Classification of Paddy Fields using Deep Learning Networks with MODIS imagery in Northeast Asia

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Introduction

- A satellite image-based classification for crop types can spatially provide information on an arable land area and its changes over time.
- The classified information is also useful as a base dataset for various geospatial projects to retrieve crop growth and production processes for a wide area.
- Recently, the food shortage is expected to worsen further due to the effects of climate change, such as abnormal temperature, drought, flood, and disease in a crop.
- Continuous spatial monitoring of arable cropland and its changes can be significant data to prepare future food shortages and protect food security in the world.

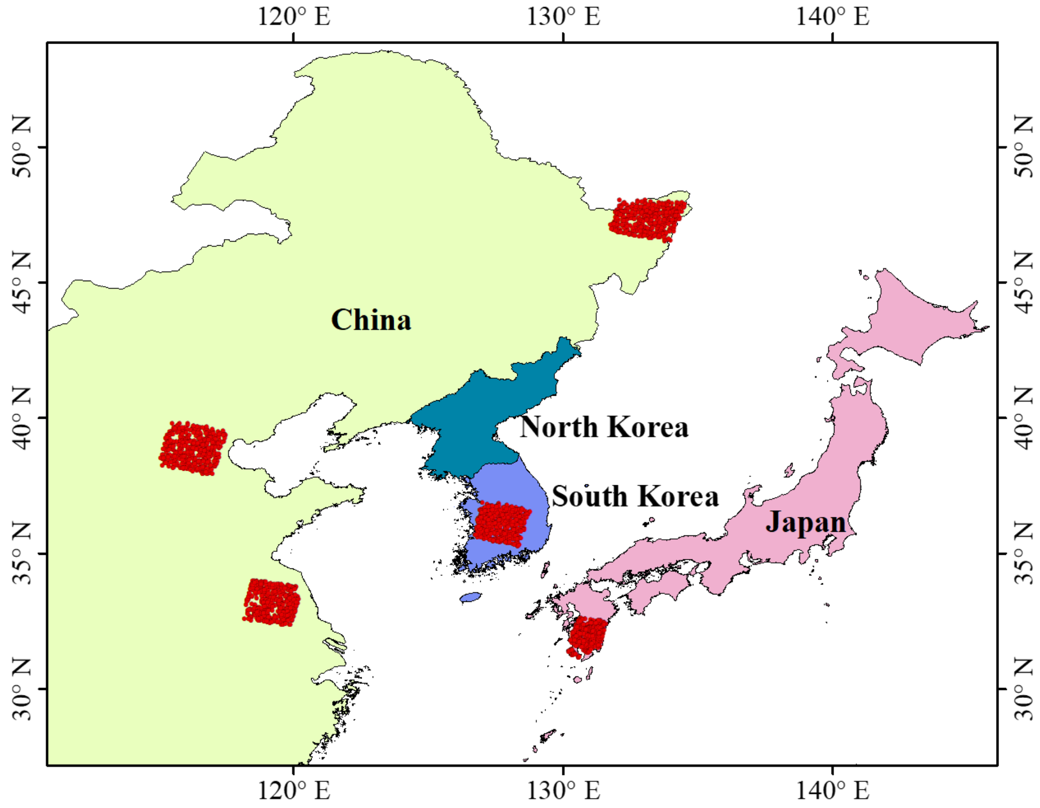
Introduction

- Satellite image-based approaches have been used for land cover classification in a wide area from a regional to global scale using the images from various satellites including moderate resolution imaging spectroradiometer (MODIS), LANDSAT, or RapidEye.
- The most common approach is to use multi-temporal satellite images based on decision tree algorithms that use the maximum vegetation indices (VIs), the VIs values at a specific period, or two or more VIs relationships with different characteristics (Xiao et al., 2005; Peng et al., 2007; Jeong et al., 2012).
- A support vector machine (SVM) or random forest (RF) based on a machine learning algorithm has also been applied to the satellite image for the classification (Khatami et al., 2016; Gislason et al., 2006).

