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Mapping spatiotemporal dynamics of maize in China from 2005 to 2017 through designing leaf moisture based indicator from Normalized Multi-band Drought Index

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ABSTRACT

Maize agriculture is experiencing substantial changes in the spatiotemporal pattern of planting areas in the most populous country-China. However, there is no spatially explicit and continuous information at national scale. Mapping maize at national scale is challenging due to intra-class variability of Vegetation Indices (VIs) temporal profile. This study coped with this challenge through combined utilizations of the EVI with two bands (EVI2) and Normalized Multi-band Drought Index (NMDI) time series datasets. A novel **M**aize mapping algorithm was proposed through **E**xploring **L**eaf moisture variation during flowering **S**tage (**MELS**). An indicator, the Ratio of Cumulative Positive slope to Negative slope (*RCPN*) during flowering stage, was developed based on NMDI and utilized as the unique metric for maize mapping. The capability of the MELS method was verified using the 8-day composite MODerate resolution Imaging Spectroradiometer (MODIS) datasets in China from 2005 to 2017. The derived maize map was consistent with the agricultural census data (r^2 = 0.8875 in 2015) and 2020 ground truth observations (overall accuracy = 91.49%). Validation with Landsat-interpreted images in the test regions further confirmed its fairly good accuracy, with overall accuracy of 87.91% and kappa coefficient of 0.8577. We first generated annual maize maps from 2005 to 2017 in China. Maize planting areas increased continuously 100,130 km^2 (by 33.20%) during the period 2005–2015 and decreased 10,424 km^2 (by 2.60%) from 2015 to 2017. The increase of cropping intensity, replacement of paddy rice and other non-maize dryland crops areas accounted for 36.48%, 34.23% and 29.29% of the dramatic increased maize areas from 2005 to 2015, respectively.

1. Introduction

Maize is considered globally as the most important grain for both human beings and livestock (Ngie et al., 2014; Tan et al., 2014). Updated information on crop area mapping can provide important scientific evidence to estimate agricultural production and plan for food security (Ngie et al., 2014; Song et al., 2017; Tan et al., 2014; Zhang et al., 2014). Despite of the increasing availability of global land cover products, more specific information on crop type is still limited over large areas (Dong et al., 2015; Song et al., 2017). Considerable mapping studies have been conducted on primary crops such as paddy rice (Dong et al., 2016; Xiao et al., 2005), wheat (Pan et al., 2012; Qiu et al., 2017c; Sun et al., 2012), and maize (Tang et al., 2018; Yu and Shang, 2017; Zhang et al., 2014). Compared with mapping land cover, identification of agricultural crops is much more challenging due to the high diversity of agricultural planting structure (Dong and Xiao, 2016; Tang et al., 2018; Wardlow et al., 2007; Zhang et al., 2017, 2014). More studies should be explored to provide additional information on specific crops to enrich land-cover data (Sun et al., 2012).

The phenology-based algorithms were promising in estimating crops areas compared with other traditional methods based on individual or multiple images (Qin et al., 2015; Wang et al., 2017). The commonly applied phenology-based algorithm was based on the original time-series of vegetation indices such as the Normalized Difference Vegetation Index (NDVI) or Enhanced Vegetation Index (EVI) (Lunetta et al., 2010; Wardlow and Egbert, 2008). This phenology-based algorithm depends on the assumption that each specific crop has a unique phenology reflected in its corresponding temporal profiles of vegetation indices (Pan et al., 2012).

Mapping crop type is much more challenging than land use theme

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(King et al., 2017). Challenges in proposing efficient crop mapping methods based on vegetation indices temporal profiles existed in two aspects: the similarities in vegetation indices temporal profiles between different agricultural crops, and the intra-class variability in vegetation indices temporal profiles for specific crop (Qiu et al., 2017c). The major challenge was the intra-class variability of vegetation indices temporal profiles (Lunetta et al., 2010; Peña and Brenning, 2015; Qiu et al., 2015, 2016a; Wardlow et al., 2007). There were at least three typical groups of intra-class variability of VIs temporal profiles (Qiu et al., 2016c): shifted ones due to phenology shift, intensified/lessened ones owing to site-specific conditions such as fertility, water condition and farming practice, and even more complex variations due to complexity of crop calendars, natural conditions, and tillage management (Lunetta et al., 2010; Peña and Brenning, 2015; Qiu et al., 2015; Wardlow et al., 2007). Therefore, it is extremely difficult to develop efficient methods to extract each crop across large regions simply applying the vegetation indices temporal profiles.

Several strategies have been put forward in order to cope with these challenges. The first strategy is to apply a shifted standard EVI time series based on crop calendar (Zhang et al., 2014). The second strategy is to incorporate auxiliary conditions such as temperature and rainfall data (Howard et al., 2012; Zhang et al., 2015). For example, the land surface temperature data was successfully utilized to determine the temporal window of rice transplantation in order to improve phenology-based rice mapping method (Zhang et al., 2015). The third strategy is to explore unique signals of selected targets on specific time and frequency (Qiu et al., 2017c, 2014; Zhang et al., 2013; Zhong et al., 2016). For example, a winter wheat mapping method was developed through combining variations before and after estimated heading dates (Qiu et al., 2017c). The forth strategy is to combine NDVI/EVI with other spectral indicators (Dong et al., 2015; Qiu et al., 2015; Xiao et al., 2005). For example, a rice mapping method was proposed through developing combined indicator based on EVI and Land Surface Water Index (LSWI) (normalized difference in Near-infrared band and short wave infrared band) (Qiu et al., 2015).

