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Developing an integrated indicator for monitoring maize growth condition using remotely sensed vegetation temperature condition index and leaf area index

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ABSTRACT

Early and accurate assessment of maize growth is important for national food security. To improve the accuracy of maize growth monitoring in the central plain of Hebei Province, PR China, multiple growth-related factors, including water stress and vegetation coverage, should be comprehensively considered. This study derived the ten-day vegetation temperature condition index (VTCI) and leaf area index (LAI) from the first ten days of July to the third ten-day of September during 2010–2017 from MODIS data. Then, the grey relational analysis (GRA) method and analytic hierarchy process (AHP) were used to determine the weight coefficients of the VTCI and LAI at four maize growth stages (the emergence-jointing, jointing-booting, booting-filling and filling-mature stages). Thus, an integrated maize growth monitoring index (*G*) was formulated for maize growth estimation at the main growth stage. Linear regression models between maize yields and *G* values for counties in five cities of the Hebei Plain from 2010 to 2015 were constructed to verify and analyze the precision of maize growth monitoring. The weight coefficients of the VTCI and LAI varied at the four growth stages. In Cangzhou City, the LAI weight coefficient at the jointing-booting stage was the highest, followed by the VTCI at the booting-filling stage, indicating that maize growth conditions and yields were highly correlated with vegetation coverage at the jointing-booting stage and that maize growth was most sensitive to water stress at the booting-filling stage. Linear regression models between *G* values and maize yields for the counties in the five cities all passed the significance test at the 0.01 level. Moreover, the correlation between *G* values and maize yields was closer than that between maize yields and VTCI or LAI alone and illustrated a high accuracy of the integrated maize monitoring results derived from the synthetic approach combining the two indices. According to the maize growth monitoring results, from 2010 to 2017, the best year regarding maize growth conditions was 2011, and the worst year was 2014. Growth in the northwestern plain was better than that in the other regions.

1. Introduction

Accurate and timely regional crop growth monitoring and early estimations of crop yield greatly benefit agricultural planning and policy making. In the past several decades, the application of remote sensing technology for crop growth monitoring has been studied extensively (Doraiswamy et al., 2004; Khanal et al., 2017). Many vegetation indices derived from remotely sensed data are used to estimate or forecast crop growth conditions and production.

A particularly useful index for crop growth monitoring has been the normalized difference vegetation index (NDVI). Esquerdo et al. (2011) used the advanced very high-resolution radiometer (AVHRR) NDVI time series data for soybean crop monitoring in Brazil and showed that the temporal profiles of NDVI described the crop biomass condition well and explained a major part of the crop yield variability in eighteen cities. Ren et al. (2008) estimated winter wheat yield with a MODIS-NDVI-based model at a regional scale, and the accuracy of the predicted yields was significantly better than those provided by agro-climate models. Wu et al. (2014) mapped the spatial and temporal heterogeneity of crop conditions at national and global scales based on multi-year comparison of NDVI curves. Aside from the NDVI, methods for applying the enhanced vegetation index (EVI), the leaf area index (LAI) and net primary productivity (NPP) were proposed for evaluating crop growth conditions and grain yield in previous studies (Zhang and

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Zhang, 2016; Sakamoto et al., 2013; Wang et al., 2018).

Crop conditions and production are affected by various factors (e.g., temperature, soil moisture, management strategies). Crop growth monitoring models based on two or more growth-related variables provide improved precision of growth and yield estimations (Xie et al., 2017; Ines et al., 2013). Among these variables, the VTCI is an effective approach for monitoring water stress during the crop growing season. Sun et al. (2008) compared the linear correlations between the VTCI and soil moisture in the 0–10 cm layer and showed that the VTCI indicated drought more effectively than indices developed from precipitation data. Peng et al. (2016) calculated the VTCI from MODIS and developed a downscaling method to estimate soil moisture (SM) status, and they found that the downscaled SM maintained high accuracy and presented greater spatial detail. Han et al. (2010) forecasted drought on the Guanzhong Plain, China, using the ARIMA model and VTCI time series data to increase modeling accuracy. Additionally, the LAI can be employed to monitor crop growth as a key indicator of vegetation photosynthetic rate in agriculture (Xie et al., 2017). Clevers and van Leeuwen (1996) proposed the LAI as the essential link between remote sensing techniques and crop growth models and computed and simulated the daily growth rate and dry production from emergence to maturity. Fang et al. (2008) predicted the maize yield in Indiana, USA, using the LAI simulated by a crop model, and the estimated yield compared reasonably well with the data from the National Agricultural Statistical Service (NASS). The integration of crop growth information reflected by the VTCI and LAI may be a promising approach for improving monitoring accuracy for crop growth and production.