Introduction

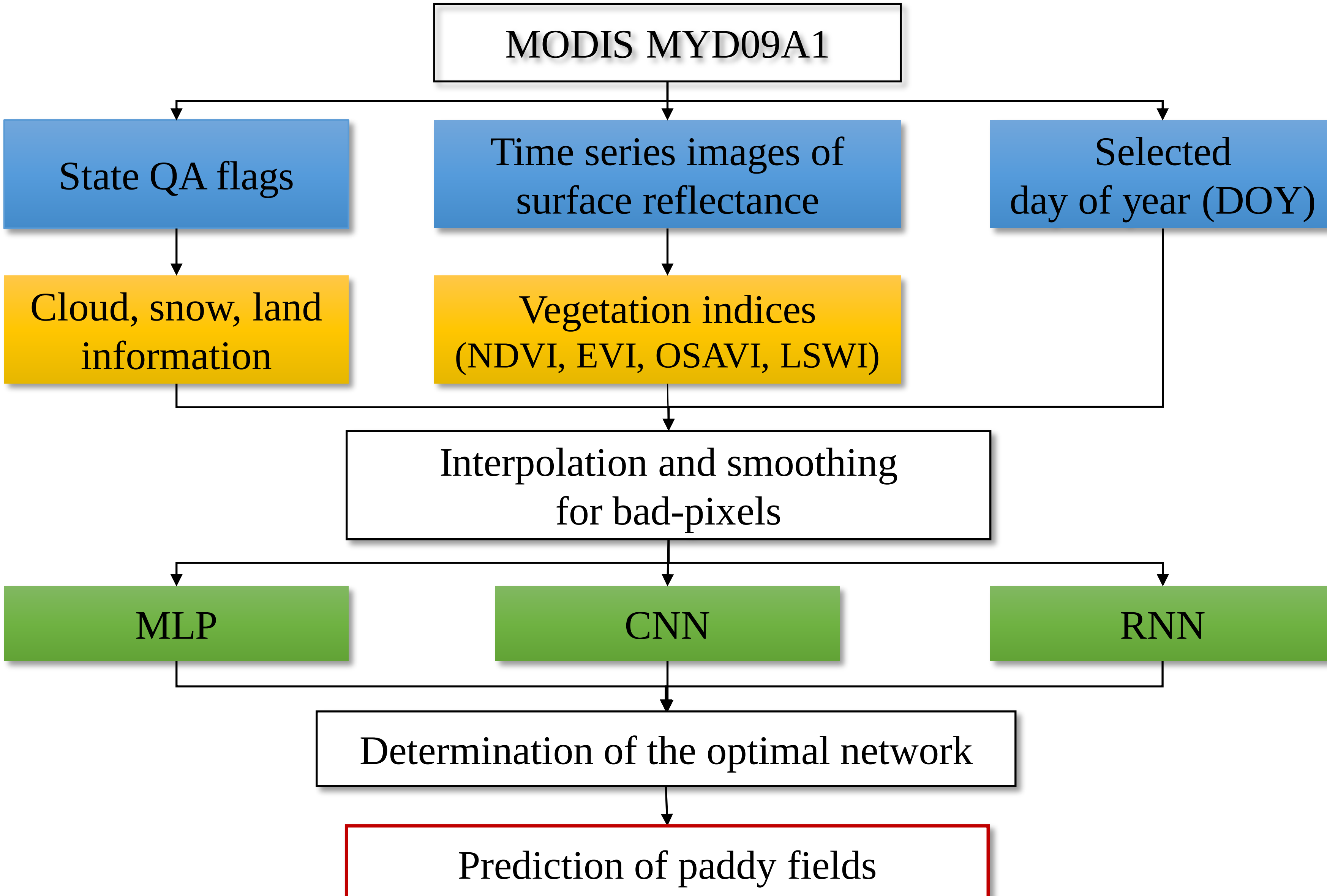
- Over the few years, deep learning techniques have been frequently applied for land cover classification using satellite images with a high spatial resolution, producing reliable classification outcomes.
- It is still challenging to adopt the coarse resolution images such as MODIS for deep learning-based classification purposes mainly because of uncertainty from mixed pixels, which can cause difficulty in collecting and labeling actual land cover data.
- Nevertheless, it is a very efficient approach for obtaining high temporal and continuous land spectral information for extensive areas (e.g., those at national and continental scales).
- In this study, we tried to classify paddy fields applying deep learning networks to MODIS time-series images in Northeast Asia.

