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Monitoring winter wheat drought threat in Northern China using multiple climate-based drought indices and soil moisture during 2000–2013

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ABSTRACT

Increasing drought poses a big threat to food security over recent decades, highlighting the need for effective tools and adequate information for drought monitoring and mitigation. This study analyzed the performance of five climate-based drought indices and soil moisture measurements for monitoring winter wheat drought threat in China. We employed the Standardized Precipitation Index (SPI), the Standardized Precipitation Evapotranspiration Index (SPEI), the Palmer Drought Severity Index (PDSI), the Palmer Z index and the self-calibrated Palmer Drought Severity Index (scPDSI). On average, soil moisture at 50-cm depth correlated better with winter wheat yield during October-December of the previous year of harvest compared to soil moisture at 10-cm and 20-cm depths. Moreover, the 3-layer soil moisture and reference evapotranspiration (ETo) correlated weakly (Pearson's $r < 0.3$) and even negatively with winter wheat yield. The SPI and SPEI at shorter (1–5 months) timescales during September-December in the previous year of harvest showed higher correlations with winter wheat yield. The SPEI trend in March-June has a significant positive influence on trend in winter wheat yield ($r > 0.40$, $p < 0.05$). The climate-based drought indices can facilitate crop drought monitoring in water-limited regions due to the wide-availability of climatic data, particularly in the light of uncertainties arising from the crop model. Among the investigated indices, results revealed that the SPEI is advantageous for drought monitoring over the study area due to its multiscalarity and effective characterization of agricultural droughts.

1. Introduction

Based on observational and model data, numerous studies have demonstrated an increase in the frequency and intensity of droughts (Dai, 2013), which implies a growing threat to food security. As such, a wide range of studies has assessed the possible impacts of drought on agriculture in many regions worldwide (e.g., Ledger et al., 2012; Simelton et al., 2012). Given that agriculture in China feeds about 22% of the world's population, depending only on 7% – 8% of its arable land, food security in China is an urgent issue in the context of climate change. Over China, droughts have become more frequent and intense during the last decades, which presents a direct threat to crop growth in vast areas across the country (Dalin et al., 2015; Piao et al., 2010; Wang et al., 2011). Accordingly, there is an urgent demand for effective monitoring of crop droughts, especially in areas of limited water resources.

Crop models that account for multiple climatic data, in addition to crop, soil and management parameters, can enhance current understanding of crop response to climate variations (Brisson et al., 2003; Osborne and Wheeler, 2013 Rosenzweig et al., 2014Shuai et al., 2015). However, the applicability of crop models may largely be constrained by possible uncertainties originating from the ambiguity of some input parameters and/or the initial conditions of the

Abbreviations: SPI, standardized precipitation index; SPEI, standardized precipitation evapotranspiration index; PDSI, palmer drought severity index; scPDSI, self-calibrated palmer drought severity index; AWC, available water capacity; ETo, reference evapotranspiration.

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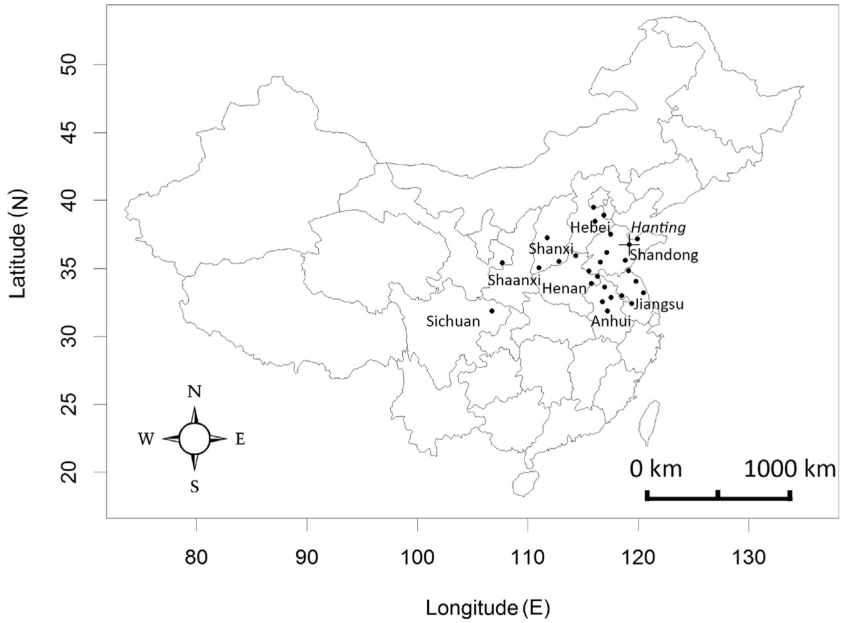

