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Assessing the remotely sensed Drought Severity Index for agricultural drought monitoring and impact analysis in North China

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ABSTRACT

Remote sensing can provide real-time and dynamic information for terrestrial ecosystems, facilitating effective drought monitoring. A recently proposed remotely sensed Drought Severity Index (DSI), integrating both vegetation condition and evapotranspiration information, shows considerable potential for drought monitoring at the global scale. However, there has been little research on regional DSI applications, especially concerning agricultural drought. As the most important winter wheat producing region in China, North China has suffered from frequent droughts in recent years, demonstrating high demand for efficient agricultural drought monitoring and drought impact analyses. In this paper, the capability of the MODIS DSI for agricultural drought monitoring was evaluated and the drought impacts on winter wheat yield were assessed for 5 provinces in North China. First, the MODIS DSI was compared with precipitation and soil moisture at the province level to examine its capability for characterizing moisture status. Then specifically for agricultural drought monitoring, the MODIS DSI was evaluated against agricultural drought severity at the province level. The impacts of agricultural drought on winter wheat yield during the main growing season were also explored using 8-day MODIS DSI data. Overall, the MODIS DSI is generally effective for characterizing moisture conditions at the province level, with varying ability during the main winter wheat growing season and the best relationship observed in April during the jointing and booting stages. The MODIS DSI agrees well with agricultural drought severity at the province level, with better performance in rainfed-dominated than irrigation-dominated regions. Drought shows varying impacts on winter wheat yield at different stages of the main growing season, with the most significant impacts found during the heading and grain-filling stages, which could be used as the key alert period for effective agricultural drought monitoring.

1. Introduction

Drought is a common and recurring event for all climatic regimes, both dry and humid. Of all natural hazards, drought is the most complex and least understood, affecting large numbers of people and resulting in significant economic, social and environmental impacts (Wilhite, 2005). According to the International Disaster Database, the number of drought occurrences makes up only 5% of all natural disasters; however, drought results in 30% of the total people affected, ranking the top among all natural disasters (http://www.emdat.be/). With global warming and the frequent occurrence of extreme events, concerns about global drought and its impacts have become more pronounced in recent years (Dai, 2011), drawing increasing attention from governments, scientists and the public. Agriculture is the major sector to be affected by drought. Although the overall agricultural production has risen in recent years, agricultural drought constitutes the primary cause of crop failure, resulting in global food price instability and threatening global food security (World Bank, 2012). This calls for further study of agricultural drought and its impacts on crop production.

Most standard drought indices require precipitation data as a primary input (Wilhite, 2000), and many meteorological drought indicators have been developed, such as the Percentage of Normal Precipitation (NDMC, http://www.drought.unl.edu/), Percentage of Precipitation Anomaly (Zhang et al., 2009), Deciles Index (Gibbs and Maher, 1967), Palmer Drought Severity Index (PDSI, Palmer, 1965) and Standardized Precipitation Index (SPI, McKee et al., 1993). While near real-time and high-quality precipitation data are available in some regions, many parts of the world lack sufficient

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rain-gauge networks, which influences the accuracy of drought indictors derived from meteorological data and presents significant challenges for global agricultural drought monitoring (Anderson et al., 2011). Drought can cause a decline in vegetation vigor which is detectable by remote sensing (Tucker, 1979). Satellite observations overcome some limitations of station-based meteorological observations, providing potential for cost-effective, spatially explicit and dynamic large-scale drought monitoring. The use of time-series satellite observations for drought monitoring began in the 1980s using AVHRR NDVI data (Tucker et al., 1986; Tucker and Choudhury, 1987; Tucker, 1989). Since then, many remotely sensed indicators have been developed based on vegetation conditions, surface temperature, combinations of vegetation conditions and surface temperature. Among those indicators, NDVI-based metrics are commonly used as indicators of vegetation stress and drought (Henricksen and Durkin, 1986; Tucker and Choudhury, 1987; Tucker, 1989; Gutman, 1990). Many drought indicators have been developed based on NDVI, such as Anomaly Vegetation Index (AVI) (Chen et al., 1994), Vegetation Condition Index (VCI) (Kogan, 1990, 1995a, 1995b; Liu and Kogan, 1996), Standardized Vegetation Index (SVI) (Peters et al., 2002), Monthly Vegetation Condition Index (MVCI) (McVicar and Jupp, 1998), and the Percent of Average Seasonal Greenness (PASG) (Brown et al., 2008). Also, land surface temperature (LST) data can provide vital information on evapotranspiration and vegetation water stress (Goward and Hope, 1989; Carlson et al., 1990; Nemani et al., 1993) and can be used as an indicator of surface moisture status. To remove the effect of seasonal temperature variations, McVicar and Jupp (1998) developed the Normalized Difference Temperature Index (NDTI) and Kogan (1995a) developed the Temperature Condition Index (TCI) for drought monitoring based on LST. Several indicators based on combinations of vegetation indices and temperature have also been developed, such as the Vegetation Health Index (VHI) (Kogan, 1995a), Temperature Vegetation Index (TVI) (McVicar and Jupp, 1998), Vegetation Supply Water Index (VSWI) (McVicar and Jupp, 1998) and Temperature Vegetation Drought Index (TVDI) (Sandholt et al., 2002). While these indicators prove very useful for drought monitoring, they also have their limitations. Usually, there is a varying time lag between a drought event and vegetation response, which thus limits the responsiveness of vegetation condition derived indices for drought monitoring (Ji and Peters, 2003), and also NDVI alone cannot fully represent the drought information (Saleska et al., 2007; Atkinson et al., 2011; Morton et al., 2014). In addition, missing data, for example in LST products due to cloud contamination (Williamson et al., 2013), can also impact their capability for continuously effective drought monitoring.

