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Rice Terrace Extraction from Medium Resolution Satellite Images using Machine Learning Methods

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1. Introduction

Rice terrace is agriculture production in hilly areas which reduces soil erosion and control water resource. They are historical agricultural landscape, and an essential factor in the ecosystem conservation. Most of studies about rice terrace classification have been used high-resolution remote sensing data which is costly and difficult to use in monitor rice terrace over a large-scale (Zhang *et al.*, 2017). In recent years, machine learning methods has used frequently on remote sensing area. In this study, we evaluated the capability of two medium resolution remote sensing RapidEye and Landsat images in rice terrace classification in Lao Cai area, Vietnam. Pixel-based and object-based approaches were compared to obtain the best classification result. Feed-forward neural network (FNN), Random Forest (RF), and Support Vector Machine (SVM) algorithms were used for rice terrace classification.

2. Data and Methodology

Figure 1 showed the methodology of the study. Pixel-based and object-based (OBIA) were approached to classify terrace and no terrace classes from RapidEye and Landsat imageries using FNN, RF and SVM classification algorithms. Training and validation datasets were used to train and optimize the models of FNN, RF and SVM classifiers. Finally, test dataset was employed to assess the classification accuracy and evaluate the capability of RE, and LS on rice terrace extraction.

2.1. Data and Study area

Lao Cai area is in North of Vietnam where rice terrace is the primary, long history agriculture practice. The remotely sensed data used are 5 bands (blue, green, red, NIR, redegde) of 5-m RapidEye and 6 bands (blue, green, red, NIR, SWIR1, SWIR2) of 30-m Landsat images. Reference data has collected from Google map in order to be used as training, validation dataset for classification and test dataset for accuracy assessment and evaluation.

2.2. Optimal threshold of OBIA

OBIA is generated by image segmentation process. The key parameter to partition the image into objects is threshold of segmentation (T). In order to obtain optimal threshold of segmentation, Rate of Change of Local Variance (ROC-LV) was used (Dragut *et al.*, 2010). In this study, thresholds ranged from 0.01 to 0.5, step is 0.01. Optimal thresholds were list at the first row of Table 1 and Table 2.

2.3. Feed-forward neural network

Feed-forward back propagation neural network (FNN) is a well-known model which has powerful computing capabilities base on the propagation of information between neurons (Zhang *et al.*, 2016). Input layers are spectral bands of the remotely sensed images. 8 hidden layers which include 128 nodes for each layer is setup. Rectifier is chosen as activation function with dropout ratio of hidden layers is 0.2. L1 and L2 are set as 10^{-5}. Logloss metric is exploited to decide the best model it can be reached.

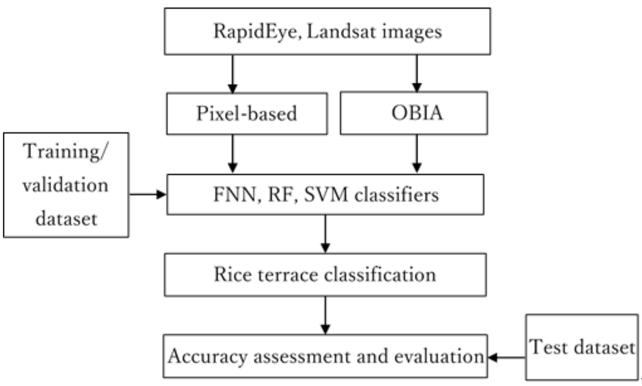

Figure 1. Flow chart of the study

2.4. Random Forest

Random forest (RF) classifier is an ensemble learning method that uses a randomly selected subset of training samples and variables to produces multiple decision trees (Belgiu, 2016). Two parameters of the model were set as: the number of decision trees (Ntree) equals 500, and the number of variables in the random subset at each node (Mtry) is chose as default in caret.

2.5. Support Vector Machine

SVM works by finding a hyperplane with the largest margin in the feature space that separates input data into target classes (Abe, 2010). In this study, Radial Basic Function (RBF) kernel of the SVM classifier is used, due to commonly used and shows an excellent performance of the function. Size of subset equals 9.

3. Result

3.1. RapidEye classification

Pixel-based approach showed the most accurate results in comparison with object-based approach, at 91.9% of FNN classifier, 92% of RF and SVM (Tabel 1). With object-based approaches, the classification accuracy achieved the highest values at the first peak of ROC-LV graph. In general, the values slightly decreased when threshold values increased, the lowest accuracies belonged to very high thresholds. FNN, RF, and SVM classifiers produced almost same accuracy at same approach.

