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A 30-m landsat-derived cropland extent product of Australia and China using random forest machine learning algorithm on Google Earth Engine cloud computing platform

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ABSTRACT

Mapping high resolution (30-m or better) cropland extent over very large areas such as continents or large countries or regions accurately, precisely, repeatedly, and rapidly is of great importance for addressing the global food and water security challenges. Such cropland extent products capture individual farm fields, small or large, and are crucial for developing accurate higher-level cropland products such as cropping intensities, crop types, crop watering methods (irrigated or rainfed), crop productivity, and crop water productivity. It also brings many challenges that include handling massively large data volumes, computing power, and collecting resource intensive reference training and validation data over complex geographic and political boundaries. Thereby, this study developed a precise and accurate Landsat 30-m derived cropland extent product for two very important, distinct, diverse, and large countries: Australia and China. The study used of eight bands (blue, green, red, NIR, SWIR1, SWIR2, TIR1, and NDVI) of Landsat-8 every 16-day Operational Land Imager (OLI) data for the years 2013–2015. The classification was performed by using a pixel-based supervised random forest (RF) machine learning algorithm (MLA) executed on the Google Earth Engine (GEE) cloud computing platform. Each band was time-composited over 4–6 time-periods over a year using median value for various agro-ecological zones (AEZs) of Australia and China. This resulted in a 32–48-layer mega-file data-cube (MFDC) for each of the AEZs. Reference training and validation data were gathered from: (a) field visits, (b) sub-meter to 5-m very high spatial resolution imagery (VHRI) data, and (c) ancillary sources such as from the National agriculture bureaus. Croplands *versus* non-croplands knowledge base for training the RF algorithm were derived from MFDC using 958 reference-training samples for Australia and 2130 reference-training samples for China. The resulting 30-m cropland extent product was assessed for accuracies using independent validation samples: 900 for Australia and 1972 for China. The 30-m cropland extent product of Australia showed an overall accuracy of 97.6% with a producer's accuracy of 98.8% (errors of omissions = 1.2%), and user's accuracy of 79% (errors of commissions = 21%) for the cropland class. For China, overall accuracies were 94% with a producer's accuracy of 80% (errors of omissions = 20%), and user's accuracy of 84.2% (errors of commissions = 15.8%) for cropland class. Total cropland areas of Australia were estimated as 35.1 million hectares and 165.2 million hectares for China. These estimates were higher by 8.6% for Australia and 3.9% for China when compared with the traditionally derived national statistics. The cropland extent product further demonstrated the ability to estimate sub-national cropland areas accurately by providing an R^2 value of 0.85 when compared with province-wise cropland areas of China. The study provides a paradigm-shift on how cropland maps are produced using multi-date remote sensing. These products can be browsed at www.croplands.org and made available for download at NASA's Land Processes Distributed Active Archive Center (LP DAAC) https://www.lpdaac.usgs.gov/node/1282.

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1. Introduction

Accurate, and precise agricultural cropland extent products over very large areas that map small to large farms are of great importance to assess and monitor global food and water security. They are a critical part of land system studies (Verburg et al., 2013). Such products are also of great importance for assessing global crop water use, crop productivity (productivity per unit of land), water productivity (productivity per unit of water or crop per drop), and food security studies (Foley et al., 2011; Thenkabail et al., 2010; Teluguntla et al, 2015b; Matejicek and Kopackova, 2010). Remote sensing based spatially distributed cropland maps with high spatial resolution provide an efficient way to monitor croplands (Foley et al., 2011; Fritz et al., 2015; Yu et al., 2013). Over the last two decades, several global and regional cropland products have been produced using medium to coarse resolution (250-m to 1-km) remote sensing data such as the Advanced Very High-Resolution Radiometer (AVHRR) and the Moderate-Resolution Imaging Spectroradiometer (MODIS) data (Biradar et al., 2009; Kumar et al., 2018; Thenkabail et al., 2009, 2012; Pittman et al., 2010; Portmann et al., 2010; Siebert and Döll, 2010; Salmon et al., 2015; Waldner et al., 2015, 2016). These products are very useful for a preliminary understanding of agricultural croplands in terms of their spatial distribution patterns and their characteristics such as crop dominance and cropping intensities. However, the coarse resolution of these products limits their usefulness in assessing small agriculture fields (Teluguntla et al., 2015b; Thenkabail et al., 2010). Further, there are several global to regional land use/land cover (LULC) products produced using multiple remote sensing data in which agricultural croplands is one or more classes. Some examples are: DIScover (Loveland et al., 2000); GLC500m (Friedl et al., 2010); MCD12Q1 (Liang et al., 2015); Globecover (Defourny et al., 2009); FROM-GC (Gong et al., 2013); FROM-GLC (Yu et al., 2013); and Globeland30 (Arsanjani et al., 2016; Chen et al., 2015). However, these products were focused on LULC in which mapping croplands in detail was not the primary objective. Hence, the cropland accuracies suffer (Yang et al., 2017). Further, most of these products are also coarse resolution. Most of these products fail to map individual farm fields, especially when they are small and\or fragmented. Definitions of croplands also vary from product to product, resulting in different results of cropland extent and their characteristics in each of these products. Overall, existing cropland extent products are coarse resolution, lack field level details, and/or are mapped as part of other LULC classes where specific cropland class focus is missing. As a result, uncertainties and errors in cropland locations are very high.