Study Area



- Red circles in the figures are training (60%), validation (20%), and test (20%) points with 2,350 from 2013 to 2017 (total of 11,750 samples) to develop the deep learning network for the paddy classification.
- The points were selected by using stratified random sampling with a 1:1 ratio of paddy and non-paddy from the rice map made by IRRI and labeled using LANDSAT-8 images and Google Earth software by the person directly.

Flowchart


MODIS MYD09A1
State QA flags
Time series images of surface reflectance
Selected day of year (DOY)
Cloud, snow, land information
Vegetation indices (NDVI, EVI, OSAVI, LSWI)
Interpolation and smoothing for bad-pixels
MLP
CNN
RNN
Determination of the optimal network
Prediction of paddy fields

MODIS time series images

- MODIS is a key instrument aboard the Terra (EOS AM-1) and Aqua (EOS PM-1) satellites for earth observation.
- MYD09A1 surface reflectance product, which includes Aqua MODIS bands 1-7 at 500 m spatial resolution and corrected for atmospheric conditions, was used to classify the paddy fields.
- From the reflectance data, vegetation indices (normalized difference vegetation index, NDVI; enhanced vegetation index, EVI; optimized soil-adjusted vegetation index, OSAVI; land surface water index, LSWI) were calculated.
- As satellite images have some low-quality pixels caused by clouds, these pixels were interpolated and smoothed using the Savizky-Golay algorithm (Press and Teukosky, 1990).

Vegetation indices

$$\mathrm{NDVI} = (R_{\mathrm{NIR}} - R_{\mathrm{Red}})/(R_{\mathrm{NIR}} + R_{\mathrm{Red}})$$

$$\mathrm{EVI} = 2.5 \cdot (R_{\mathrm{NIR}} - R_{\mathrm{Red}}) \big/ (R_{\mathrm{NIR}} + 6 \cdot R_{\mathrm{Red}} - 7.5 \cdot R_{\mathrm{Blue}} + 1)$$