Crop conditions and yields are comprehensive results of changes in multiple factors, such as water stress, during all phenological stages. The impacts of different factors vary at different crop growing stages (Li et al., 2014; Dente et al., 2008). Li et al. (2014) determined the weight coefficients of drought impact at four winter wheat growing stages using a normalized combination approach for the improved AHP and variation coefficient method. The results showed that winter wheat was most sensitive to water stress at the elongation stage, followed by the heading-filling stage. Dente et al. (2008) investigated the sensitivity of the assimilation process to the acquisition time of the Advanced Synthetic Aperture Radar (ASAR) and MEdium-spectral Resolution Imaging Spectrometer (MERIS) LAI data and found that the LAI after the heading stage was not as important as the LAI at the stem elongation and heading stages when determining the final yield. Esquerdo et al. (2011) compared linear regressions between the municipal yields and the quantitative parameters measured from the profiles based on a full-time or partial phenological cycle, and their results showed that the most significant correlation occurred when the entire time period was considered. Therefore, the comprehensive crop growth conditions at the main growth period can be obtained through the combination of useful information reflected by indices (e.g., VTCI and LAI) derived from multi-temporal remote sensing data.

In this work, the main maize growth period, i.e., from the first ten days of July to the last ten days of September, was divided into four growth and development stages: the emergence-jointing, jointing-booting, booting-filling and filling-mature stages. The aim of this study was to establish a new integrated maize growth monitoring index (*G*) that comprehensively considers water stress and vegetation growth status. Thus, the VTCI and LAI were selected as indicators of maize growing conditions and production potential. Appropriate weights were assigned to the VTCI and LAI at different maize growing stages using grey relational analysis (GRA) and the analytic hierarchy process (AHP). Then, the spatiotemporal characteristics of maize growth were evaluated in the years from 2010 to 2017, and monitoring accuracy was assessed based on linear correlations between the integrated growth monitoring indices and maize yields recorded in the provincial yearbooks.

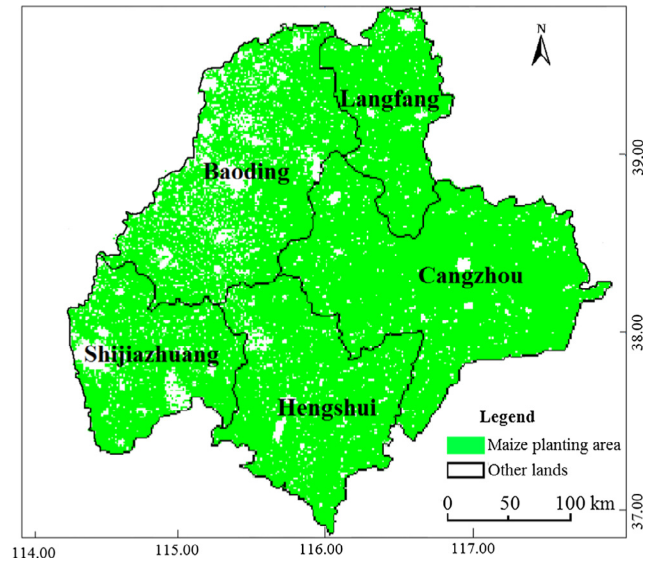

Fig. 1. Location of the study area and map of the crops.

2. Study area and data

2.1. Study area

The study area is located in central Hebei Province, China, with coordinates of 36°57′N to 39°50′N and 114°32′E to 117°36′E (Fig. 1). Its total area is 53,000 km^2, covering 5 cities, including Baoding, Shijiazhuang, Cangzhou, Hengshui, and Langfang. The area is very suitable for planting crops, and its prevailing planting pattern is an intensive double cropping system of winter wheat and summer maize (Pan et al., 2012). The region has a continental monsoon climate and is mainly located in the arid/semiarid area of the mid-temperature zone and in the humid/sub-humid area of the warm temperature zone (Meng et al., 2016). An uneven annual precipitation spatial distribution decreases from 800 mm in the south to 400 mm in the northern part of the study area, with the average annual temperature ranging from 4 °C to 13 °C. Crop growth in this area is subjected to drought and floods because of the deficiency and inhomogeneity of precipitation.

In this study, the maize growing stages for the years from 2010 to 2017 were analyzed. According to the official statistical data, cropping seasons showed different meteorological conditions, leading to different maize growing conditions and yield levels. Due to the well-distributed precipitation, maize growth in 2011 was significantly improved compared to normal years. However, the average maize yields in 2014 were the lowest since the drought was longer than the maximum duration of the corresponding period in history. The region is part of the largest maize production area. The planting system, climatic and phenological characteristics of this region are typical of the primary maize production bases. The establishment of a new maize growth monitoring approach for this region could provide information on growing conditions and production throughout China's main maize cropping area.

2.2. Remotely sensed VTCI

The VTCI was developed to monitor drought at a regional level with the assumption that the shapes of the LST and NDVI scatter plots are triangular. The time series of the VTCI calculated using MODIS indicates the spatiotemporal characteristic of water stress and has been widely applied to monitor near-real-time drought conditions (Sun et al., 2008; Wan et al., 2004; Patel et al., 2012). The VTCI was defined as follows: