PADDY RICE RECOGNITION USING AN INTEGRATION OF SATELLITE IMAGE DATA AND AI MODELS

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ABSTRACT: Since the temporal variation for growing period of paddy rice can be shown clearly in optical and radar images, a Long-Short Term Memory (LSTM) model is introduced to construct paddy rice recognition systems using Sentinel-1 and FORMOSAT-2 time-series data.
Firstly, we investigate a one-stage paddy rice recognition system by using multi-sensor satellite images, respectively. Then a two-stage paddy rice classification is proposed to overcome the drawback in previous study. We also investigate the inconsistencies of ground truth and remote sensing data. In this article, several cases of study would also be compared.

1. INTRODUCTION

Paddy rice is an important crop in Taiwan, for it is a staple food crop for national need. However, paddy fields in Taiwan are very limited in area and distribute irregularly in crop types. Actually, they change rapidly and make field survey labor-intensive and costly.

In this study, methodologies in paddy fields recognition by an integration of optical and radar remote sensing data are carried out. Because satellite time-series data can present the temporal variation for growing period of paddy rice, an RNN-type (Williams et al., 1986) deep learning model, LSTM (Hochreiter and Schmidhuber, 1997), is proposed to construct a paddy rice detecting system using multi-sensors data. Typically, an optical satellite supplies spectral data with high spatial and temporal resolution, while affected by cloud and shadow easily. Radar image data eliminates this drawback with lower resolution and more spackles. Therefore, a two-stage algorithm using the integration of optical and SAR data is introduced to increase the efficiency of classification.

Then we consider the effects of inconsistencies of the ground truth and remote sensing data. In this case, a suitable threshold is proposed to detect the inconsistencies in the two-stage procedure.

Finally, the results of these studies are compared and investigated.

2. METHODOLOGY

To construct a paddy field identification model, a small part of satellite temporal data is sampled as the training data. Then a LSTM model is established. We use this AI model to classify testing data as paddy rice and non-paddy rice in the study area. The predictions would be validated by the ground truth data.

2.1 One-stage Paddy Rice Algorithm

For a one-stage paddy rice identification, radar and optical temporal images are applied as the researching data, respectively. The following figure shows the flow chart of this algorithm.

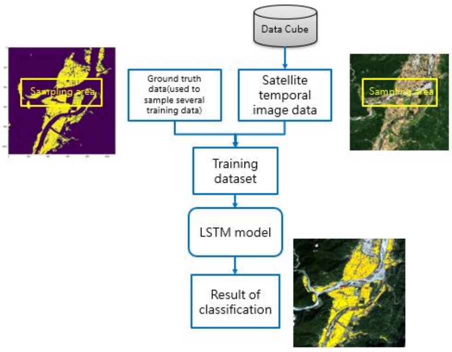

Figure 1. The flow chart of the one-stage paddy rice identified algorithm.

According to Figure 1, optical or SAR time-series data is loaded from Data Cube. To reduce the cloud effect in optical images, cloud mask and custom mosaic are applied for clear researching dataset. Then several pre-processes including spatial moving average, temporal linear interpolation are applied for data preparation. For a spectral bands augmentation, normalized difference vegetation index (NDVI) and normalized difference water index (NDWI) are introduced as indirect measurements. The equations of NDVI and NDWI are shown as:

$$NDVI = \frac{NIR-R}{NIR+R} \quad (1)$$

$$NDWI = \frac{G-NIR}{G-NIR} \quad (2)$$

where NIR = near-infrared band
R = spectral reflectance visible red
G = spectral reflectance visible green

Then training data is sampled randomly and applied to construct a paddy rice detecting system using LSTM model. The result of AI model classification would be validated by using the ground truth data.

2.2 Two-stage Paddy Rice Algorithm

In reality, a study area with sever cloud effect might decrease the accuracies of AI model trained by optical satellite images only. On the other hand, radar image data containing stronger speckle effect and lower spatial resolution would make an adverse impact to paddy rice identification. A two-stage classification using the integration of optical and radar image data is suggested in this case. The flow chart of the two-stage algorithm is presented in Figure 2 below.

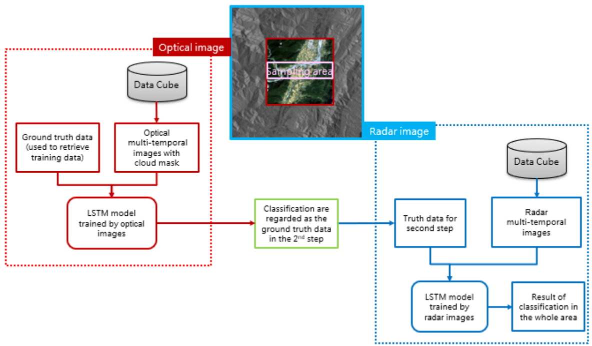

Figure 2. The flow chart of the two-stage paddy rice identified algorithm.

