Efficient Multi-temporal and In-season Crop Mapping with Landsat Analysis Ready Data via Long Short-term Memory Networks

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Abstract

Globe crop analysis from plentiful satellite images yields state-of-the-art results about estimating climate change impacts on agriculture with modern machine learning technology. Generating accurate and timely crop mapping across years remains a scientific challenge since existing non-temporal classifiers are hardly capable of capturing complicated temporal links from multi-temporal remote sensing data and adapting to interannual variability. We developed an LSTM-based model trained by previous years to distinguish corn and soybean for the current year. The results showed that LSTM outperformed random forest baseline in both in-season and end-of-the-season crop type classification. The improved performance is a result of the cumulative effect of remote sensing information that has been learned by LSTM model structure. The work provides a valuable opportunity for estimating the impact of climate change on crop yield and early warning of extreme weather events in the future.

1. Introduction

Climate change is affecting agricultural land use in a complicated manner. According to the fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC), a temperature rise of 3 to 4 °C is projected in cropland dominated areas by the year 2100(Stocker et al., 2013). Crop production and food supply are extremely vulnerable to the changes in climate factors caused by global warming(Nelson et al., 2009; Vermeulen et al., 2012). The shift of U.S. Corn Belt(Napton & Graesser, 2011) and extension of North American wheat areas(Ortiz et al., 2008) have been observed in past decades, indicating the significant long-term impact of climate change on agricultural land use. To understand the cropping pattern changes and estimate the potential socio-economic impact, monitoring changes of cropland use at a high spatiotemporal scale are greatly needed.

Extracting general features from historical data and generating near-real-time crop maps are of great significance for estimating the impact of climate change on crop yield and early warning of extreme weather events. Remote sensing with machine learning technology provides a viable option for crop classification. Existing methods have achieved considerable success in many applications depending on pre-defined feature crafting and general classifiers such as random forest (RF) and support vector machine (SVM)(Löw et al., 2013; Zhang et al., 2014; Waldner et al., 2015; Shi & Yang, 2016). Considering real-world applications, implementing accurate and timely crop mapping using satellite imagery across years remains a scientific challenge(Zhong et al., 2014; Wang et al., 2019). Many existing modeling and non-temporal algorithms are hardly capable of capturing complicated temporal links from multi-temporal remote sensing data and adapting to interannual variability which is even greater due to accelerated climate change. An efficient classifier is required to model the cumulative effect in the dynamic response of crops to the environment, which represents unique growth features. Thus, a data-driven deep learning based approach is suggested to learn general patterns from past years and distinguish the crop classes for the current year in the early season.

We present a long short-term memory (LSTM) based approach to identify crop types at a scalable spatiotemporal scale in this study. Introduced by Hochreiter and Schmidhuber (Hochreiter & Schmidhuber, 1997), LSTM units are a variant of recurrent neural networks (RNN), which allows exhibiting long-term temporal dynamic dependencies from sequence data. Considering that individual phenological profiles of crop types are relatively consistent across years (Zhong et al., 2014), extracting long-term cumulative information from multi-temporal data may model crop vegetation cycles. Hence the LSTM-based approach is expected to recognize general patterns from historical remote sensing data and address multi-temporal in-season crop mapping problem.

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Preliminary work. Under review by the International Conference on Machine Learning (ICML). Do not distribute.

2. Data and Methods

2.1. Remote Sensing Imagery and Ground Truth

Landsat Analysis Ready Data (ARD) surface reflectance composites from April 1st to September 30th were exploited as inputs in each year, publicly available from USGS's Earth-Explorer web portal (https://earthexplorer.usgs.gov). ARD provides non-spatially overlapping six-band imageries at 30m resolution. In order to remove the gaps resulted from missing acquisitions and invalid data, we employed linear interpolation based on the nearest valid values before and after the target time step for each pixel to obtain time series with 7-day intervals (Figure 1). For ground truth, we used USDA's 30m CDL maps downloaded from the CropScape website portal (https://nassgeodata.gmu.edu/CropScape/) as the reference map for both training and test datasets.

