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APPLICATION OF FINE QUAD-POLARIZATION RADARSAT-2 DATA AND SUPPORT VECTOR MACHINES TO CLASSIFY OFF-SEASON RICE PADDIES

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ABSTRACT: In monsoon areas in Asia, most seasonal rice paddies are destroyed annually by flooding. To secure rice production, farmers in these areas grow off-season rice crops, which can be produced only with irrigated water. However, due to prevailing drought conditions, the cultivation of off-season rice crops cannot commence simultaneously. The availability of irrigated water is the critical factor for farmers in deciding when to begin off-season cultivation. To assess off-season rice production, a map of the cultivated area is required. Using multi-polarization/multi-temporal RADARSAT-2 data, this study aims to estimate and map the off-season rice paddies. The potential of using support vector machine classification to map off-season rice paddies with C-band SAR data was also established. Multi-temporal fine quad-polarization RADARSAT-2 data can be effectively used to estimate off-season rice cultivated areas.

Keywords: Synthetic aperture radar (SAR), Multi-polarization, Supervised classification, Rice paddies

1. INTRODUCTION

For approximately half of the global human population, rice is one of the primary staple foods. In addition, approximately 70% of the rice in international markets has been supplied by South and Southeast Asian countries such as India, Thailand, and Vietnam. However, during the seasonal monsoon, rice production worth more than US$ 1 billion in these rice-exporting countries is damaged by flooding each year [1]. In addition, seasonal rice paddies in these countries, including Thailand (one of the major rice-exporting countries), are continually destroyed by seasonal flooding, causing reductions in rice production and in global food security [2]. Thus, to improve global food security, the cultivation of off-season rice crops could be an alternative and effective solution.

In Thailand, farmers typically grow off-season rice crops only in the irrigated zone, which is the same area that is frequently affected by monsoon flooding. Additionally, some off-season rice crop zones are limited by drought conditions. As a result, to grow off-season rice crops, farmers must make decisions based on the water availability in their area. Consequently, off-season rice crops cannot be cultivated simultaneously [3]. To ensure that there is enough irrigated water for agricultural purposes, farmers delay off-season rice crops for two to three weeks or more. To estimate the off-season rice production, it is essential to map the off-season rice cultivation areas. However, because the off-season rice crops are not started simultaneously, it is not easy to estimate off-season rice production areas using ground observations. Thus, over large areas, the assessment of off-season rice paddies using ground observations alone is difficult, inefficient, imprecise and expensive and often results in an overestimation of off-season rice production areas.

Remote sensing is a practical way to map rice paddies and offers advantages over partial ground surveys [4]. In the monsoon season, Asian countries such as Thailand are often obscured by cloud cover. Synthetic aperture radar (SAR) instruments such as RADARSAT-1 [5], ALOS/PALSAR [6] and ENVISAT/ASAR [7], which can penetrate cloud cover, are suitable for observing off-season rice paddies. The past studies [5] – [7] have demonstrated the potential of the SAR data with co-polarization (HH or VV) obtained from these instruments for assessing the seasonal rice paddies, yielding the overall accuracy of up to 80%. However, the more reasonable accuracy of classification results could be produced in mapping of rice paddies if "multi-polarization" SAR imagery was used [6].

The multi-polarization SAR data is expected to provide much more information on the ground cover, particularly on vegetation conditions, than a single C-HH image [8]. The C-band SAR RADARSAT-2 data was designed to provide information with multi-polarization (HH, VV and HV/VH). A past study [9] applied polarimetric decomposition technique to the full-polarization RADARSAT-2 SAR data in order to map the seasonal rice paddies, thereby yielding an overall accuracy of above 91%. However, the use of polarimetric decomposition technique requires a lot of parameters such as scattering type, magnitude and phase. For the off-seasonal rice paddies, whose rice is not simultaneously grown, these parameters can have a wide range of values: consequently, this technique may be too complicated for mapping the rice crop areas.

In the past, a band-combination technique for a set of multiple SAR imageries was successfully applied to extract more information about rice paddies such as flood-affected paddies [10]. Therefore, employing the band-combination technique, it is of interest to evaluate the potential of multi-polarization SAR data in mapping off-season rice paddies in Thailand. In addition, for mapping off-season rice paddies, it is interesting to use multi-temporal RADARSAT-2 data because the cultivation of off-season rice does not start simultaneously over a large area. Located in the Great Mekong Sub-region (GMS), the Chi River Basin is one of the multiple rice cropping regions in Thailand and prone to recurrent flooding due to flat terrain.