These strategies proved to be efficient in phenology-based crop mapping, particularly integrated applications of these strategies. E.g. the strategy of focusing on key phenological stages and incorporating multiple spectral indices/bands besides vegetation indices (Qiu et al., 2017c; Wang et al., 2017; Zhang et al., 2013). Up to date, the primary input variables of the phenology-based methods were NDVI/EVI time series (Wang et al., 2017). There existed great opportunities when multiple remote sensing indices were combined to address the challenges by the intra-class variability of vegetation indices. A combination of multiple indices might substantially improve the estimations of site-level phenology (Tornos et al., 2015).

Spectral indices sensible to water irrigation (land surface water index, LSWI) have long been successfully utilized in deriving paddy rice fields through combing with the vegetation indices (Dong et al., 2015; Qiu et al., 2015; Xiao et al., 2005). These improved phenology-based methods provided great insights for estimating specific crop areas. However, compared with NDVI/EVI/EVI2 and its combinations with LSWI (Dong et al., 2015; Qiu et al., 2015; Xiao et al., 2005), other spectral indices were rarely exploited. Compared with paddy rice that required transplanting and an inundation environment, there is no uniqueness phenomena in dryland crops (e.g. maize, bean) cultivation which could be utilized for identification. In addition, since maize is widely distributed at large scale and even in different elevations, the complexity introduced by its diverse crop phenology and planting structure should be incorporated in maize mapping.

Maize has been major crop in China since the early 20th century (Zhang et al., 2014). Some recent research efforts have been drawn on maize mapping based on vegetation indices (de la Casa et al., 2014; Jiang et al., 2016; Yao et al., 2015; Yu and Shang, 2017; Zhang et al., 2014). The established literature has made significant contributions to dryland crops mapping research community (Tang et al., 2018; Yu and Shang, 2017; Zhang et al., 2014). Despite of these progresses, the challenges by the VIs intra-class variability have not been efficiently accounted for yet (Foerster et al., 2012; Gumma et al., 2015; Liu et al., 2012; Yan and Roy, 2014). Strategy for dealing with the VIs intra-class variability of maize was limited to relief the shifted vegetation phenology across different areas (Zhang et al., 2014). These maize mapping studies primarily focused on province or regional scale (i.e. Hetao Irrigation District, Northeast China). Ranking as the second major maize production country, there is no national-scale spatiotemporal explicit and continuous information on maize planting area information in China during the past few decades (Tan et al., 2014).

The objective of this study is two folds: (1) to develop a novel Maize mapping algorithm by Exploring Leaf moisture variation during flowering Stage (MELS) which could be applied to large areas; (2) to obtain maize distribution maps and explore the spatiotemporal changes in China from 2005 to 2017 based on the proposed MELS method. The MELS algorithm was developed through designing a novel leaf moisture based indicator from Normalized Multi-band Drought Index (NMDI) (Wangle and Qu, 2007). The flowering stage which reflected the prominent features of different agricultural crops was considered with references to EVI2 temporal profiles. Variations of leaf moisture conditions were quantified by NMDI. One indicator was designed through highlighting the leaf moisture increase during the flowering stage compared with other dryland crops.

2. Study area and data source

2.1. Study area

China presents a complex environment for crop mapping due to its diversity of cropping intensity and cultivation habits across the mainland area (Li et al., 2014). The cropping intensity gradually increases from one in Northern China to two or three in Southern China (Qiu et al., 2017b). Rice, wheat and maize were the three major agricultural crops in China. Compared to other major crops such as paddy rice (Dong et al., 2016; Qiu et al., 2016b) and winter wheat (Qiu et al., 2017c), maize is more widely distributed across the whole country such as in Northeast China, Inner Mongolia and Ningxia provinces (spring maize), North China plain (summer maize), mountain regions in Southwest China and hilly areas in the south China (http://www.stats.gov.cn/english/) (Fig. 1). There is high diversity of maize phenology and its planting structure (Zhang et al., 2014). There are primarily single cropping pattern of spring maize, double cropping patterns of summer maize plus other crops (e.g. winter wheat).

2.2. Datasets

2.2.1. The MODIS EVI2 and NMDI time series datasets

The 500 m 8 day composite MODIS surface reflectance products from 2005 to 2017 were applied. The MOD09A1, a collection 6 products of level 3, has been applied the procedures of atmospheric/radiometric corrections, which were downloaded from https://ladsweb.nascom.nasa.gov/. Two spectral indices were calculated: the 2-band Enhanced Vegetation Index (EVI2) and Normalized Multi-band Drought Index (NMDI). The EVI2 was computed by the surface reflectance values from red and near infrared red bands (Eq. (1)) (Jiang et al., 2008). The NMDI was computed based on the near infrared band, and two short waves infrared (Eq. (2)) (Wangle and Qu, 2007).

$$\mathrm{EVI2} = 2.5 \times (\rho_{NIR} - \rho_{\mathrm{Red}})/(\rho_{NIR} + 2.4 \times \rho_{\mathrm{Red}} + 1) \tag{1}$$

$$NMDI = \frac{\rho_{NIR} - (\rho_{SWIR6} - \rho_{SWIR7})}{\rho_{NIR} + (\rho_{SWIR6} - \rho_{SWIR7})} \tag{2}$$

where ρ_{NIR}, ρ_{Red}, ρ_{SWIR6} and ρ_{SWIR7} represented the surface reflectance values from the Near-infrared (841–875 nm), red (620–670 nm), short wave infrared band centered at 1640 nm (1628–1652 nm) and 2130 nm