National Cropland Classification with Agriculture Census Information and EO Datasets

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Abstract

National cropland classification is critical to monitor food security, comprehend environmental circumstances and climate change, and participate in agricultural policy development. The increasing earth observation datasets, especially the free available Sentinel and Landsat, open unprecedented large-scale mapping opportunities. However, most applied machine learning techniques have relied on substantial training datasets, which are not always available and may be expensive to create or collect. Focusing on Japan, this work indicates what kinds of information can be extracted from agriculture census information then used for mapping different crop types. Different classification approaches of pixel-based and parcel-based are compared. Then, the efficient method is used to generate Japan's first national cropland classification with Sentinel-1 C-band and Landsat-8 time series. For 2015, the overall accuracies for the prefectures range between 71% and 94%. This national cropland classification map, which particularly succeeds in extracting high-precision rice products for the whole of Japan and other classes for different prefectures, can be treated as the base map of Japan for future studies related to agriculture, environment, and climate change.

1 Introduction

Food insecurity is exacerbated by climate change and environmental deterioration [4]. According to the report on climate change and its impacts in Japan provide by the Ministry of Environment, Japan (available at: https://www.env.go.jp/en/earth/), the rising temperatures and more frequent heavy rains decrease the quality of cropland and crop products. Thus, timely and precise processes and investments to enhance food security surveillance and provision have become increasingly crucial [9]. High-quality crop mapping has become an urgent need to meet this demand. By recognizing and comprehending the distributions, types, and changes of crops, the management of agriculture policies can be more effectively applied to minimize pollution, protect and restore biodiversity, and prevent crop disease transmission [6].

Earth observation (EO) data with machine learning techniques provide a promising solution to map cropland. Multi-temporal data from satellites such as the Moderate Resolution Imaging Spectroradiometer (MODIS) [12], Landsat [3], and Sentinel [6] are extensively used.

Many existing methods from random forest [11] to the recent deep learning techniques [14] have achieved remarkable success. The benchmark datasets, including BreizhCrops [8] and TimeSen2Crop [13], further promote the application of cropland classification using multi-temporal data. However, existing studies are usually limited to small or homogeneous areas due to the lack

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of labeled datasets and insufficient resolution of small crops. The Cropland Data Layer (CDL) is a crop-specific land cover map for the continental United States using moderate resolution satellite images and extensive ground truth via decision tree classifier [2]. Such ground truth may be expensive and costly to collect. For the majority of Asian countries, multi-type cropland mapping products do not exist or are not publicly accessible.

In this paper, we present a new framework for multi-type classification of national croplands that uses agriculture census information. We present a comprehensive comparison of different classifiers on the labeled datasets extracted from the census information. We also present a new nation-wide 30 m resolution cropland map for 2015 in Japan, and then clean with agricultural field polygons provided by the Ministry of Agriculture, Forestry and Fisheries (MAFF), Japan. These are the highest resolution and most up-to-date farmland maps for Japan that are publicly available.

2 Data

Study area. In this work, we focus on Japan, which includes 43 prefectures proper, two urban prefectures (Osaka and Kyoto), one "circuit" or "territory" (Hokkaido) and one metropolis (Tokyo). These prefectures can be divided into eight regions: Hokkaido, Tohoku, Kanto, Chubu, Kansai, Chugoku, Shikoku, and Kyushu-Okinawa.

Agriculture census information. Agriculture census information for Japan in 2015, which is based on the rural community, is developed by the MAFF, Japan. Rural communities are originally spontaneous communities and are the basic unit of social life in which houses are connected to each other in a territorial and blood relationship to form various groups and social relationships. The database contains rural community statistics on crop sown area for planted area, total cropland area, crops for sale, livestock for sale, farming workforce, farm management activities etc. The number of rural communities for each prefecture range from 912 (Okinawa) to 7542 (Hokkaido). The total number of rural communities in Japan is around 142K. Agricultural field polygon data were obtained from MAFF (available at: https://www.maff.go.jp/j/tokei/porigon/hudeporidl.html) and used to draw the shape of each parcel of agricultural land on 0.5 m spatial resolution of remote sensing images. Each rural community contains multiple field polygons. The minimum area of each polygon is 200 m^2 (400 m^2 for Hokkaido). The number of polygons for each prefecture range from 200K (Okinawa) to 1375K (Niigata). The total number of polygons is Japan is around 31 million.