3.2 Landsat classification

Overall accuracies of pixel-based approach were at 89.7% of FNN, 89.2% of RF, and 89.9% of SVM, higher than all object-based classification cases (Table 2). With object-based approaches, the classification accuracy achieved the highest values at the first peak of ROC-LV graph. The classification accuracies crucially declined from pixel-based to the second peak of ROC-LV graph, then slightly reduced to the lowest accuracies. Furthermore, three classifiers produced almost similar accuracy at same approach.

4. Discussion and Conclusion

This study presents an evaluation of 5-meter RapidEye and 30-meter Landsat image on rice terrace extraction by using FNN, RF, and SVM classifiers at pixel-based and OBIA approaches. Both remote sensing imageries showed the highest and almost similar accuracy at pixel-based approach. At OBIA, the accuracies decreased when thresholds increased. However, the degree of reduction was more significant at Landsat data. Also, the difference of accuracy among three classifiers was small.

It recommended that both imageries are useful for rice terrace extraction at pixel-based approach, however, only RapidEye image could be used for rice terrace classification at OBIA. Furthermore, rice terrace classification from remote sensing data is not affected much by the classification methods.

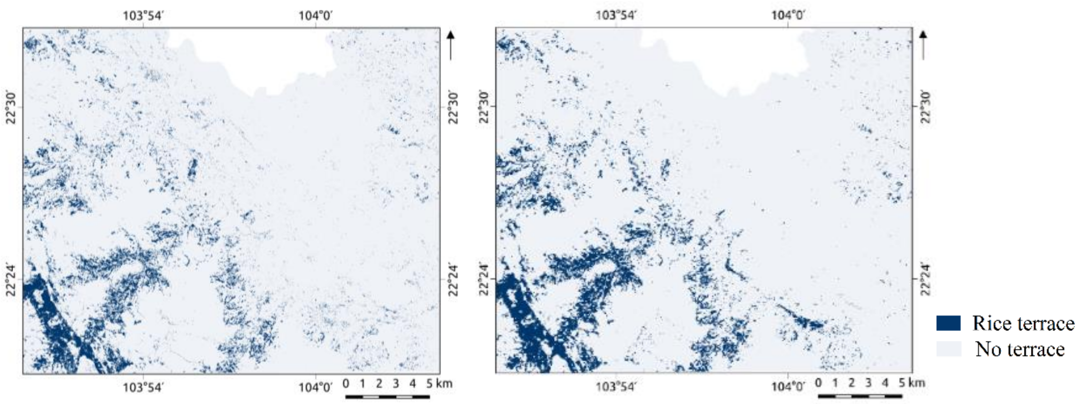

Figure 1. Rice terrace maps classification of (left) Rapideye and (righ) Landsat at pixel-based

Table 1. Overall accuracy of rice terrace from RapidEye image classification. First row showed threshold of OBIA

	pixel	0.06	0.09	0.12	0.14	0.20	0.22	0.25	0.28	0.32	0.37	0.40	0.43	0.45
FNN	91.9	90.0	88.7	88.1	88.5	87.2	86.6	86.5	86.3	85.9	86.4	85.4	85.4	85.4
RF	92.0	90.3	89.2	88.9	88.8	87.8	87.6	87.2	87.3	87.0	86.7	86.6	86.5	86.7
SVM	92.0	89.8	88.5	88.3	87.9	87.0	86.7	86.5	86.5	86.5	86.3	86.0	85.6	86.3

Table 2. Overall accuracy of rice terrace from Landsat image classification. First row showed threshold of OBIA

	pixel	0.05	0.09	0.13	0.15	0.18	0.23	0.27	0.33	0.35	0.37	0.43	0.45	0.47
FNN	89.7	83.3	78.5	77.8	77.8	76.1	75.6	75.7	75.7	75.4	74.0	74.0	73.7	73.8
RF	89.2	83.9	78.6	77.8	77.4	76.3	75.8	75.9	75.9	75.7	74.0	74.1	73.6	73.6
SVM	89.9	83.4	78.8	78.0	78.0	76.7	76.3	76.3	76.3	76.1	74.5	74.5	74.3	74.3

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