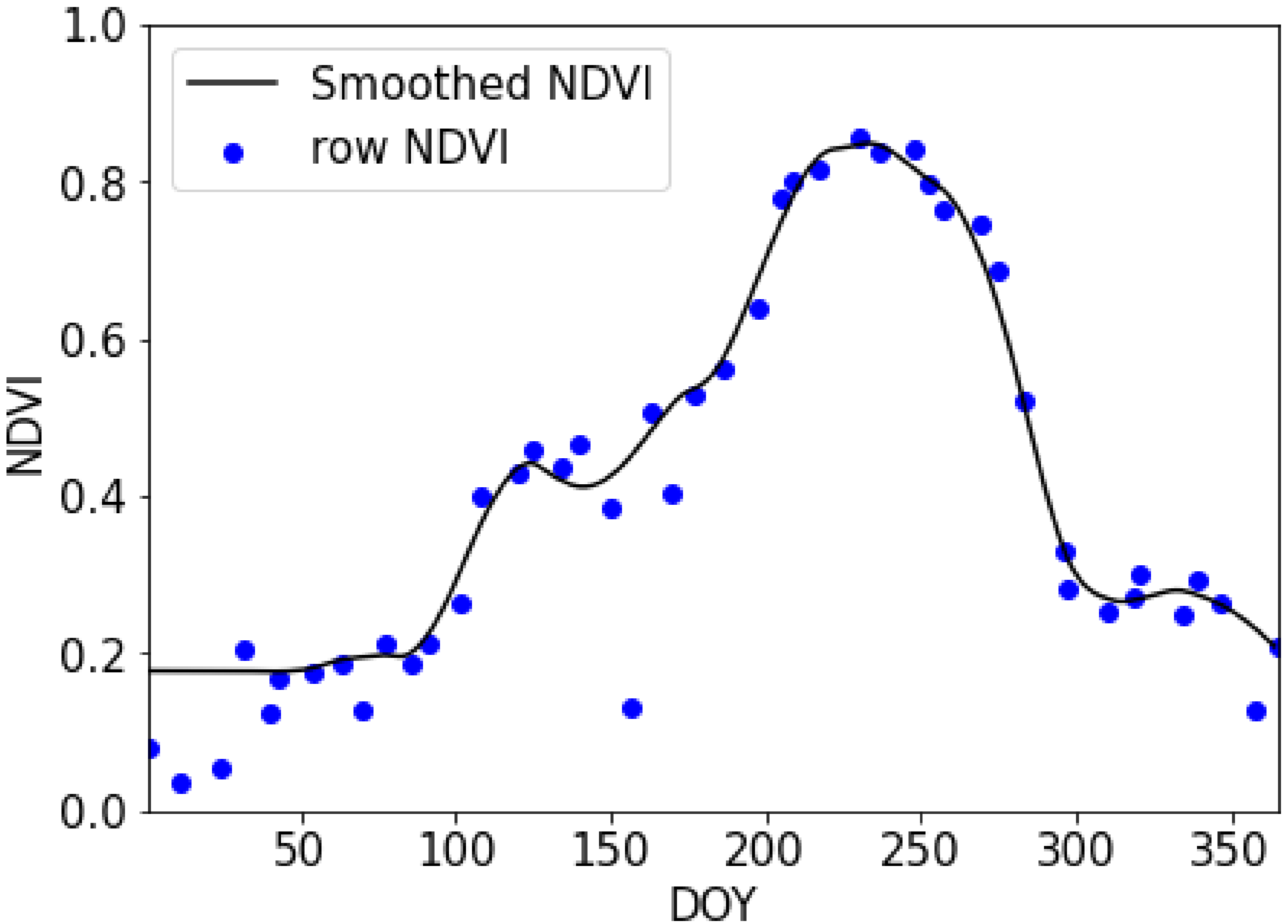
$$\mathrm{OSAVI} = (R_{\mathrm{NIR}} - R_{\mathrm{Red}})/(R_{\mathrm{NIR}} + R_{\mathrm{Red}} + 0.16)$$

$$\mathrm{LSWI} = (R_{\mathrm{NIR}} - R_{\mathrm{SWIR}}) / (R_{\mathrm{NIR}} + R_{\mathrm{SWIR}})$$

- This study tried to find the optimal deep learning network through a combination of four vegetation indices as inputs.
- NDVI and EVI were widely used as vegetation indices to classify the land cover, and OSAVI helps to prevent saturation of VI values in the growing season by considering the soil effect.
- LSWI has been used to detect the irrigated fields, which only appears in the paddy fields.

