Toward efficient farm management with remote sensing technologies in lowland rice fields in Laos

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Abstract

This paper reports our current activities in Laos for monitoring rice production with remote sensing technologies in lowland field toward efficient farm management at small farm scale (<1 km^2) or local scale (village, <100 km^2). At farm scale (Research 1), the grain yield of lowland rice was evaluated from field hyperspectral data of paddy fields during the reproductive stage to the ripening stage in conjunction with iterative stepwise elimination partial least squares (ISE-PLS) regression. At local scale (Research 2), we established a land infrastructure data set in a lowland rice field at Koudkher village combining with UAV images and geographic information system (GIS) in order to assess the potential yield and its environmental effects. In Research 1, the highest R^2 values and the lowest root mean squared error of cross-validation (RMSECV) values were obtained from the ISE-PLS model at the booting stage (R^2 = 0.873, RMSECV = 22.903); the residual predictive deviation was >2.4. Selected hyperspectral (HS) wavebands in the ISE-PLS model were identified in the red-edge (710–740 nm) and near-infrared (830 nm) regions. These results confirmed that the booting stage might be the best time for in-season rice grain assessment and that rice yield could be evaluated accurately from the HS sensing data via the ISE-PLS model. In Research 2, a GIS-based land infrastructure information dataset was established in rain-fed paddy field (Koudkher village) from UAV images and digital terrain model. Using the data set, Ikeura et al. (2019) assessed the relationship between rice yield and water/soil conditions in the rainfed rice fields in Koudkher village.

Introduction

Lao People's Democratic Republic (Laos) is one of the major rice (*Oryza sativa* L.)-consuming countries in South-East Asia (Partnership, 2013). While Laos achieved a self-sufficient rice production status in the late 1990s, and the national economy has continuously grown, rice remains the main staple food for people in Laos, and its demand is continuously growing (World Bank 2012). For example, the government of Laos plans to increase rice production not only for domestic consumption but also for export, with the goal of producing 4.7 million tons in 2020 and 5.0 million tons in 2025 (MAF 2015). Thus, improvements of rice yield and efficient management are important for rice sector and farmers.

Nowadays, remotely sensed imageries from satellite or aircraft become a practical tool for monitoring agricultural production at regional or global scales (Atzberger 2013; Doraiswamy et al. 2003; Sakamoto et al. 2013). However, the satellite platforms have limited ability to assess crop production at a farm or local scale applications because of coarse spatial (pixel) resolutions, infrequent coverage, clouds, and slow delivery of information to users. Such difficulties related to spatial and temporal resolutions can recently be overcome using low-altitude platform remote sensing technologies, such as balloon, unmanned aerial vehicle (UAV).

Currently, a large number of studies are underway to realize precision farming with UAV based remote sensing technologies (Zhang and Kovacs 2012). Moreover, recent advances in sensor technologies provide large opportunities for assessing crop production and nutritive status (Inoue et al. 2012; Wang et al. 2014). In this paper, we reports our current activities in Laos, including two topics as Research 1: rice grain assessment at ground scale with canopy hyperspectral measurements (Kawamura et al. 2018b); and Research 2: establishment of land infrastructure data set at local scale combining with UAV images and digital terrain model (DTM) based on a geographic information system (GIS) (Kawamura et al. 2018a).

In site specific fertilizer management, in-season assessment of rice grain yield could benefit for farmers to improve productivity, and for rice-processing industries by quantifying produce supply and market prices. Therefore, Research 1 tried to clarify the optimal timing for assessing rice yield from field hyperspectral (HS) measurement at an experimental lowland rice field (Kawamura et al. 2018b). In order to scaling up from farm to local scale, in Research 2, land infrastructure information was established in a rain-fed paddy field in a selected village (Koudkher village) (Kawamura et al. 2018a).