First of all, a new ground truth is established in a cloudless area with less optical data. In this stage, optical temporal images without cloud effect are loaded as the researching dataset. After data pre-processes and augmentation, a small part of data is labelled randomly as training data for AI model construction in the first stage. The predictions of optical pixels in the cloudless area is regarded as an enlarged ground truth, which would be applied in the next stage for training data sampling.

In the second stage, radar temporal data with weather effect in the whole study area is suggested for paddy fields detection. Training dataset is sampled randomly referring to the new ground truth produced in the last stage. Then a LSTM model is established by SAR data, and used for paddy rice identification. The result is validated by the ground survey data.

2.3 The Investigation of Inconsistencies

In a traditional image data detecting system, inconsistencies of the ground truth and remote sensing data may due to the incompletion of image data and error of ground truth. On the other hand, the limitation of AI models and data type may affect the performance of AI classifiers.

In a case of paddy rice recognition, cloud mask makes image data difficult to cover the whole temporal variation. Satellite image data cannot reflect ground truth, study area planted with various crops, and a lack with training data may result in a low-performance AI model.

To overcome the problem about low-efficiency in a paddy field recognition system, a threshold of predicted chance is proposed to detect the inconsistencies. Data with high predict chance is classified as paddy rice and non-rice easily. And the rest of data with lower predicted chance is regarded as uncertainty which contains inconsistency to training dataset. The idea about inconsistencies detection and two-stage identification algorithm can be integrated in the following flow chart.

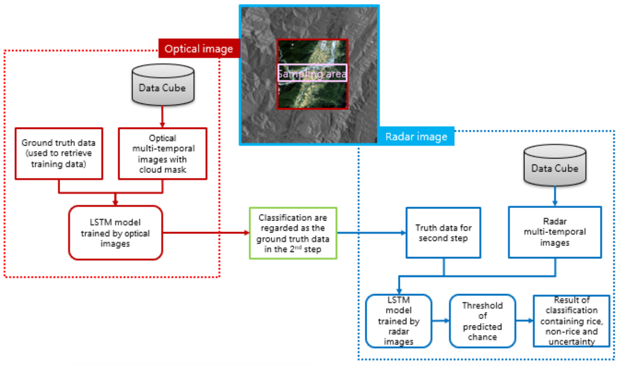

Figure 3. The flow chart of the integration of inconsistencies detection and two-stage paddy rice identification.

3. DATA AND RESULTS

3.1 Researching Dataset

In this study, we chose FORMOSAT-2 and Sentinel-1 time-series data acquired during the second-half year in 2015 as the researching dataset. The remote sensing data acquisition area for paddy rice detection is at Hualien and Taitung Counties, Taiwan. For the training data sampling and AI model validation, paddy field survey shared from Agriculture and Food Agency is regarded as the ground truth data.

3.2 Results of the One-stage Paddy Rice Algorithm

In the case of one-stage paddy field identification, study area is chosen as a 10 km x 10 km square in Hualien City. We regarded all pixels in study area as testing data. The sampling area is squared as 2.9 km x 10 km in a small part of study area. Then 15,000 paddy rice and non-paddy rice training data is sampled randomly in the sampling area to establish a paddy rice identifying system using LSTM model. Here, the LSTM model derived from Keras is constructed as a four-layer neural network with Sigmoid active function and batch size =1,000, epoch = 500, validation split =0.1. The result of prediction would be validated by the ground survey.

The following figures and tables show the validations of paddy fields classifications using FORMOSAT-2 and Sentinel-1 image data, respectively.

In Figure 4 and 5, true-positive parts are denoted as yellow. Pixels labelled as red and blue are regarded as commission error (false-positive) and omission error (false-negative). And true-negative pixels are not labelled. Then UA, PA and OA are the shortens of user accuracy, producer accuracy and overall accuracy in Table 1, 2.

Figure 4. Validation of the result using FORMOSAT-2 dataset.

Table 1. Confusion matrix of LSTM model using FORMOSAT-2 dataset.

	classification					
validation	result	rice	non-rice	total	PA(%)	OA(%)
	rice	327928	10325	338253	96.95	96.52
	non-rice	45920	1231938	1277858	96.41	
	total	373848	1242263	1616111		
	UA(%)	87.72	99.17			

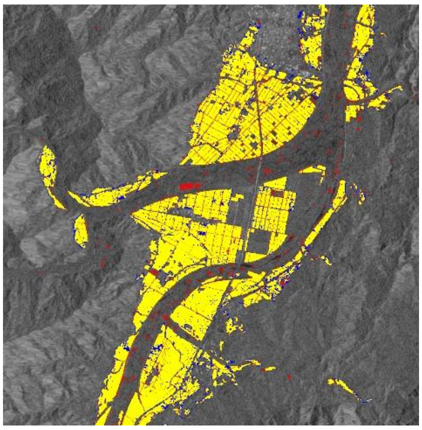

Figure 5. Validation of the result using Sentinel-1 dataset.