In this paper, we chose a study site of 51km $\times$ 51km in north-central Iowa for the experiments. The area of 3375 $\times$ 3375 pixels is fully covered in the footprint of h18v07 in ARD grid system. The site locates in the U.S. Corn Belt region, which is a major area for corn and soybean production. As a result, we took corn, soybean and other as the classes of interest and assigned a label to each pixel of the thematic maps annually from 2015 to 2018.

2.2. LSTM-based Classification Model

As shown in Figure 2, the proposed LSTM-based model contains five components: the input layer, LSTM layer, attention layer, and output layer. Each ARD observation is encoded as a vector $x_t = \{sb_1, sb_2, sb_3, sb_4, sb_5, sb_5\}$ consisting of six spectral bands at time step t during the crop growth period. The input is expressed as a time series $X = \{x_1, x_2, \ldots, x_t, \ldots, x_T\}$, where T is the length of the observation sequence fed into the network. We employed LSTM layers to capture high-level temporal feature matrix h. The final representation of the whole time sequence h^* is calculated by multiplying weight matrix α derived from an attention layer by h. In the output layer, We applied a softmax layer to produce the predictive distribution p. The cross-entropy function is adopted as the loss function, and the Adam optimizer (Kingma & Ba, 2014) is used for training the network.

2.3. Experiment Design

We designed two groups of experiments to explore the practical capability of LSTM in remote sensing based crop mapping tasks. For comparison, RF baseline is applied in all scenarios.

The first one aims to study the temporal transferability of classification models across years. Classifiers are usually required to learn general patterns from past years and distinguish the crop classes for the current year. Overfitting can easily occur due to lacking labels in the current year and interannual difference such as climate variability. In order to evaluate the performance of models under such restrictions, we used the data from the last year (2018) as the test set and sampled the data from previous years (2015-2017) as the training set. This group of experiments was designed to mimic real-life situations and examine the influence of interannual variability in remote sensing data on classifiers.

The goal of the second group of experiments is to address the in-season classification problem. To provide accurate and early-season crop type maps, a classifier is expected to perform well on the remote sensing time series with limited length. We gradually increased the length of the input observation sequence until all time steps were included. It is a simulation of the practical situation that more and more satellite images are available as the growing season progresses. This group of experiments was designed to quantify how models depend on the sequence integrity and when there are sufficient multi-temporal scenes to make satisfactory crop discrimination. In this scenario, we trained models on the data from 2015 to 2017 and validated them by comparing results with the reference classes in 2018.

3. Results and Discussion

3.1. Temporal Transferability Across Years

The test accuracy metrics of LSTM-based models and RF-based models are reported in Table 1, using three groups of training years. Under the same conditions, LSTM-based models always outperformed RF-based models for the crop type prediction in 2018. The best overall accuracy achieved by LSTM was 92.1% which is superior to RF with 88.3%. The corresponding kappa score of LSTM (87.0%) was much higher than RF (81.1%), which indicates LSTM has better applicability to imbalanced classification.

Both classifiers benefited from the increase in training years. The gain of LSTM in accuracy was weak compared to RF, which reflects the more powerful capability to capture general crop type features from data of limited years. Considering that distinct phenological profiles of crop types are relatively consistent across years (Zhong et al., 2014), the characteristic of LSTM to extract long-term cumulative information from multi-temporal data may model crop vegetation cycles and explain why it was less affected by the interannual variability.

3.2. In-season Classification

Figure 3 shows the trends of model performance with the progression of time. With remarkable progress after the 13th time step, LSTM achieved a relatively high accuracy after the 18th time step which corresponded to the end of July

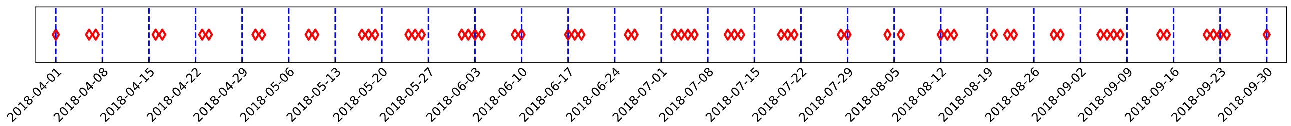

Figure 1. Calendar of raw and interpolated ARD time series for the year 2018. The red rhombuses refer to raw acquisitions and the blue dashed lines refer to interpolated dates. It is worth noting that the raw acquisition here does not exclude the pixel-level invalid data and each pixel has an individual raw time series of valid observations.