Materials and methods

Study area

Fig. 1 shows study areas of the Rice Research Center (RRC) and Koudkher village for Researches 1 and 2, respectively, with the UAV images. Research 1 was conducted in an experimental field at the RRC of National Agriculture and Forestry Research Institute (NAFRI), in the central part of Vientiane in Laos (Fig. 1b). This area has a hot, humid summer season and belongs to a tropical climate (‘Aw’ in Kȍppen’s climate classification). The mean annual temperature is 25ºC, and the annual precipitation is 1,622 mm. The soil type is characterized by clay loam (0–30 cm) and light clay (40–60 cm).

Research 2 was conducted in Koudkher village, Outhoumphone District, Savannakhet Province, Laos (Fig. 1c). The Koudkher village locates approximately 300 km to the southeast of the Vientiane capital, and 34 km to the east of Savannakhet city (Ikeura et al. 2019). The mean annual temperature is 26.1ºC (average from 2014, 2016 and 2017), and the annual precipitation is 1,533 mm (average from 2001 to 2013). The soil type is classified as sand and loamy sand at the surface layer (0–20 cm), and sand, loamy sand, sandy loam, sandy clay loam, and sandy clay at the subsurface layer (20–40 cm).

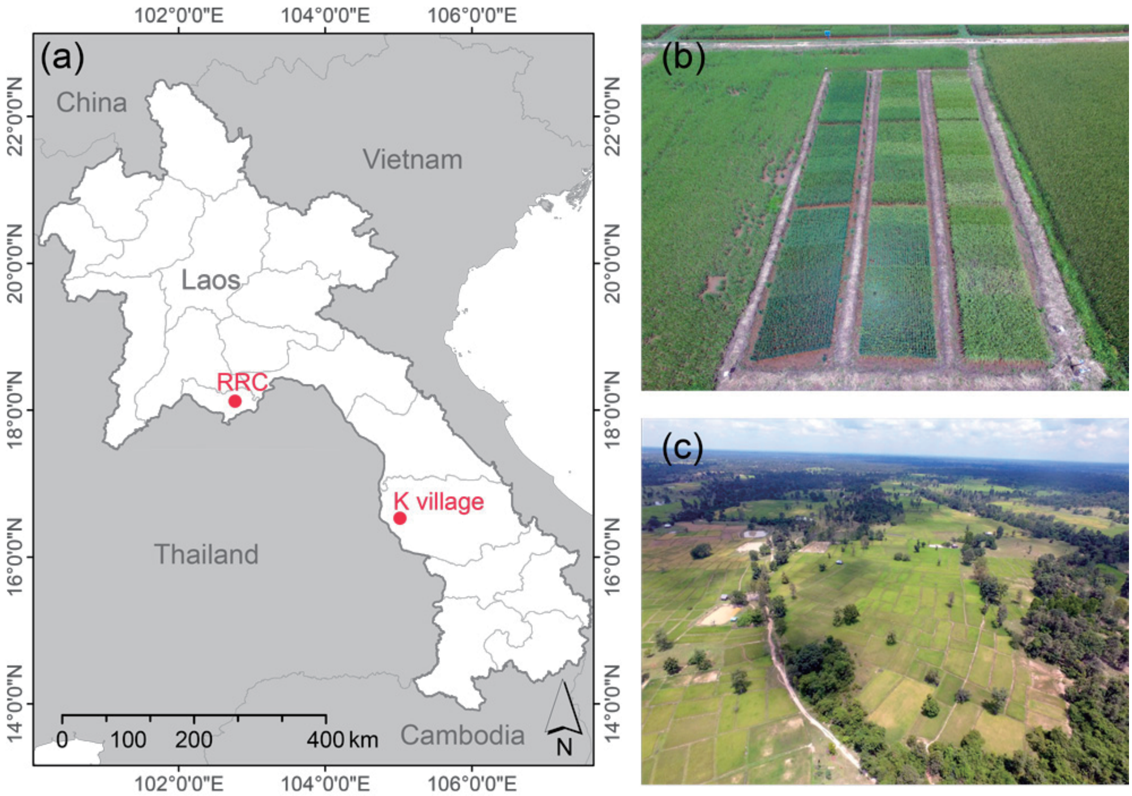

Fig. 1. Locations of the rice research center (RRC) and Koudkher village (a); and the UAV images for RRC (Research 1) (b) and Koudkher village (Research 2) (c).