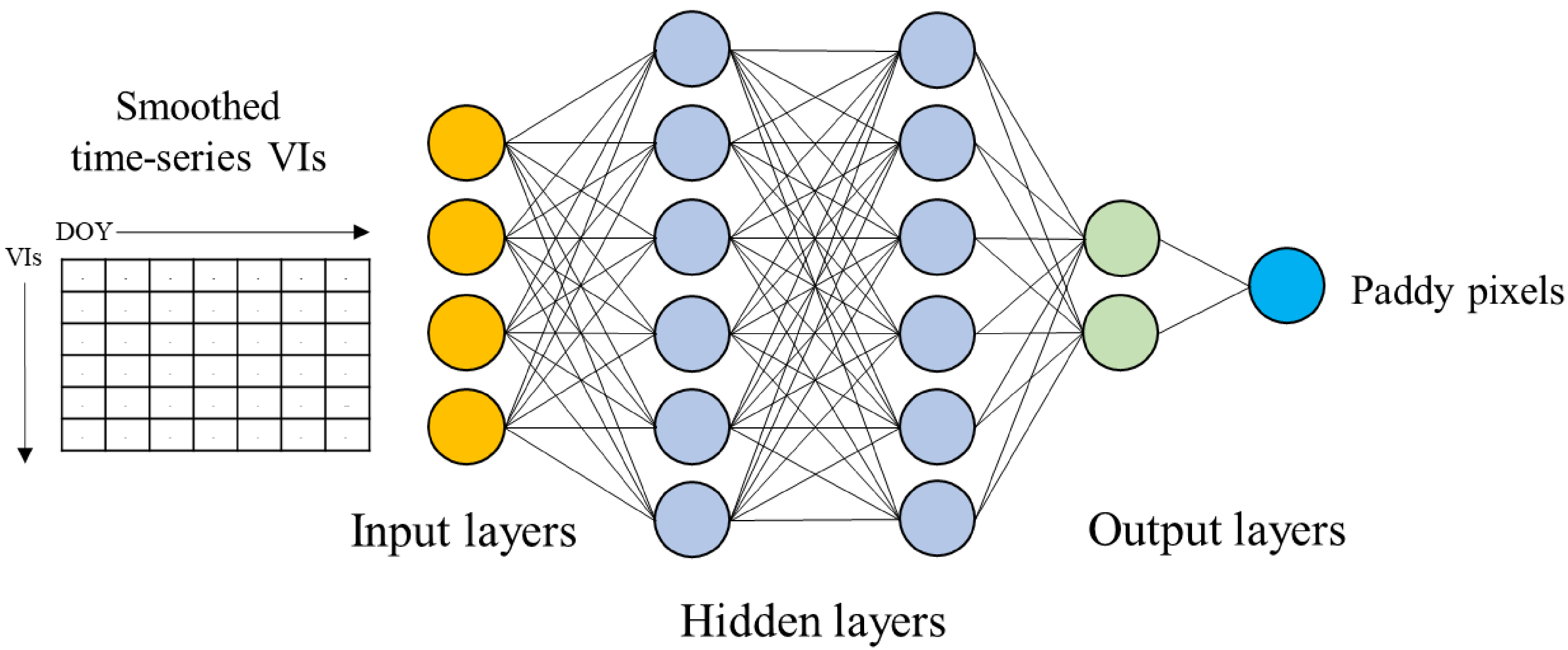
Interpolation and smoothing for cloudy pixels

- To minimize the uncertainty caused by clouds, Savitzky-Golay smoothing method was applied to low-quality VIs pixels determined by MYD09A1 state QA flag data.