Using a part of the Chi River basin as a study area and the band-combination technique for mapping off-seasonal rice paddies, the study objectives are to evaluate the potential of multi-polarization/multi-temporal RADARSAT-2 data. Three different evaluating scenarios were considered, such as difference in: (1) classifiers; (2) polarization combinations; and (3) acquisition time combinations. The accuracy of the classification results was determined with the in situ ground truth.

2. STUDY AREA

The study area consists of nine sub-districts in Kalasin province and five sub-districts in Roi-et province. The region is situated in the flood-prone area of the Lower Chi River Basin in northeastern Thailand. This area is among the most famous places for cultivating off-seasonal rice paddies in Thailand and extends between 103˚30’ and 103˚45’ E and between 16˚00’ and 16˚30’ N, covering an area of 502 km^2 (Fig. 1). The terrain ranges from 100 to 200 m above mean sea level (MSL). The rice production yields are quite high compared to those in other areas in northeastern Thailand [11]. In addition, the average annual rainfall is approx. 1800 mm.

3. DATA AND PROCESSING

3.1 Data

In this study, a set of fine quad-polarization RADARSAT-2 imageries acquired in three periods: (1) January 17, 2011, vegetative and reproductive stages; (2) March 3, 2011, the grain filling and maturation stages; and (3) April 23, 2011, the harvesting season as shown in Table 1, were used. The RADARSAT-2 imageries were obtained in the fine quad-polarization mode, providing full polarimetric RADARSAT-2 imageries in the fine-resolution beam mode FQ14 (33.6º incidence angle) and a pixel spacing of 3.13 m with single looks (Fig. 2). In this study, the digital vector maps series L7018 at a scale of 1:50,000 compiled from aerial photography from 1999 produced by the Royal Thai Surveying Department (RTSD) were employed as geo-referenced data in order to geo-register the RADARSAT-2 SAR imageries. To assess the classification accuracy for the off-season rice-producing area, in situ ground truth data comprising positions collected by a Global Navigation Satellite System (GNSS) instrument in 2011 were employed. Additionally, algorithms available in ENVI® software were used for image processing and to manipulate the SAR data. ArcGIS® ArcInfo software was utilized for geo-processing and map compilation.

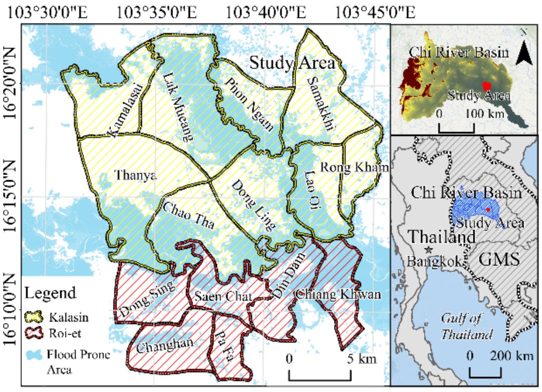

Fig. 1 Location of the study area in the lower part of the Chi River Basin, northeastern Thailand

3.2 Processing of RADARSAT-2 data

3.2.1 Pre-processing SAR Data

The ENVI® software was used to preprocess single-look RADARSAT-2 SAR data. Because the terrain of the study area is relatively flat, there is no serious geometric distortion from foreshortening or layover. Consequently, a first-order polynomial equation was applied to register the RADARSAT-2 imageries in the UTM projection and the WGS 84 spheroid. The images were resampled to a pixel size of 4×4 m using the nearest neighborhood method. To reduce speckle noise, a 7×7 enhance Lee filter was employed to smooth out the data.

Table 1 Acquisition date of RADARSAT-2 data for assessing off-season rice production

Acquisition Date	Stage of Off-season Rice
27th January 2011	Vegetative and Reproductive Stage
6th March 2011	Grain Filling and Maturation Stage
23rd April 2011	Harvesting Stage