Research 1: Plot design, canopy HS measurements and statistical analysis

The experiment was performed during the growing period in 2017 using a randomized complete block design with three replications (R1–R3). Each plot size was 5 m × 2 m. The treatments included three different transplanting dates (T1: July 12, T2: July 26, and T3: August 8) and six rice cultivars (cv.) (V1: cv. Tadokkham [TDK] 8, V2: cv. TDK11, V3: cv. Tasano 7 (TSN7), V4: cv. Homsavanh [HSV], V5: cv. Khaophorbane [KPB], and V6: cv. Khaokongkane [KKK]); V4, V5 and V6 were planted in Koudkher village in southern Laos, V1, V2 and V3 were improved varieties expected to be introduced to southern rain-fed paddy fields in the future. Plants were sampled on the harvest dates: T1 was harvested from October 18–27 (day of year [DOY] = 291–300), T2 was harvested from October 27–November 10 (300–314), and T3 was harvested from November 6–16 (314–320) in 2017. For rice yield, the rice grain weights were calculated with a moisture content of 14%.

Canopy HS measurements were carried out on October 2, 2017 using a portable MS-720 spectroradiometer (EKO Instruments, Tokyo, Japan). On that date, the rice growth stages at T1, T2, and T3 included the ripening (with the exception of V4), booting and panicle initiation stages, respectively. The spectroradiometer has a spectral sampling wavelength of 3.3 nm in the 350–1050 nm range, which was reproduced as a 1 nm-resolution wavelengths for outputting the data using MS720 software (EKO Instruments).

Standard full-spectrum PLS (FS-PLS) and ISE-PLS were performed using smoothed reflectance data to evaluate the biomass (BM) and grain yield for all combined data (n = 54) and for the T1, T2, and T3 data sets (n = 18), respectively. To assess the predictive abilities of the FS-PLS and ISE-PLS models, the coefficient of determination (R^2), RMSECV, and residual predictive deviation (RPD) in conjunction with leave-one-out (LOO) cross-validation were used in this study. High R^2 and low RMSECV values indicate the best model for predicting grain yield. The RPD was defined as the ratio of the standard deviation (SD) of the reference data for predicting the RMSECV (Williams 2001). For the performance ability of the calibration models, the RPD is suggested to be at least 3 for agricultural applications; RPD values between 2 and 3 indicate a model with a good predictive ability, 1.5 < RPD < 2 indicates an intermediate model needing improvement, and an RPD < 1.5 indicates that the model has a poor predictive ability (D'Acqui et al. 2010). All the data handling and linear regression analyses were performed using Matlab software ver. 9.0 (MathWorks, Sherborn, MA, USA).

Research 2

A small consumer UAV, the DJI Phantom 4 (DJI, Shenzhen, China), was used to capture the red-green-blue (RGB) color images in May 30–June 1 in 2017 and June 1 in 2018 at a flight altitude of 100 m, to cover the entire Koudkher village area. The UAV flights followed autonomous flight plan using DJI Ground Station Pro application (DJI, Shenzhen, China) to ensure substantial overlap (85% forward and 60% side). Using 3D modeling software, Agisoft Photoscan Pro ver. 1.4.3 (Agisoft LLC, St. Petersburg, Russia), the 3D point clouds, ortho-mosaic images and DSMs were constructed from 4,344 images taken by the UAV with the geographic coordinates of 52 ground control points (GCPs) (UTM 48N). The spatial resolution (pixel size) was 5 cm.

In order to analyze the water resources environment, calculate watersheds and surface water flow was calculated using high-resolution digital terrain model (DTM) data from AW3D (https://www.aw3d.jp/) and GRASS software (https://grass.osgeo.org).