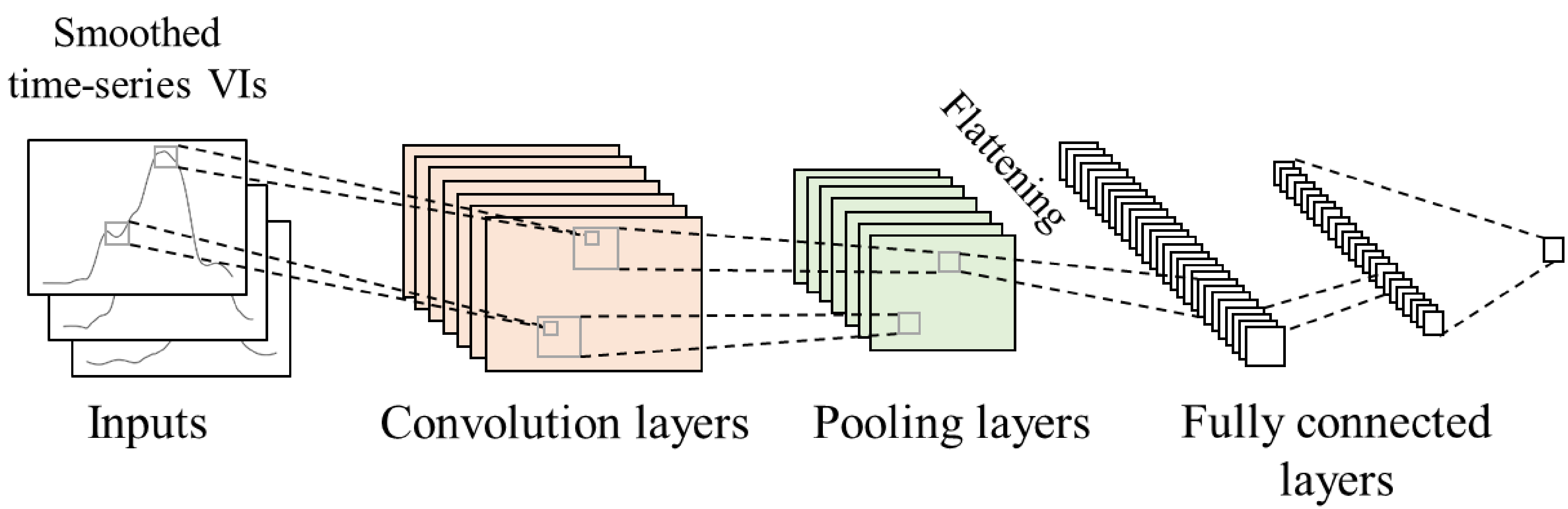
Deep learning algorithms

- MLP (multi layer perceptron)
  - MLP is also referred to as a feed-forward neural network (FFNN), and it is a form in which several layers of perceptron are sequentially attached.
  - As inputs of MLP network, the interpolated and smoothed times-series values of MODIS VIs for 365 DOY were used.