Table 1. Predictive results obtained by LSTM-based models and RF-based models for the year 2018, using three groups of previous training years. LSTM achieved higher performance than RF in all cases and are less influenced by the reduction of training years.

Training years	LSTM			RF		
	Overall accuracy	Kappa	Micro-F1	Overall accuracy	Kappa	Micro-F1
2017	89.5	82.6	87.7	82.4	72.6	81.7
2016-2017	91.2	85.6	89.4	86.2	77.9	84.4
2015-2017	**92.1**	**87.0**	**90.3**	88.3	81.1	86.6

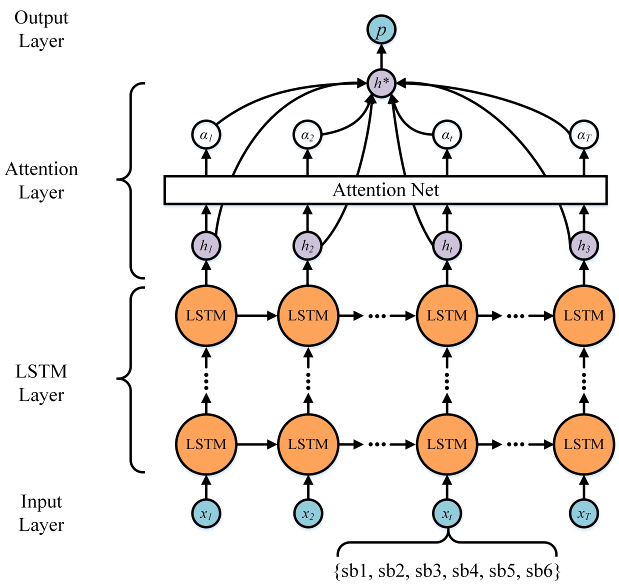

Figure 2. LSTM-based classification model for multi-temporal and multi-spectral crop mapping.

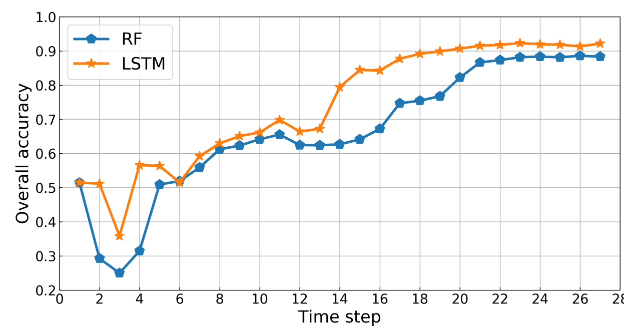

Figure 3. Overall classification accuracy as a function over time. The first time step corresponds to April 1st and the last September 30th. LSTM almost always outperformed RF during the whole growing season and reached high performance at a relatively early stage for monitoring applications.

and reached a plateau then. For comparison, RF had been improving until the 21st time step and performed poorly until the final stage.

The abnormal decrease before the sixth time steps is anticipating. The planting stage began in late April or early May in the study area for the year 2018 and thus remote sensing data could not contribute much useful information to crop mapping tasks. Cloud contamination in ARD may also lead to slight performance decreases.

4. Conclusion

In this study, we proposed an LSTM-based approach for practical in-season multi-temporal crop mapping using moderate resolution satellite remote sensing data. Compared to RF baseline, LSTM achieved higher performance in both scenarios of temporal transferability across years and in-season prediction. The study demonstrates that LSTM is applicable for accurate and timely crop mapping. It can make a significant contribution to estimating the potential impact of climate changes on agriculture and early warning of extreme weather events.t. Further work can concentrate on the spatial transferability of the LSTM-based approach in order to produce adaptable classifiers for those areas lacking labeled training data.

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