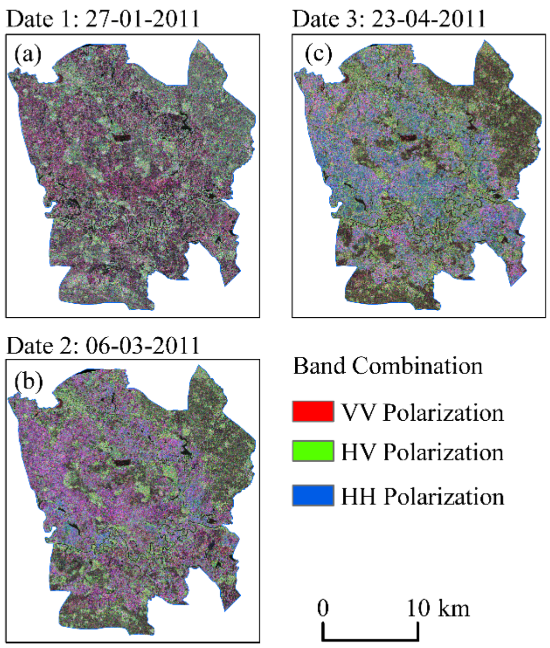

Fig. 2 A set of full-polarization RADARSAT-2 data acquired on off-season rice cultivation were used in this study.

3.2.2 Classification of SAR Data

Support vector machines (SVMs) have been shown to have high accuracy even with limited training samples [12]. This concept is suitable for classifying SAR data due to the difficulty in obtaining training samples. In this study, the use of a SVMs technique was, therefore, compared with a maximum likelihood (ML) classifier. SVMs are techniques based on the principle of supervised non-parametric statistical learning [13].

To separate a focal dataset into a predefined number of land use classes, the process for finding the "optimal separation hyperplane" or "decision boundary" is the basic step in SVMs classification. As shown in Fig. 3, a simple two-class scenario was classified using the SVMs classifier with a different kernel. A linear kernel was used to construct the decision boundary in order to divide the dataset into two groups, as shown in Fig. 3 (a). This decision boundary and its maximum margin were defined by the subset of points lying on the margin. Techniques such as "the soft margin method" and "the kernel trick" have been used to solve the inseparability problem by adopting variables called "slack variables." Typically, remote sensing involves the identification of two or more classes. Therefore, linear kernel SVMs classifiers using one-against-all, one-against-others and directed acrylic graph approaches were used in the multi-class classification [14].

Generally, a statistical technique such as ML classifier assumes that the data distribution is known a priori, while SVMs minimize classification error on unseen data without prior assumptions made about the probability distribution of the data. In this light, ML estimation assumes a multivariate normal data distribution, which does not necessarily match this assumption. Remotely sensed data in particular commonly have an unknown distribution. Past studies [15] have demonstrated that when comparing SVMs for classifying data "with" or "without" the presence of prior knowledge, the accuracy of both SVMs classifications are approximately the same. In addition, the choice of kernels is key in determining the capability of SVMs. Some kernel functions may not provide an optimal SVMs configuration for remote sensing applications. By applying different kernels such as the "radial basis function" kernel and "2nd-degree polynomial" kernel to classify remotely sensed data, different results could be obtained.

Therefore, in this study, an attempt to evaluate the effectiveness of different classifications in classifying RADARSAT-2 data was conducted. Subsequently, the classified maps were checked with well-distributed in situ ground truth data for accuracy assessment.

4. RESULTS AND DISCUSSION

4.1 Comparison of classification results obtained from different classifiers

In this section, the potential of SVMs and ML classifiers was evaluated. Multi-date, full polarization RADARSAT-2 imageries were used as for the classification process. The classification results obtained from (a) linear SVMs; (b) radial basis function (RBF) SVMs; (c) 2nd-degree polynomial (2nd PL) SVMs; and (d) an ML classifiers are shown in Fig. 4.

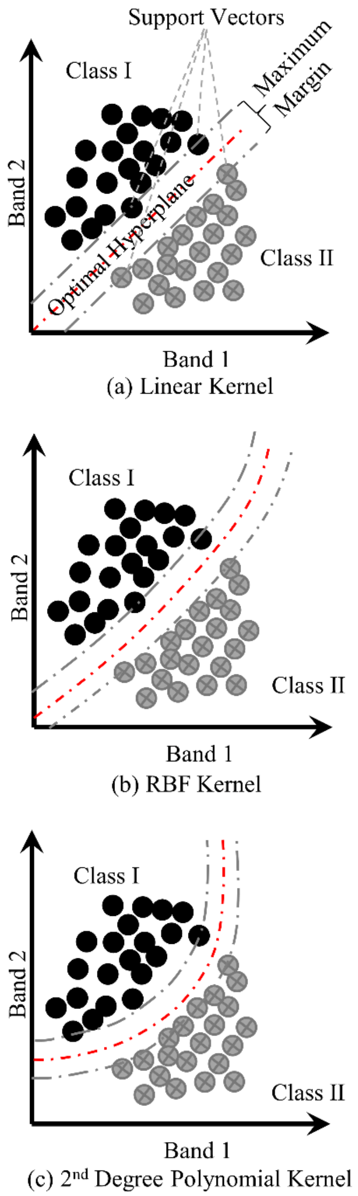

Fig. 3 SVMs with different kernels such as the (a) linear kernel, (b) radial basis function kernel, and (c) 2nd degree polynomial kernel

