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A high-performance and in-season classification system of field-level crop types using time-series Landsat data and a machine learning approach

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ABSTRACT

Accurate and timely spatial classification of crop types based on remote sensing data is important for both scientific and practical purposes. Spatially explicit crop-type information can be used to estimate crop areas for a variety of monitoring and decision-making applications such as crop insurance, land rental, supply-chain logistics, and financial market forecasting. However, there is no publically available spatially explicit in-season crop-type classification information for the U.S. Corn Belt (a landscape predominated by corn and soybean). Instead, researchers and decision-makers have to wait until four to six months after harvest to have such information from the previous year. The state-of-the-art research on crop-type classification has been shifted from relying on only spectral features of single static images to combining together spectral and time-series information. While Landsat data have a desirable spatial resolution for field-level crop-type classification, the ability to extract temporal phenology information based on Landsat data remains a challenge due to low temporal revisiting frequency and inevitable cloud contamination. To address this challenge and generate accurate, cost-effective, and in-season crop-type classification, this research uses the USDA's Common Land Units (CLUs) to aggregate spectral information for each field based on a time-series Landsat image data stack to largely overcome the cloud contamination issue while exploiting a machine learning model based on Deep Neural Network (DNN) and high-performance computing for intelligent and scalable computation of classification processes. Experiments were designed to evaluate what information is most useful for training the machine learning model for crop-type classification, and how various spatial and temporal factors affect the crop-type classification performance in order to derive timely crop type information. All experiments were conducted over Champaign County located in central Illinois, and a total of 1322 Landsat multi-temporal scenes including all the six optical spectral bands spanning from 2000 to 2015 were used. Computational experiments show the inclusion of temporal phenology information and evenly distributed spatial training samples in the study domain improves classification performance. The shortwave infrared bands show notably better performance than the widely used visible and near-infrared bands for classifying corn and soybean. In comparison with USDA's Crop Data Layer (CDL), this study found a relatively high Overall Accuracy (i.e. the number of the corrected classified fields divided by the number of the total fields) of 96% for classifying corn and soybean across all CLU fields in the Champaign County from 2000 to 2015. Furthermore, our approach achieved 95% Overall Accuracy by late July of the concurrent year for classifying corn and soybean. The findings suggest the methodology presented in this paper is promising for accurate, cost-effective, and in-season classification of field-level crop types, which may be scaled up to large geographic extents such as the U.S. Corn Belt.

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1. Introduction

Accurately classifying crop types is important for both scientific and practical purposes. Classifying land cover is a classic question in the remote sensing field, and has been an active research topic for decades (Hansen et al., 2014, 2011, 2000; Hansen and Loveland, 2012; King et al., 2017; Sexton et al., 2013b; Song et al., 2017; Vogelmann et al., 2001; Zhan et al., 2002). However, how to generate accurate and timely maps for crop types with high spatial resolution remains a scientific challenge. Currently, we have no in-season crop type data available for large-scale US croplands. For example, though the USDA publishes the Cropland Data Layer (CDL) data at 30-m spatial resolution, it is usually released in the spring of the subsequent year, with a time lag of at least four to six months after the previous year's harvest time (Boryan et al., 2011). For practical purposes, accurate and timely crop-type classification provides estimations of the planting/harvesting crop areas for a variety of monitoring and decision-making applications of government and private sectors such as crop insurance, land rental, supply-chain logistics, commodity markets, etc. Furthermore, crop-type classification is also the prerequisite for conducting crop yield prediction (Bolton and Friedl, 2013; Lobell et al., 2015). As a result, accurate and in-season information of crop types has considerable importance for management decision-making in public/private sectors and regional economic forecasting.

Extensive research has been done in crop-type classification using two major classification strategies (Chang et al., 2007; Foerster et al., 2012; Lobell and Asner, 2004; Van Niel and McVicar, 2004). One is to solely use the spectral features from a single satellite scene sampled during a certain day within a growing season (Boryan et al., 2011; Van Niel and McVicar, 2004; Yang et al., 2011), and the other is to use both spectral and temporal information during one or multiple growing seasons (Chang et al., 2007; Foerster et al., 2012; Wardlow et al., 2007; Wardlow and Egbert, 2008). The first strategy is based on the rationale that different land covers have distinctive spectral features, and these spectral features in turn can be used for classification. However, some crops have similar spectral information during the peak-growing season when the satellite image is usually acquired, which makes separation of crop types difficult. In addition, spectral differences between crops and natural vegetation (e.g. grass or trees) may be small at certain times of a year. As a result, the similar spectral features between different crops as well as between crops and natural vegetation pose a major challenge for accurate classification. The second strategy utilizes both the spectral and temporal information, which leads to improvements in classification accuracy. Crops usually have different seasonal variations and sowing dates. For example, in the U.S. Corn Belt, corn is usually sown earlier than soybean, and grass usually starts its growing season in spring that is earlier than most crops. These temporal features can be used to improve the accuracy of crop classification. However, the second strategy requires time-series information from multiple satellite images rather than from a single image, and traditionally researchers have implemented this approach using data from sensors with low- or medium- spatial resolution such as the Moderate Resolution Imaging Spectroradiometer (MODIS) (Wardlow et al., 2007; Wardlow and Egbert, 2008).