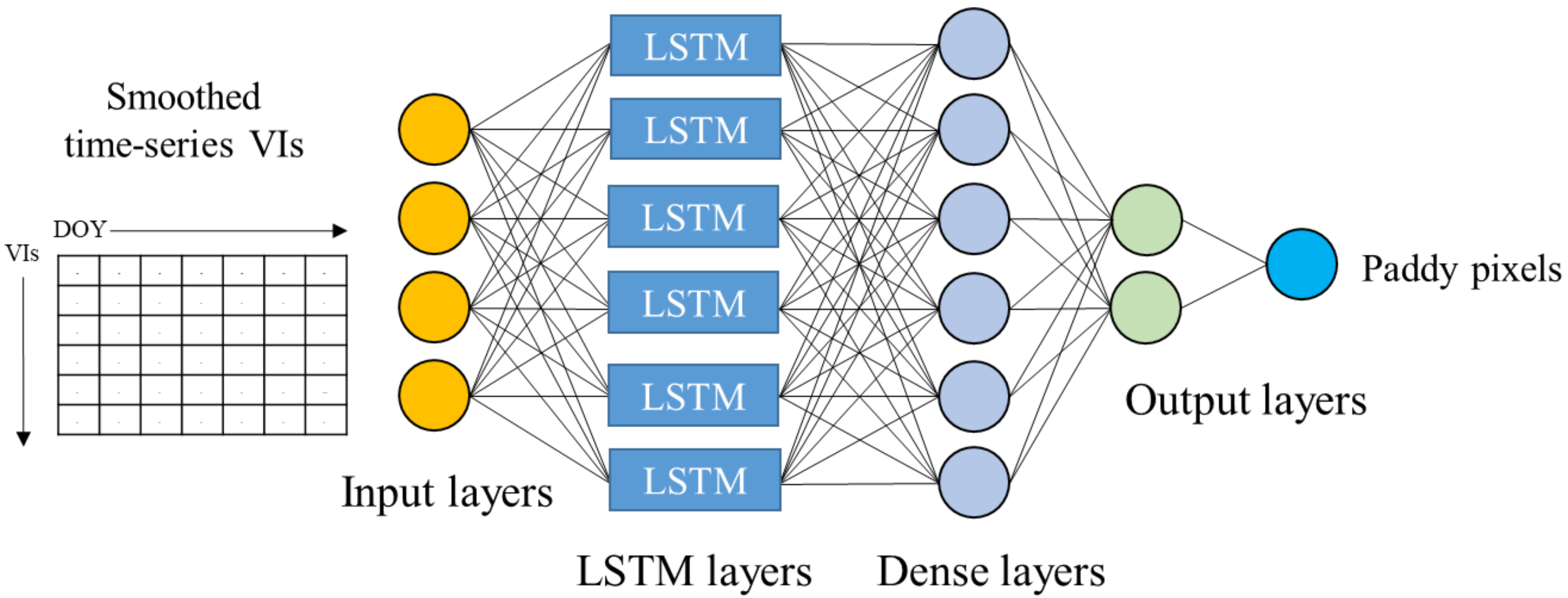
Deep learning algorithms

- CNN (Convolutional Neural Networks)
  - CNN can effectively recognize the characteristics of adjacent images while maintaining spatial information of the images. Also, using the filter as a shared parameter, the learning parameters are very small compared to general artificial neural networks.
  - In this study, the smoothed VIs values were imaged and used as inputs of the CNN.



Deep learning algorithms

- LSTM (long short-term memory)
  - LSTM is a type of RNNs (recurrent neural networks). It can solve long-term dependency problems proposed by Hochreiter (1997).
  - Interpolated and smoothed time-series values of MODIS VIs for 365 DOY were used as inputs of the LSTM network.