As a key component of the terrestrial water and energy cycle, evapotranspiration (ET) represents an important constraint on water availability, which thus is a more direct and effective parameter for describing ecosystem moisture status as compared to meteorological drought indices (Anderson et al., 2011), vegetation condition and LST derived indicators. Remote sensing has been recognized as the most feasible and cost-effective approach to provide spatially explicit ET information across terrestrial ecosystems (Jackson, 1984). In recent years, there has been an increasing trend of using ET for drought monitoring (Anderson et al., 2007, 2011, 2013; Choi et al., 2013; Otkin et al., 2013). The Evaporative Stress Index (ESI) has been developed for drought monitoring by Anderson et al. (2007, 2011), quantifying anomalies in the ratio of actual to potential ET (PET). Using inputs from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS), Mu et al. (2007, 2011) developed a model to estimate ET and PET, and produced the global MOD16 ET product at 8-day, monthly and annual intervals. Insufficient moisture limits the available water that vegetation can absorb and is frequently the leading cause of reduced photosynthetic capacity when large areas exhibit persistent vegetation stress. Utilizing surface ET information while taking into account vegetation response at the same time, a new remotely sensed drought index, Drought Severity Index (DSI), was recently proposed, integrating ET, PET and NDVI based on the MOD16 ET product (Mu et al., 2007, 2011) and the MOD13 NDVI (Huete et al., 2002) product. The DSI shows considerable potential for drought monitoring at the global scale (Mu et al., 2013a).

Agricultural production, especially in poor areas, remains highly dependent on weather conditions. The rapidly changing climate during the past decades has undoubtedly resulted in significant impacts on agricultural production. According to a global scale study on climate change and crop productivity, as of 2002, global warming since 1981 has led to a combined loss of roughly 40 Mt or $5 billion for wheat, maize and barley per year (Lobell and Field, 2007). Another more recent study shows that global maize and wheat production, respectively, declined by 3.8% and 5.5%, as compared to the case without climate trends (Lobell et al., 2011b). In addition to global studies, there is a growing body of regional impact research. In Sub-Saharan Africa, climate change has robust negative impacts on agriculture (Schlenker and Lobell, 2010). Lobell et al. (2011a) discovered that, with a 1 °C increase in temperature, about 65% of African maize growing regions would experience yield losses under well-irrigated conditions versus 100% under drought conditions. In Wisconsin, each additional degree higher than normal temperature in summer will decrease the corn and soybean yields by 13% and 16%, respectively, while a modest increase in summer precipitation would boost the production by 5–10% (Kucharik and Serbin, 2008). In the central US, a drought impact study from 1995 to 2012 demonstrated that maize yields became more sensitive to drought associated with high vapor pressure deficiency (Lobell et al., 2014). With the exacerbated climate warming and irregularity of precipitation in the future, the drought issue and associated impacts will become even more pronounced. The agricultural areas suffering from high and very high agricultural drought hazard account for approximately 23.57% and 27.19% of the global agricultural areas, most of which are located within the major crop producing regions in China, Europe, Southeast Asia, U.S. and South America (Geng et al., 2015). Another recent study on global drought impacts on agriculture demonstrates that, despite the inconsistency between the magnitude of crop failure and that of drought severity, the historical severe droughts in five drought-prone countries (Brazil, Peru, Spain, Iran and China) have caused significant crop loss (Maize/Rice/Wheat/Soybean/Barley/Sorghum) (Wang et al., 2014). Also, at the regional scale, despite varying drought impacts across different regions, crop types and time periods, severe droughts are also found to be linked with significant crop yield reduction in Czech (Hlavinka et al., 2009), Midwest U.S. (Mishra and Cherkauer, 2010), Ghana (Antwi-Agyei et al., 2012), Eastern Sahel (Elagib, 2014) and China (Hu et al., 2014; Qin et al., 2014; Ming et al., 2015).

The direct impacts of drought on agriculture involve the reduction in crop production and the drought impacts on crops are often investigated through crop simulation modeling. Crop growth models are eco-physiological models which simulate the plant behavior under different conditions and output the simulated crop production as well as various parameters (leaf area index, evapotranspiration, soil moisture and biomass) during crop growth (Huth et al., 2008; Huang et al., 2015a, 2015b, 2016). These models incorporate the impacts of changing weather conditions and improved technology & management practices on crop yields (Sivakumar et al., 2011), and thus can be used to simulate the response of crop yields to drought. Up to now, there has been some work on drought and its agricultural impacts based on crop growth models (Bryant et al., 1992; Song and Dong, 2006; Jia et al., 2011; Yu et al., 2014). Most existing crop models can be successfully used for simulating crop development process at the field scale; however,