Fig. 1. Spatial distribution of the 27 agrometeorological stations in Northern China. Hanting station, which corresponds to Figs. 2 and 7, is labeled with a cross sign. The names of the administrative provinces that include stations are also provided.

model (Dorigo et al., 2007; Huang et al., 2015; Lobell et al., 2006 Rosenzweig et al., 2014). Moreover, the calibration of crop models from in-situ measurements is time consuming and takes much effort, as a consequence of the large variations of the measured parameters from one site to another (Wit et al., 2012; Iizumi et al., 2009). In China, the main form of the agricultural land tenure is the "household responsibility system", which yields many small croplands, with diverse individual cropping and management systems, compared to those of the industrialized agriculture (Krusekopf and Krusekopf, 2002). These arable lands are prone to the complex influences of drought as well as anthropogenic practices (e.g., fertilization and crop management). Accordingly, there are almost gaps in field measurements, which add more difficulties to the comparison of the outputs of the crop models and the applicability of these models for monitoring droughts in China.

In view of lacking detailed field measurements, visible, infrared and microwave remote sensing can contribute significantly to crop drought monitoring. In this regard, multiple remotely sensed drought indices have already been developed, including the vegetation condition index (Kogan, 1990), the temperature condition index (Kogan, 1995), the vegetation health index (Kogan, 1997), the temperature vegetation dryness index (Sandholt et al., 2002) and the microwave integrated drought index (Zhang and Jia, 2013). These indices can reflect crop water stress or surface soil moisture at a high spatiotemporal resolution. However, uncertainties can be introduced in space-based products, limiting their application for drought assessment and monitoring. These uncertainties can be associated with various aspects, such as atmospheric conditions (King et al., 1992; Li et al., 2009b), data acquisition (Biggar et al., 1994; Leeuwen et al., 2006) or data processing (Pal and Mather, 2005; Toutin, 2004).

Water availability is one of the main environmental constraints for crop development, as water shortage can induce a reduction of crop yield and even crop failure (Kang et al., 2002; Zwart and Bastiaanssen, 2004). Drought is a complex phenomenon, with several environmental, agricultural, hydrological and socioeconomic implications (Boken et al., 2005; Dracup et al., 1980; Quiring and Ganesh, 2010; Tallaksen and Lanen, 2004). Agricultural drought is usually associated with crop reduction or failure, as induced by the shortage of soil moisture for a period of time. However, soil moisture observations are often irregular over space and time, which makes it difficult to define appropriate thresholds to characterize crop failure, especially in regions with different cultivation types or climates. Although agricultural droughts are difficult to monitor, they usually have a climate origin. In particular, the decreased rainfall and the increased atmospheric evaporative demand can result in a depletion of water content in the soil and thus an increase in water stress for plants (Meze-Hausken, 2004; Oladipo, 1985).

The strong dependency between climate and droughts makes it possible to develop climate-based drought indices, particularly in regions where climate observations are available while soil moisture measurements are unevenly distributed. Previous studies have proven that climate-based drought indices have great potential for characterizing agricultural impacts associated with droughts (e.g., Quiring and Papakryiakou, 2003; Vicente-Serrano et al., 2012, 2006). Thus, monitoring drought using climate-based drought indices can contribute significantly to drought mitigation at the agricultural level (Keyantash and Dracup, 2002; Svoboda et al., 2002). There are numerous studies, which employed climate-based drought indices for assessment and monitoring of crop drought. A representative example is Yamoah et al. (2000) who used the Standardized Precipitation Index (SPI) for crop yield monitoring and assessment in the Great Plains, USA. More recently, Potopová et al. (2015) employed the Standardized Precipitation Evapotranspiration Index (SPEI) to assess drought severity over Moldova. Other drought indices were also used for assessing agricultural droughts in many regions worldwide (e.g., Akinremi et al., 2009; Hlavinka et al., 2009; Li et al., 2009a; Tunalıoğlu and Durdu, 2011).

Assessing spatiotemporal changes in drought based on gridded precipitation products has shown divergent results in many regions worldwide (Bindoff et al., 2012; Dai, 2013; Sheffield et al., 2012). This feature is particularly due to uncertainties introduced in the gauge-based gridded products, which can be a consequence of the selected interpolation algorithm, data density or data assimilation scheme (Trenberth et al., 2013). In contrast, drought assessment based on in situ data demonstrates that there is a statistically significant drying trend since 1950s in most parts of China (Yu et al.,