In this study, five types of land use were classified: (1) BL, bushland; (2) SA, settlement areas; (3) WR, water resources; (4) OR, off-seasonal rice paddies; and (5) SR, seasonal rice paddies. The results for each land use obtained from each classifier were compared in Table 2. In addition, using 444 data points from the in situ ground truth data, an accuracy assessment for each classifier was conducted, and the results are shown in Table 3. All the SVMs classifiers could provide a classification accuracy of over 85%, which is in the acceptable range suggested by Anderson's classification scheme [16]. The classification result obtained from the ML method exhibits an accuracy of 69%, which is relatively low compared to the other classification results. The highest classification accuracy, approximately 89%, was obtained from the linear kernel SVMs, whereas the other two kernel SVMs classifiers give an accuracy of 88%, which is slightly different from the highest. For off-season rice paddies, in terms of the producer's accuracy, all of the SVMs classifiers could provide an accuracy of approximately 98%, whereas only the linear kernel SVMs can provide a user's accuracy of over 95%.

Table 2 Comparison of results obtained from each type of classifier

Classifier	Linear SVM	RBF SVM	2nd PL SVM	ML
Land use	km^2	km^2	km^2	km^2
BL	87	79	79	49
SA	13	14	14	56
WR	10	9	9	6
OR	257	255	255	290
SR	135	145	145	101
Total	502	502	502	502

Note: BL, bushland; SA, settlement area;
WR, water resource; OR, off-seasonal rice paddies;
SR, seasonal rice paddies

The linear kernel SVMs yielded the highest accuracy of 89%. This result indicates that the linear kernel SVMs is suitable for classifying the multi-polarization/multi-temporal RADARSAT-2 data and has a high potential for classifying off-season rice paddies as shown in Fig. 4 (a). Therefore, the linear kernel SVMs was used to further classify the land use types for further processing of the other combinations of RADARSAT-2 data.

4.2 Comparison of classification results obtained from different polarization combinations

To test the potential of using multi-polarization data, another classification of the multi-date RADARSAT-2 data with different polarization combinations was performed. Using the linear SVMs classifier, the classification results were divided into six polarization combinations: (a) full polarization; (b) dual polarization with HH and VV; (c) dual polarization with HH and HV; (d) single HH polarization; (e) single VV polarization and (f) HV polarization (Fig. 5). Using the same in situ ground truth data as described in section 4.1, the classification results indicated that the full polarization and both of the dual polarization data can be used to produce classification accuracies of over 85% (see Table 4). For the single polarization cases, only the single HH polarization classification result provided a classification accuracy over 80%.

Table 3 Comparison of results derived from multi-polarization/multi-temporal data using different techniques

Classifier Acc. Ind.	Linear SVMs	RBF SVMs	2nd PL SVMs	ML
OA (%)	89.2	87.8	87.8	69.8
KI	0.9	0.9	0.9	0.6
Land use	Producer's Accuracy (%)			
BL	97.8	97.8	97.8	55.6
SA	72.5	72.5	72.5	82.5
WR	78.0	76.0	76.0	30.0
OR	97.6	97.8	97.8	95.2
SR	100.0	95.2	95.2	93.3
Land use	User's Accuracy (%)			
BL	81.5	81.5	81.5	80.7
SA	100.0	100.0	100.0	49.3
WR	100.0	100.0	100.0	100.0
OR	95.4	75.9	75.9	78.4
SR	79.0	93.0	93.0	72.4

Note: OA, overall accuracy; KI, kappa index; Acc. Ind., Accuracy Index

4.3 Comparison of classification results obtained from different acquisition time combinations

To examine the potential for using multi-polarization/multi-temporal RADARSAT-2 data, an additional classification of the RADARSAT-2 data with different combinations of acquisition times was conducted. Using the linear SVMs classifier, the classification results were divided into three acquisition time cases: (a) case 1, the multi-date case, in which data were acquired in the early, middle and final stages of rice crop growth; (b) case 2, the single-date case, in which data were acquired in the middle stage of rice crop growth; and (c) case 3, the dual-date case, in which data were acquired in the early and middle stages of rice crop growth (Fig. 6). As shown in Table 5, the classification accuracies of both the multi-date and dual-date cases are over 85%, whereas the single date yielded a classification accuracy of 79%.