Deep Learning Tools

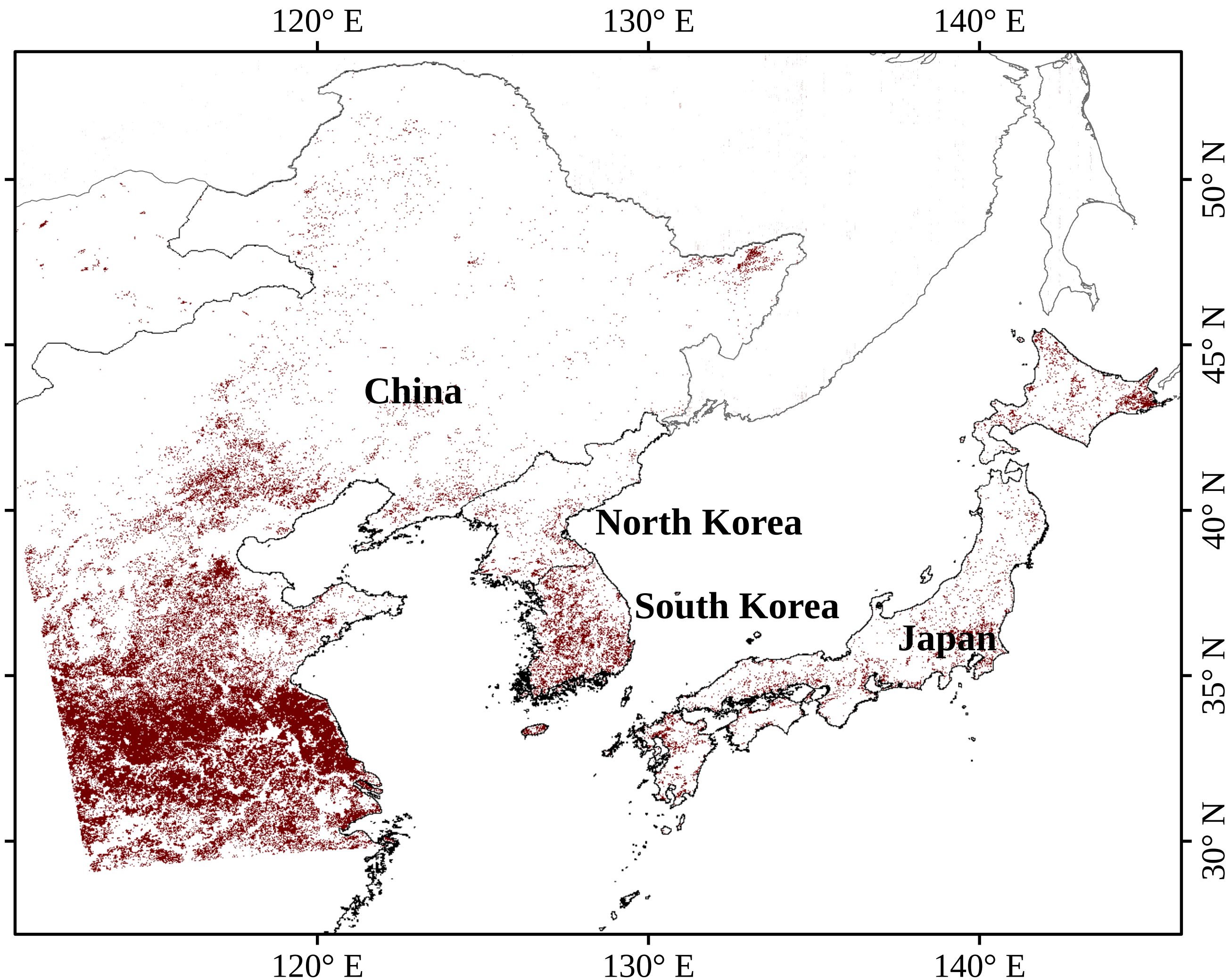
- Keras used in this study is an easy and concise deep learning library implemented in Python.
- Keras provides an intuitive API so that even non-experts can easily develop and utilize deep learning models in their respective fields.
- Keras is a library built on how users can code more easily and designed to run on Tensorflow as well as R, Theano, etc.
- Main features
  - Modularity, Minimalism
  - User Friendliness. Easy Extensibility

Results

- The model using MLP and EVI, OSAVI, LSWI combination showed the best results.
- CNN showed similar performance to MLP, and the accuracy of LSTM network was lower than that of both networks in front.

Rank	Network Type	Input VIs	Accuracy	Kappa Coefficient
1	MLP	EVI, OSAVI, LSWI	82-83%	63-64%
2	MLP	NDVI, OSAVI, EVI	81-82%	62-63%
3	CNN	NDVI, OSAVI, EVI	81-82%	60-61%
4	CNN	EVI, OSAVI, LSWI	80-81%	60-61%
⋮	⋮	⋮	⋮	⋮
-	LSTM	EVI, OSAVI, LSWI	77-78%	52-53%

Results



- Paddy map was demonstrated using the MLP deep learning network with MODIS time-series VIs (EVI, OSAVI, and LSWI) in 2013.

Summary and Conclusion

- The current study performed classification of paddy fields by applying MLP, CNN, and LSTM deep learning networks to MODIS time-series images.
- When using the MLP network, it had the highest accuracy, and the performance of EVI, OSAVI, and LSWI combination was the best.
- As a result of applying the optimal model to the entire study area, the spatial distribution was generally well reproduced, but there were also significant errors in some regions.
- Given the uncertainty from the spatial resolution of 500 m, our results shown in this study were considered reliable.
- In future studies, if more training data is obtained by focusing on securing additional label (or reference) data, the accuracy of the classification is expected to be further improved.

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