Table 2. Confusion matrix of LSTM model using Sentinel-1 dataset.

	classification					
validation	result	rice	non-rice	total	PA(%)	OA(%)
	rice	180746	24630	205376	88.01	95.26
	non-rice	30691	931413	962104	96.81	
	total	211437	956043	1167480		
	UA(%)	85.48	97.42			

3.3 Results of the two-stage Paddy Rice Algorithm

In the two-stage paddy rice algorithm, we chose a 20 km x 20 km square in Hualien and Taitung Counties as the whole study area. Considering a cloud mask in the study area except in Hualien City only, the study area in the first stage is a 10 km x10 km square in the area without cloud effect. There are 30,000 FORMOSAT-2 data sampled randomly in the 2.9 km x 10 km sampling area within the study area of the first stage. Then a four-layer LSTM model is trained by optical training dataset for an enlarged ground truth generation.

In the second-stage, 30,000 Sentinel-1 data are sampled according to the new ground truth. A new LSTM model is trained by the SAR training dataset and used for paddy rice detection in the whole study area. The result is validated using the ground survey data and presented in Figure 6 and Table 3 bellow. In these figure and table, the notations and labels share the same means to Figure 4, 5 and Table 1, 2 respectively.

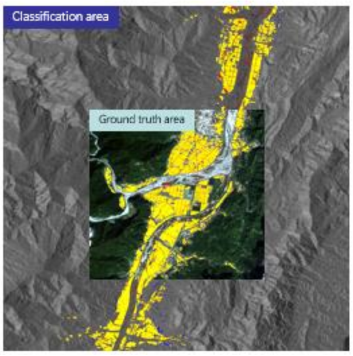

Figure 6. Validation of the result using a two-stage paddy rice algorithm.

Table 3. Confusion matrix of LSTM model using a two-stage paddy rice algorithm.

	classification					
validation	result	rice	non-rice	total	PA(%)	OA(%)
	rice	308379	54089	362468	85.08	97.54
	non-rice	60920	4244372	4305292	98.58	
	total	369299	4298461	4667760		
	UA(%)	83.50	98.74			

The study about inconsistencies investigation is a inherit of the two-stage paddy rice classification. Parameters are set as same as the previous ones. Here, the threshold of predicted chance is chosen as 85%. Therefore, 89.63% of testing data with predicted chance higher than 85% is identified and validated. The rest of data with lower predicted chance is regarded as unknown which contains inconsistency to the training dataset.

Figure 7 and Table 4 show the result of validation in this study. Notice that the true-negative parts in Figure 7 are denotes as green. And the uncertainties are pixels without labels.

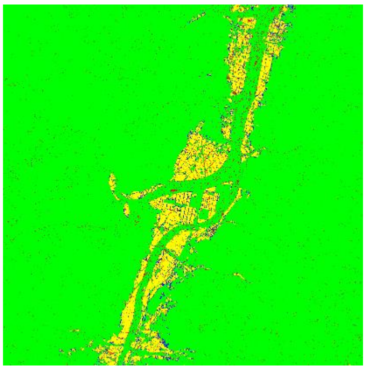

Figure 7. Validation of the result using an integration of inconsistencies detection and two-stage paddy rice algorithm.

Table 4. Confusion matrix of LSTM model using an integration of inconsistencies detection and two-stage paddy rice algorithm.

	classification					
validation	result	rice	non-rice	total	PA(%)	OA(%)
	rice	296171	44958	341129	86.82	98.06
	non-rice	44151	4218666	4262817	98.96	
	total	340322	4263624	4603946		
	UA(%)	87.03	98.95			

4 CONCLUSIONS

Since the temporal variation of growing period for paddy rice can be observed in radar and optical satellites time-series data, LSTM deep learning model is applied for paddy field recognition using multi-sensor dataset. With the adjustable gate weightings (including input, output and forget gates), LSTM algorithm can perform better in capturing the long-term temporal information inherent in time series data (Hochreiter, 1991; Chung et al., 2014; Jozefowicz et al., 2015).

According to the results in one-stage paddy rice identification, the performance of AI model trained by FORMOSAT-2 data is better than the model constructed using Sentinel-1 data. Due to the cloud coverage, the applicable spatial area in optical images generally is limited. However, because of the better spatial and temporal resolution of optical images, higher accuracy of identified results normally can be obtained when compared in using radar images.

In the case of sever cloud effect in the study area, a two-stage paddy rice classification is proposed. The identified results with optical images are applied as training data to train the AI model with SAR images. Then, the larger coverage of identified paddy rice area can be obtained.

Considering the inconsistency of ground truth and image data, a well-defined predicted chance is valid for data classification with high confidence and inconsistencies detection. An integration of inconsistencies detection and two-stage algorithm may increase the performance of AI model.

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