EO data. Landsat 8 surface reflectance product and Sentinel-1 SAR Ground Range Detected (GRD) product from January 1st to December 31th were exploited as inputs in 2015 for the whole of Japan (except Hokkaido and Okinawa). Due to the typical snow season from December to March in Hokkaido, we only consider the datasets from March 1st to November 31th. There is no Sentinel-1 SAR in Okinawa, thus, we only consider Landsat-8. We prepared monthly or bimonthly, cloud-free time series of Landsat-8 and Sentinel-1 mosaic inputs with 30 m spatial resolution for each prefecture in Japan. The number of temporal datasets for each prefecture range from 3 (Niigata) to 12 (Ibaraki). All input data were normalized to have a band-wise mean of 0 and a standard deviation of 1.

3 Methods

3.1 Pure label extraction

The census information contains agricultural data on the total cropland area in each rural community, but not areas in any specific crop types. Crops planted and cultivated for the purpose of sales have nice crop types, including *rice*, *wheat*, *millet*, *potato*, *beans*, *industrial crops*, *vegetation*, *flower* and *others*. Then, we establish a set of rules to extract labels by using a pure label ratio for the crop types. In each prefecture, for each rural community, we calculated the pure ratio for each crop type:

$$\beta_k^n = a_k^n / A_n \tag{1}$$

where, β_k^n is the pure ratio of kth crop type in rural community n for the sale-purposed. A_k is total cropland area in rural community n. It should be noticed that the sum of pure ratios is lower than 1.

Then, the pure labels are extract based on the set of rules (seen the examples in Table 1). It should be noticed that in all prefectures expect Okinawa, the pure ratio of rice greater than 0.8 or 0.9 are used to extract as the labels. For other crop types, Taking Hokkaido as an example, the pure ratio greater than

0.8 and 0.5 are used to extract the labels for *rice*, *wheat*, *millet*, *beans*, *industrial crops*, *vegetation*. For the classes of *potato*, *flower* and *others*, we select the ten and five largest (top 10 and top 5 in the table) pure ratios. Fig. 1 has shown the selected rural communities of Hokkaido. In each selected community, the agricultural field polygons are rasterized as the labels for the inputs of EO datasets.

Table 1: Pure label extraction rules

Prefecture	Rice	Wheat	Millet	Potato	Beans	Industrial crops	Vegetation	Flower	Others
Hokkaido	>0.8	>0.5	>0.5	Top 10	>0.5	>0.5	>0.5	Top 5	Top 10
Ibaraki	>0.9	Top 5	>0.4	Top 5	Top 5	>0.1	>0.1	>0.1	>0.3
Tokyo	>0.1	All 4	None	>0.1	Top 5	>0.2	>0.1	>0.2	Top 5
Kyoto	>0.8	All 5	All 5	Top 5	Top 5	>0.6	Top 5	Top 5	Top 5
Okinawa	>0.2	None	>0.1	>0.2	all 1	>0.9	>0.1	>0.6	All 2

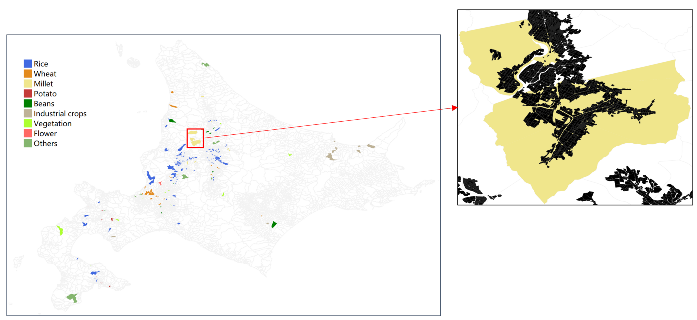

Figure 1: Selected rural communities of Hokkaido. In the enlarged one, the agriculture field polygons (black color) in the selected rural communities are treated as the pure polygons.

3.2 Classifiers

The existing algorithms, including random forest and deep learning methods, which are generally used for cropland mapping, have been assessed and compared. Random Forests (RF) [1] are an ensemble method for training series of decision trees with few parameters. For the RF, we test the pixel-based and parcel-based. In the pixel-based RF, the result in each polygon is assign to one class by a majority vote rule. For deep learning methods, we adopted the parcel-based Temporal Convolutional Neural Network (TempCNN) [5], Long Short-Term Memory (LSTM) [7] and Transformer. The architecture of TempCNN [5] contains three convolutional layers, one dense layer and one Softmax layer. LSTM is a deep recurrent neural network architecture that capture long-term temporal dependencies and extensively used in time-series classification [15]. The attention-transformer [10], which was original developed for NLP task, includes a sequence-to-sequence encoder–decoder architecture.

4 Results

Table 2: Classification accuracies of Ibaraki.