To achieve field-level classification of crop types, appropriate spatial resolution satellite data inputs to field sizes are required (Lobell, 2013). For the U.S. context, such satellites exist, such as Landsat (Hansen and Loveland, 2012; Roy et al., 2014). Landsat imagery has a higher spatial resolution (30 m) than low- or medium- spatial resolution e.g. MODIS data (gridded at 250 m, 500 m or larger pixel sizes); and unlike SPOT (Duro et al., 2012) and other commercial satellite data, Landsat data is freely available for both concurrent and historical periods. In addition, advanced Landsat products such as the surface reflectance (after atmospheric correction) are readily available from the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Schmidt et al., 2013) and the Landsat Surface Reflectance Code (LaSRC) (USGS, 2016) for Landsat 5, 7 and 8. Landsat data has been widely used for land cover classification at local, regional or continental scales (Hansen and Loveland, 2012; Homer et al., 2004; Huang et al., 2007; Liu et al., 2005; Sexton et al., 2013a; Townshend et al., 2012; Yuan et al., 2005). However, Landsat has a low temporal resolution (16-day revisiting cycle compared to the 1–2-day revisiting cycle of MODIS), and clouds frequently contaminate Landsat images. Extracting the continuous time-series information based on Landsat data (especially how to handle missing data because of cloud cover) is a challenge. To utilize both high spatial and temporal information in Landsat, researchers have explored data-fusion approaches to integrate multi-sources of remotely sensed data, for example, fusing MODIS and Landsat data to achieve both high spatial and temporal resolutions (Gao et al., 2015, 2013). However, the existing data-fusion approaches usually fill the gap values from neighboring available pixels by assuming that different periods of satellite images have unchanged land cover types, thus contradicting the purpose of identifying land cover changes over the time. Additionally, fused satellite data is currently not available or operationally provided at a large spatial scale.

As an alternative, we use the Common Land Unit (CLU) to aggregate field level information based on time-series Landsat data. CLUs are generated by the USDA to delineate the field boundary for all registered agricultural fields for the U.S. (Boryan et al., 2011). The average size of a single unit of CLU in Champaign County, IL, is 60.3 ± 52.6 acres (~244,025 ± 212,865 m^2), which is about 16 × 16 ± 15 × 15 30-meter Landsat pixels (Fig. S1). When a CLU field has a sub-field contamination by clouds/shadows in a Landsat scene, we aggregate Landsat information by averaging values from non-cloud only pixels within that field and assign the mean value to that CLU field. Thus the contamination issues can be overcome to a desirable extent, and as a result, the weakness of lower temporal-resolution Landsat data can be largely alleviated. The aggregated and field-level spectral information will then be used for classification. In addition, instead of only using the data for the same year for training/testing for crop-type classification (Boryan et al., 2011; Wardlow and Egbert, 2008), we can also use the data from multiple growing seasons for training our classification model, with the premise that multiple-year data include more scenarios of crop phenology due to various other factors (e.g. sowing date, inter-annual climate variability) and thus can make our classification algorithm more generic and robust when applying to a new year.

Machine learning approaches have been applied to a variety of data-driven predictive applications, such as natural language understanding and image processing (Collobert and Weston, 2008; Hinton et al., 2012; Krizhevsky et al., 2012). Recently, deep learning, including both the Deep Neural Network (DNN) and the Convolutional Neural Network (CNN), shows great potential in various applications compared to other machine learning techniques. Traditionally, classification or regression systems require careful engineering and considerable domain knowledge to extract features from raw data. However, deep learning has the ability to discover informative features with multiple levels of representation, from lower, primitive levels to higher, abstract levels (LeCun et al., 2015; Schmidhuber, 2015). Though neural network methods have been developed several decades ago, recently years see major development in this method through more layers and back-propagation optimization (i.e. deep neural network), which has made significant improvements in classification or other applications (LeCun et al., 2015; Schmidhuber, 2015). Deep learning is still early in its application on remote sensing data for crop-type classification; therefore questions like what information is needed and how to transform the information that can be used in deep learning model need to be answered.

This paper describes a new crop classification system that is targeted at the U.S. Corn Belt, a region dominated by corn and soybeans. We only focused on farmland and pre-filtered other types of land cover (based on CDL), and classified all the patches of farmland into three major categories: corn, soybean and others. We used CLU to aggregate