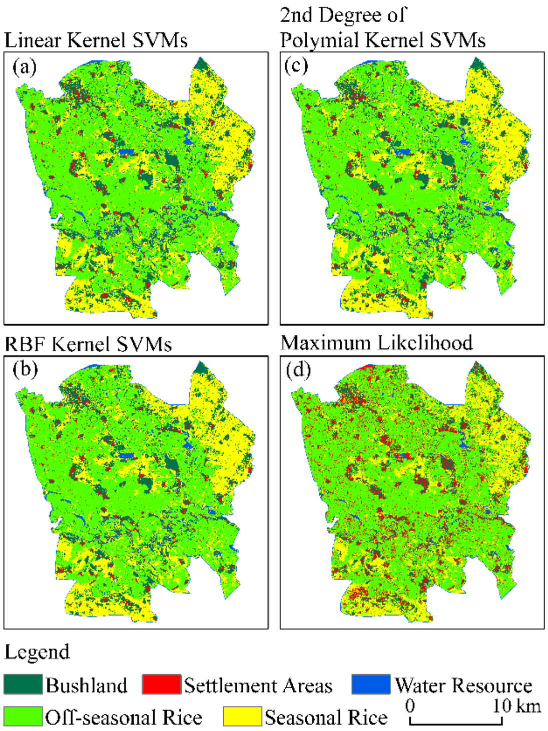

Fig. 4 A comparison of the results obtained from each type of classifier: (a) linear SVMs; (b) radial basis function (RBF) SVMs; (c) 2nd-degree polynomial (2nd PL) SVMs; and (d) maximum likelihood (ML) classifier

Additionally, for off-season rice paddies, full, single HH and single HV polarization can provide producer's and user's classification accuracies over 85%. Using the multi-temporal RADARSAT-2 data acquired during different stages of rice growth, both single HH and HV polarization can be used to classify off-season rice paddies with a satisfactory classification accuracy (Table 4).

For the off-season rice paddies, the multi-date and dual-date cases can be used to obtain producer's and user's accuracies over 80%. The producer's and user's accuracy of the off-season rice paddy classification in the single-date case are approx. 65% and 93%, respectively (see Table 5). This result indicated that a dual-date dataset with full polarization could provide a satisfactory accuracy. It was found that the use of only a single date with full polarization data cannot produce a satisfactory accuracy for the classification of off-season rice paddies. At a minimum, two-date RADARSAT-2 data are required for sufficient accuracy, and these data should be acquired in the early and middle stages of rice crop cultivation.

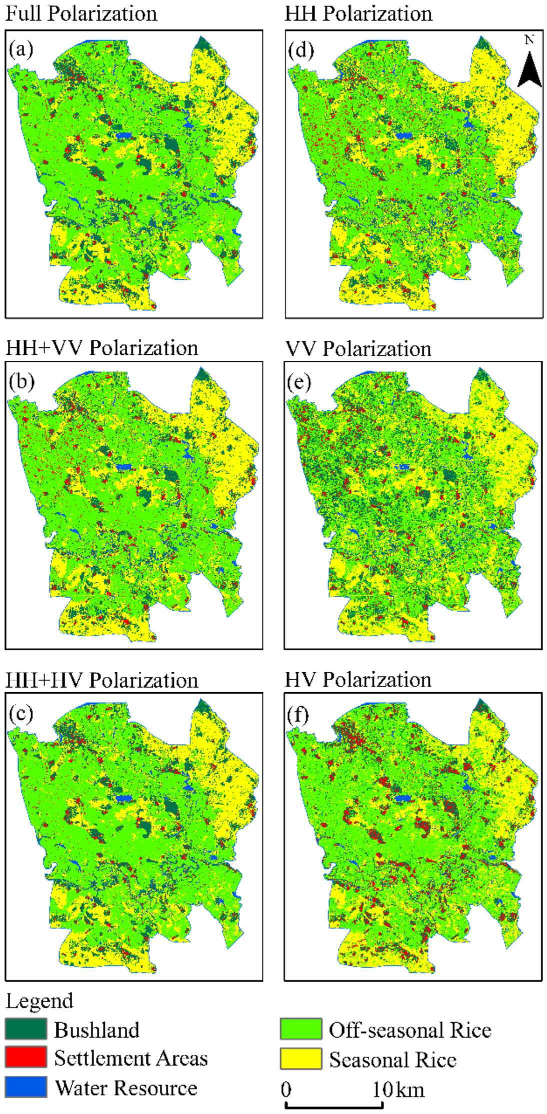

Fig. 5 A comparison of the classification results derived from different polarization combinations: (a) full polarization; (b) dual polarization with HH and VV; (c) dual polarization with HH and HV; (d) single HH polarization; (e) single VV polarization and (f) HV polarization

5. CONCLUSIONS

To assess areas with off-season rice cultivation, multi-polarization/multi-temporal RADARSAT-2 SAR data acquired in the early, middle and final stages of rice cultivation were analyzed.