Method	Rice	Wheat	Millet	Potato	Beans	Industrial	Vegetation	Flower	Others	OA	mean F1
RF (pixel-based)	0.86	0.41	0.72	0.57	0.46	0.62	0.58	0.54	0.76	0.86	0.61
RF (parcel-based)	0.87	0.40	0.71	0.58	0.45	0.63	0.57	0.55	0.75	0.87	0.62
TempCNN	0.85	0.40	0.77	0.68	0.47	0.67	0.59	0.55	0.77	0.86	0.63
LSTM	0.82	0.38	0.74	0.66	0.43	0.63	0.51	0.47	0.63	0.83	0.61
Transformer	0.86	0.41	0.71	0.63	0.46	0.68	0.57	0.55	0.84	0.88	0.63

Table 2 summarizes the experimental results of Ibaraki prefecture. Here, we extract 115K polygons, in which half of them are labeled as the *rice*. We split the datasets into training/validation/test with a ratio of 4:3:3. For the RF, the number of trees is set to be 100 with other default settings. For the deep learning methods, the parameters are determined by the suggestions in [8]. As expected, regardless of the deep learning model, the most reliable classes in Ibaraki are *Rice*, *Millet* and *others*.

This is owing to the fact that these classes have larger pure ratios than other classes. It should be emphasized that the reliable classes in different prefecture are various. The presented results indicate that the considered approaches provide comparable performance, with the OA ranging from 0.83 to 0.88. In general, the LSTM method performed a little worse results compared to other methods and Transformer has shown the best classification result. Hence, the pixel-based and parcel-based RF yield an mean F1 of 0.61 and 0.62, respectively. Considering the trade-off between the computational complexity and classification performance, RF maybe suitable for the crop classification for the national-, intercontinental-and global-scale.

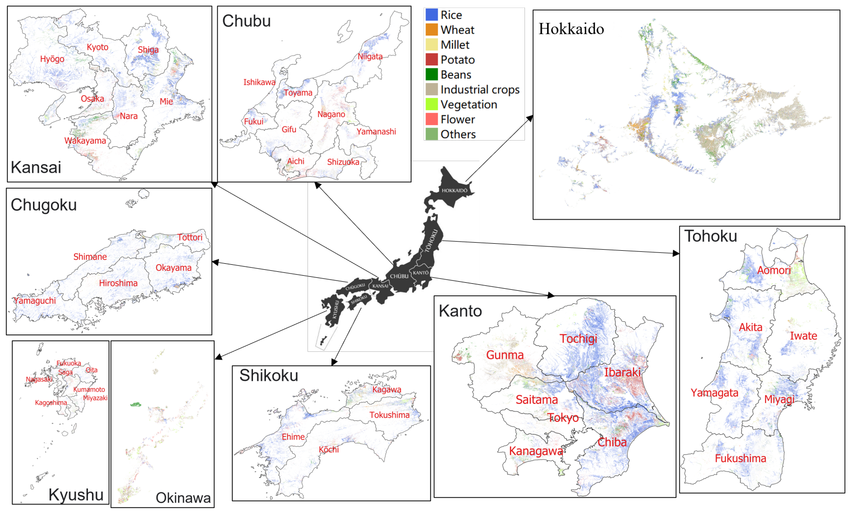

Figure 2: National cropland classification of Japan.

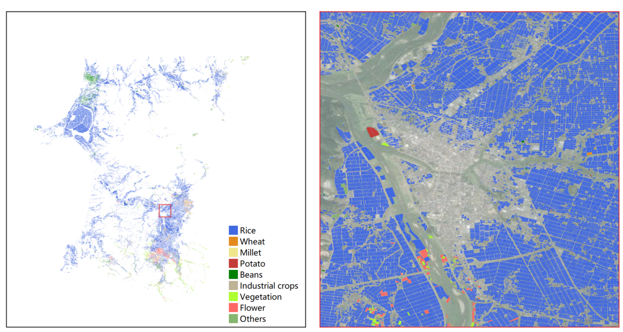

Figure 3: Cropland classification of Akita.

Moreover, national cropland classification of Japan using RF classifier can be seen in Fig. 3. We also present the cropland of Akita and its zoom to clearly see the boundary of cropland product. The overall accuracies for the prefectures range from 71% (Tokyo) to 94% (Tokushima and Kagoshima). For the specific crop types, the OAs of class *rice* are higher than 80% for 45 prefectures. Nagasaki, Okayama, Yamanashi, Mie, Shiga, Tokyo, Achi and Wakayama produce the highest accuracies of *wheat*, *millet*, *potato*, *beans*, *industrial crops*, *vegetation*, *flower* and *others*, respectively.

5 Conclusion

This work presented a framework for national crop mapping using agriculture census information and multi-temporal Landsat 8 and Sentinel-1 datasets. The final product are vectorized by the agriculture field polygons. Finally, we produced high-resolution multi-types cropland maps of the entirety of Japan for 2015. Future works will focus on addressing challenges caused by imbalanced labels and noisy labels in census information.

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