In the past, number of advanced remote sensing methods have been used for mapping agricultural croplands. These studies were conducted using data from multiple sensors across many spatial, spectral, radiometric, and temporal resolutions for both irrigated and rainfed crops (Biggs et al., 2006; Dheeravath et al., 2010; Funk and Brown, 2009; Gumma et al., 2011. 2016; Ozdogan and Woodcock, 2006; Pervez et al., 2014; Teluguntla et al. 2015a; Thenkabail et al., 2009, 2012; Velpuri et al., 2009; Xiao et al., 2006). These methods consist of pixel-based, object-based, or a combination of both approaches that used either supervised or unsupervised classification techniques. Pixel-based approaches include: a) Random forest algorithm (Tatsumi et al., 2015; Wang et al., 2015; Gislason et al, 2006); (b) Support vector machines (Mountrakis et al., 2011; Shao and Lunetta, 2012); (c) decision tree algorithms (Ozdogan and Gutman, 2008; Waldner et al., 2016); (d) Tassel cap brightness-greenness-wetness (Cohen and Goward, 2004; Gutman et al., 2008; Masek et al., 2006); (e) Spectral matching techniques (Gumma et al., 2014; Thenkabail et al., 2007; Teluguntla et al., 2017a); (f) Phenological approaches (Pan et al., 2015; Teluguntla et al. 2015a; Zhong et al., 2016; Zhou et al., 2016); (g) the Automated Cropland Classification Algorithms (Thenkabail and Wu, 2012; Teluguntla et al., 2017a; Waldner et al., 2015); and (h) Machine learning programming involving a combination of multiple methods (DeFries and Chan, 2000; Duro et al., 2012; Pantazi et al., 2016). Object-based approaches (Peña-Barragán et al., 2011; Peña et al., 2014) include Hierarchical Image Segmentation software or HSeG (Tilton et al., 2012). A combination of pixel-based and object-based methods have also been recently attempted (Xiong et al., 2017a; Chen et al., 2018). However, these methods and approaches were overwhelmingly applied on: (a) multi-temporal moderate resolution (250-m or higher) remotely sensed data, and/or (b) small areas, and/or (c) high-resolution (Landsat 30-m) remotely sensed data with limited multi-temporal images.

Hitherto, availability of cloud-free, high quality images as well as use of multi-temporal, high-resolution data over very large areas for cropland mapping has been challenging and resource intensive. However, these challenges have been overcome through a paradigm shift in remote sensing data collection, management, and processing. First, Landsat-8 Operational Land Imager (OLI) data and Landsat-7 Enhanced Thematic Mapper + (ETM +) data at 30-m spatial resolution were utilized every 16-days for 3-years (2013–2015) for entire Australia and China. Managing massive volumes of Landsat data for analysis over very large areas is a big challenge when adopting traditional remote sensing approaches that use commercial imaging processing software on workstation PC based systems. No matter how powerful the systems are, the entire process of data analysis including, pre-processing, over very large areas involving 1000's of Landsat images is cumbersome, slow, and tedious. However, in the current era of adopting powerful machine learning algorithms (MLAs) in cloud computing environments such as Google Earth Engine (GEE) these limitations have been overcome allowing planetary scale remote sensing at high spatial resolutions as illustrated by Erickson (2014) and Gorelick et al. (2017). Gorelick et al. (2017) demonstrated that multi-petabyte archive of georeferenced datasets can be combined in the GEE catalog that includes images from Earth observing satellites and airborne sensors (e.g., USGS Landsat, NASA MODIS, USDA NASS CDL), weather and climate datasets, as well as digital elevation models. This system has exceptional data organization, and has enabled geo spatial processing over very large areas. Along with computing and storage resources, GEE also supports major MLAs useful for image enhancement and, image classification, and allows batch processing through JavaScript or Python on Application Program Interfaces (APIs). These capabilities reduce most of preprocessing steps needed in traditional remote sensing approaches. Very recently, several studies have used the GEE platform for large-scale (continental, global) mapping (Xiong et al., 2017a, 2017b).

Thereby, the overarching goal of this study was to map cropland extent in detail (e.g., showing all individual farms whether small or big) using high-resolution (30-m) multi-year (2013–2015) time-series (16-day) Landsat-8 OLI data over the entirety of China and Australia. These two countries have very large cropland areas with distinct cropping systems. Australia is a major agriculture producer and exporter with large scale industrial farm fields. Pastoral farming is another major agricultural land use in Australia. Australian farmers produce cereals, legumes and oilseeds on a large scale (ABARES, 2016) for human consumption and livestock feed. In contrast, an overwhelming proportion of Chinese farms are small, fragmented, but often contiguous over large areas due to intensive land use for agriculture. Average crop field size in China is less than a hectare (Samberg et al., 2016); fine resolution satellite data is required to map such crop fields. Landsat data with 30-m spatial resolution is ideal dataset to map cropland extent in China. Whereas the average crop field size in Australia is 100 ha (Samberg et al., 2016) which is much larger than most crop fields in China. Medium resolution sensor such as MODIS at 250-m (1 pixel is approximately 6.25 ha) are highly inadequate to map smaller and/or fragmented crop fields. High-resolution 30-m (1 pixel is approximately 0.09 ha) Landsat-8 OLI 30-m imagery is expected to map small and fragmented farms in addition to large farms. Chinese farmlands are also very diverse, spread across mountains, river banks, and large plains. China's agriculture feeds 1.38 billion people whereas Australia's much smaller population allows it to be a major exporter of food. China is the