Using ArcGIS software ver. 10.3.1 (ESRI, USA), shape files for ground surface features (paddy field, irrigation pond, building and road) were created manually by visual discrimination of ortho-mosaic image. For paddy fields, the area and topographic environment (elevation, slope, direction) of each field were calculated.

Results and discussion

Research 1: Grain yield evaluations from field HS data with PLS models

Table 1 shows cross-validated calibration results between canopy HS reflectance spectra and grain yields via FS-PLS and ISE-PLS (Kawamura et al. 2018b). Based on ISE-PLS model, the selected number of wavebands (NW) and the selected NW as a percentage of the full spectrum (NW% = NW / whole waveband [531 bands] × 100) ranged from 2–131 (0.4–24.7%). In most cases (combined data set, T1, T2 and T3), the ISE-PLS models showed better predictive accuracy than the FS-PLS models. These findings support previous results indicating that the performance of FS-PLS models can be improved via waveband selection (Cho et al. 2007; Kawamura et al. 2017).

Fig. 2 shows the relationships between the observed and cross-validated prediction values of grain yield in each data set as predicted by the ISE-PLS models (Kawamura et al. 2018b). Overall, the best R^2 and lowest RMSECV values were obtained with ISE-PLS at the booting stage of the T2 data set (R^2 = 0.843, RMSECV = 22.903). Moreover, low predictive accuracy from the combined data could indicate that the in-season rice yield assessment depends on the appropriate growth stage for canopy HS measurements. The RPD value indicated that the T2 data set used in the ISE-PLS model accurately predicted the rice grain yield (RPD = 2.437).

Table 1. Optimum number of latent variables (NLV), coefficient of determination (R^2), root mean squared errors of cross-validation (RMSECV), and residual predictive values (RPD) from full-spectrum partial least squares (FS-PLS) and iterative stepwise elimination PLS (ISE-PLS) models with a selected number of wavebands (NW) and their percentages of the full spectrum (NW%) (Kawamura et al. 2018b).

Data set	Regression	NLV	R^2	RMSECV	RPD	NW	NW%
Combined	FS-PLS	3	0.113	68.927	1.050		
	ISE-PLS	2	0.157	66.734	1.085	2	0.4
T1	FS-PLS	1	0.009	86.114	0.875		
	ISE-PLS	2	0.023	80.216	0.939	84	15.8
T2	FS-PLS	3	0.078	58.480	0.944		
	ISE-PLS	10	0.843	22.903	2.437	11	2.1
T3	FS-PLS	8	0.301	66.418	1.068		
	ISE-PLS	7	0.479	54.088	1.316	131	24.7

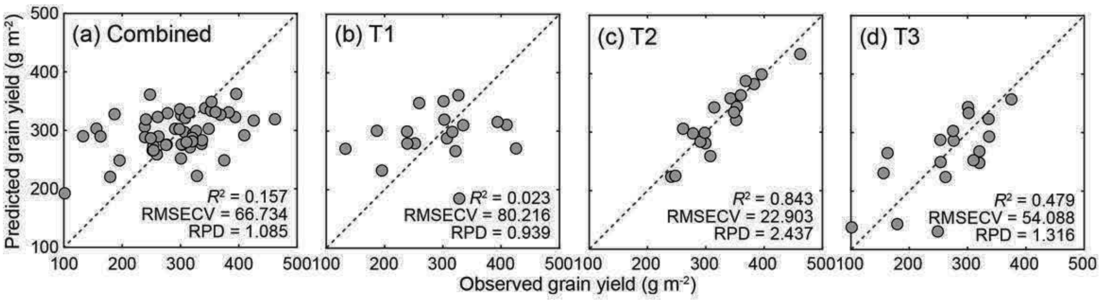

Fig. 2. Observed and cross-validated predicted values of rice grain yield (a, b, c, d) using ISE-PLS regression for the combined (n = 54) and T1, T2 and T3 data sets (n = 18), respectively (see Table 1) (Kawamura et al., 2018b).