Table 4 Comparison of the results derived from datasets with different polarizations and multiple dates using the linear SVMs classifier

Pol. / Acc. Ind.	HH + HV + VV	HH + VV	HH + HV	HH	VV	HV
OA (%)	89.2	86.0	88.7	83.8	70.7	74.3
KI	0.9	0.8	0.9	0.8	0.6	0.7
Land use	Producer's accuracy (%)					
BL	97.8	93.3	97.8	86.7	64.4	51.1
SA	72.5	72.5	72.5	65.0	72.5	72.5
WR	78.0	78.0	82.0	84.0	70.0	70.0
OR	97.6	97.8	97.8	83.3	50.0	88.1
SR	100.0	88.1	92.9	97.8	95.6	91.1
Land use	User's accuracy (%)					
BL	81.5	77.8	81.5	73.6	60.4	65.7
SA	100.0	100.0	96.7	92.9	82.9	55.8
WR	100.0	100.0	100.0	100.0	100.0	97.2
OR	95.4	74.6	80.0	87.5	55.3	88.1
SR	79.0	90.2	92.9	74.6	65.2	71.9

Note: Pol, Polarization

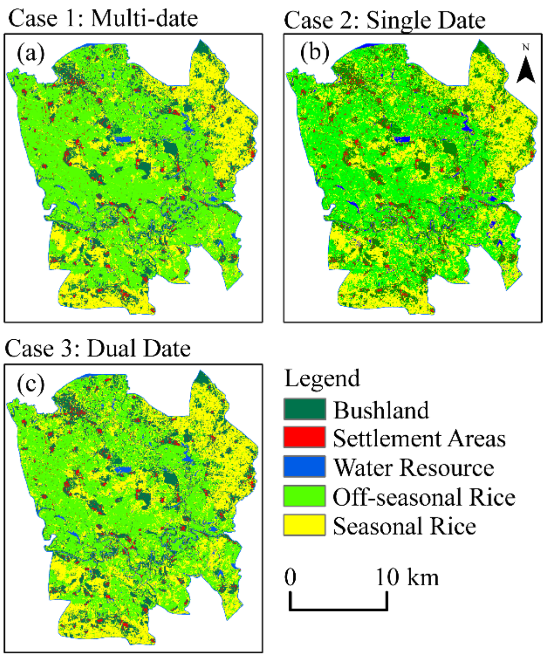

Fig. 6 A comparison of the classification results obtained with different acquisition time combinations

Table 5 Comparison of the classification results derived from different combinations of off-season rice growth stages using the linear SVMs classifier

Combination / Acc. Ind.	Multi-Date	Single-Date	Dual Date
OA (%)	89.2	79.3	85.1
KI	0.9	0.7	0.8
Land use	Producer's accuracy (%)		
BL	97.8	95.6	97.8
SA	72.5	60.0	72.5
WR	78.0	74.0	80.0
OR	97.6	93.3	81.0
SR	100.0	71.4	93.3
Land use	User's accuracy (%)		
BL	81.5	75.4	78.6
SA	100.0	92.3	93.6
WR	100.0	100.0	100.0
OR	95.4	64.6	89.5
SR	79.0	81.1	73.7

The multi-polarization/ multi-temporal RADARSAT-2 SAR dataset was classified using linear kernel SVMs, radial basis function SVMs, 2nd-degree polynomial SVMs, and ML classifiers. A classification accuracy of 89% indicates that the linear kernel SVMs can be used to produce an off-season rice crop production map effectively. Furthermore, this study shows the potential and advantages of full polarization compared to dual polarization or single-polarization. In addition, using the linear kernel SVMs classifier, the producer's and user's accuracies for off-season rice cultivation obtained from the full polarization data are over 95%. This finding showed that fine quad-polarization RADARSAT-2 data with combinations of multiple dates can be effectively used to estimate off-season rice cultivated areas, which could in turn be used to improve the global food supply.

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