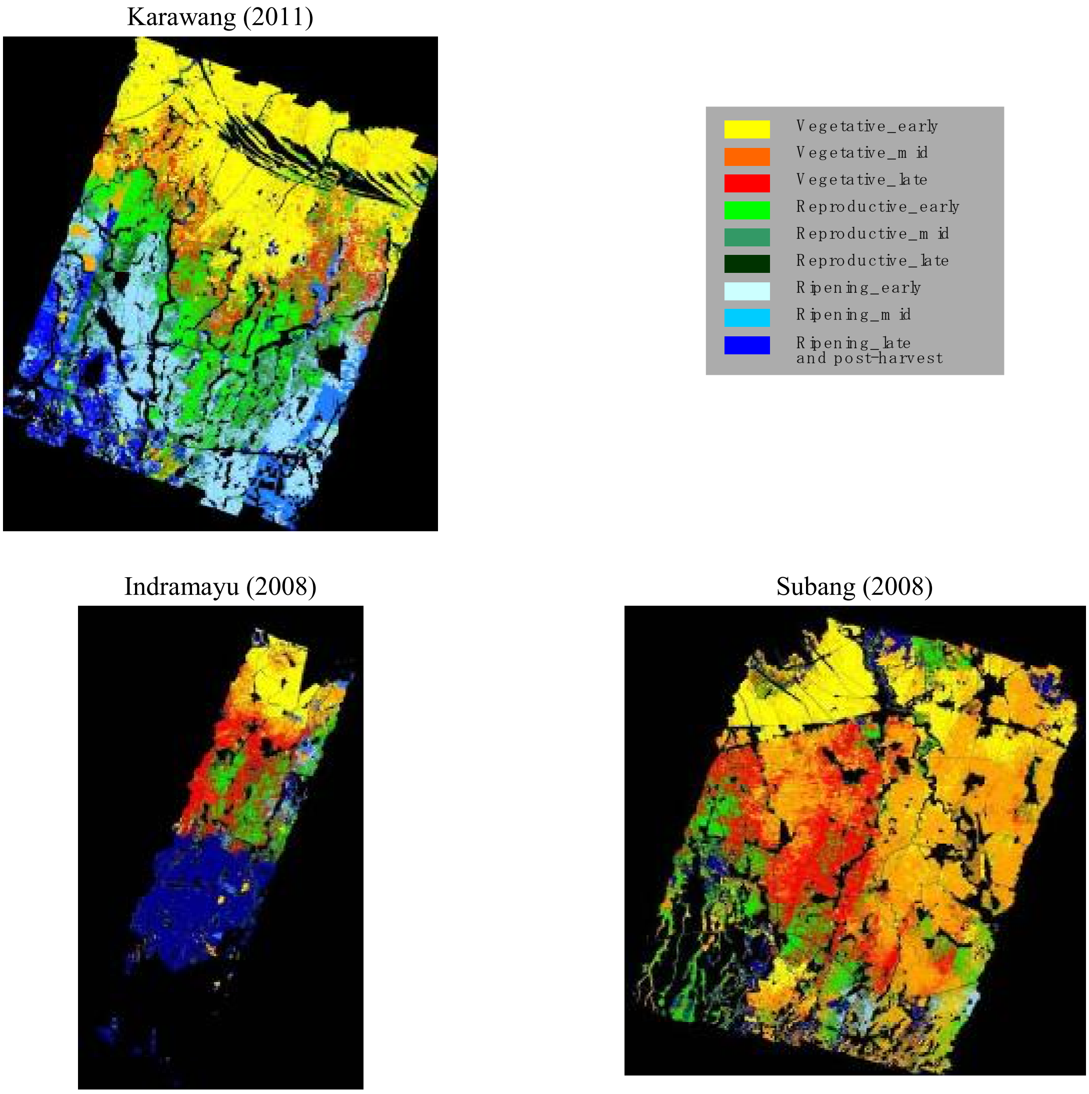


Figure 3: Growth stage classification map of three areas

CONCLUSIONS

In this study, we validate the robustness of growth stage classification model using SLDA in West Java in Indonesia based on 4 case scenarios depends on the differences of ground measurement condition. A comparison of the result of each of the cases revealed that full ground measurement case is much better than other cases. This result indicates it is quite important to conduct the ground measurement for making the robust model for time differences even if the numbers of sample are small. It is also indicated ground measurements are necessary for robustness model, that is to say, operational use for food security in Indonesia.
The hyperspectral and multispectral sensors, called HISUI is being developed by the Ministry of Economy, Trade and Industry (METI) of Japan toward its planned launch in 2015. This study result is one of the potential future operational applications in Indonesia.

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