Research 2: Establishment of GIS-based land infrastructure information

Using UAV images and DTM, land infrastructure information was established for efficient faming management in rain-fed paddy field (Koudkher village) (Fig. 3). Based on the GIS dataset, there were a total of 4,952 paddy fields (total area 1.26 km^2, 27.6% of Koudkher village). The average area of single field was 253.84 m^2, and the size was varied (2.27–8,924.44 m^2). From the analysis of topography and catchment area using DTM data, the area was divided into five catchment areas. A large proportion of paddy field were found in the catchment area E including the village's residential area and lowland, and catchments C and D facing the road with low elevation. These basic knowledge for land infrastructure is principal for efficient farm management. Moreover, combining with field data (Ikeura et al. 2019), yield prediction and efficient fertilizer management could be expected by assessing environmental factors at local scale.

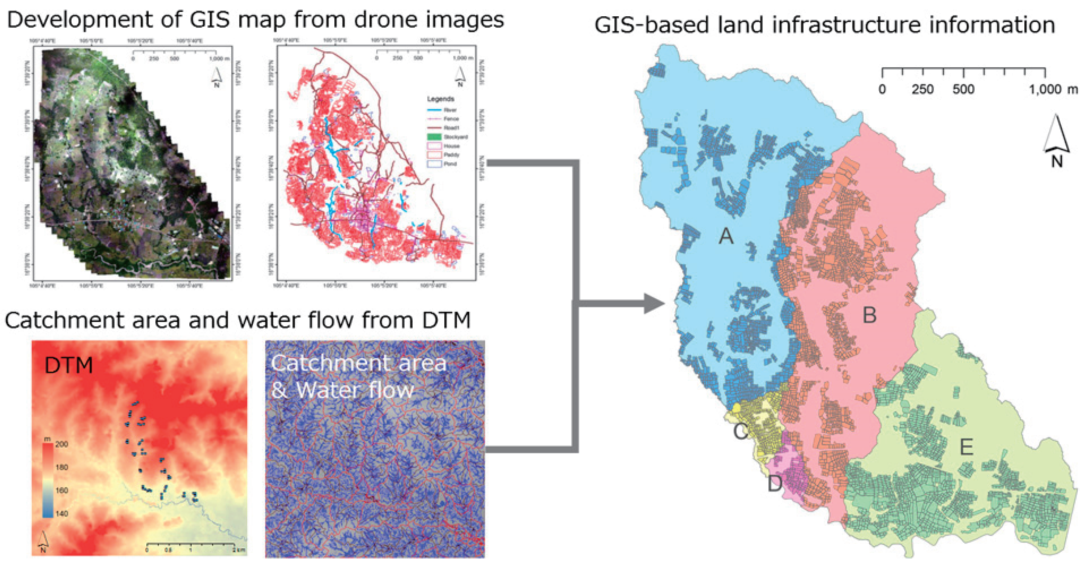

Fig. 3. Graphical flow for developing a GIS-based land infrastructure information data set in K village, Savannakhet.

Conclusion

Remote sensing technologies are being important field assessment tool in many agricultural applications. This paper summarized our on-going research activities in lowland rice field in Laos. In Research 1, we evaluated the feasibility of using canopy HS data for in-season grain yield evaluations at the reproductive phase of rice. Our results indicated that rice grain yield can be assessed by the ISE-PLS model, and the booting stage was identified as the best time for in-season evaluations via canopy HS assessments. These findings suggest that it is possible to evaluate rice yield from rice canopy reflectance approximately one month prior to harvest which could be useful information not only for famers but also for rice processing industries to quantify rice supply and market prices. Moreover, the wavebands selected with ISE-PLS in the booting stage could be tested by HS sensors or multi-spectral cameras onboard an UAV. In Research 2, to realize efficient faming management on rain-fed paddy fields in Koudkher village, Savannakhet, a land infrastructure information was established using UAV image and DTM. Based on the GIS dataset with field data (rice yield and soil chemical status), it is expected that the rice yield prediction and efficient fertilizer management could be possible in the catchment area or each unit scale.

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