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

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\textbf{ARTICLE INFO}

\textbf{Article history:}
Received 17 November 2015
Received in revised form 5 April 2016
Accepted 5 June 2016
Available online 29 June 2016

\textbf{Keywords:}
Agricultural drought threat
Drought indices
Soil moisture
Winter wheat

\textbf{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 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 (ET\textsubscript{o}) correlated weakly (Pearson’s \textit{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 (\textit{r} > 0.40, \textit{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.

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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 (Dalín 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
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; Lizumi 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., 2005b), 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., 2015, 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 Yamooah 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; Tunaliolu 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.,

![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.](image-url)
These changes often correspond to a reduction in the yield of the major crops (Tao et al., 2003; Zhang et al., 2014). China is one of the leading countries in terms of wheat production (FAO, 2012). Winter wheat is mainly distributed over Northern China, accounting for almost 85% of summer grain production in China. As wheat growth and yield are limited by water availability, it is necessary to understand the response of winter wheat production to drought occurrence in Northern China.

This study aims at analyzing the potential impacts of climate and soil moisture variability on winter wheat yield in China. In particular, we assess the performance of five climate-based drought indices for winter wheat drought monitoring in China during the period 2000–2013. Given that studies investigating different climate-based drought indices and soil moisture data for monitoring winter wheat drought are few over China, this research can not only facilitate water management for the agricultural sector in China, but it can also provide a solid base for improving current modeling efforts of future winter wheat growth and yield.

2. Data and methods

2.1. Data

In order to calculate the different drought indices, we used monthly mean daily maximum temperature (mean of maximum temperature in every single day within a month), monthly mean daily minimum temperature, monthly total sunshine hours, monthly mean daily wind speed at 10-m height, and monthly mean relative humidity. The data were provided by the Chinese meteorological sharing service system (http://cdc.nmic.cn/home.do) for 752 weather stations spanning the period from 1981 to 2013. Climatic data have already been tested for the presence of errors. Gaps have also been defined and completed by means of the linear interpolation using data from nearby observations.

Soil moisture and winter wheat yield observations were obtained from the agrometeorological stations run by the Chinese Meteorological Agency. The data were obtained for the crop-growing season during the period 2000–2013 (Fig. 1). Metadata
reveals that soil observations were collected from wheat fields at different depths (10, 20 and 25 cm) for three days (the 8th, 18th and 28th) per each month. Then, soil moisture analysis was undertaken in the lab using the oven drying method. In this work, we averaged the daily observations of each month to get the monthly observation. To account for the spatial consistency between climate observations and soil moisture measurements, we selected the nearest weather stations to each of the 27 soil moisture sites, using a threshold of 0.5° from each site. Following this procedure, we obtained 27 pairs of agrometeorological-climatic stations. The rationale behind this procedure was to guarantee that climate data recorded at the selected weather stations adequately coincide with local soil moisture conditions. The winter wheat calendar during 2012–2013 at Hanting station (Fig. 1) includes: sowing in early October, tillering in late October, green up in early March, jointing in middle April, heading in early May and ripening in early June.

Available Water Capacity (AWC) defined as the difference between field capacity and wilting point is required for the calculation of PDSI and scPDSI. In this study, AWC for each agrometeorological station within 1-m depth was obtained from the International Geosphere-Biosphere Programme- Data and Information Systems (IGBP-DIS) (http://daac.ornl.gov/cgi-bin/dsviewer.pl?dsid=569), at a regular grid spacing of 5 by 5 arc minutes.

2.2. Drought indices

There are basically two categories of climate-based drought indices: the first is based on soil-water balance, while the other considers climate data and their probabilistic calculations. The most widely used drought indices that account for soil-water balance are the Palmer Drought Severity Index (PDSI) and the Z index (Palmer, 1965). Based on the PDSI, the self-calibrating Palmer

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Fig. 3. 10-cm soil moisture as indicator of winter wheat yield. Panels (a)–(i) show the correlation analysis between winter wheat yield and soil moisture at 10-cm depth for each month in October–December in the previous year of harvest and January–June in the harvest year, respectively. Due to the limited number of effective soil moisture observations for some stations, soil moisture stations with less than 8 observations for a given month during 2000–2013 are not labeled. The size of grey circles is represented as a function of the value of the correlation coefficient. The cross sign for a station denotes the negative correlation. Winter wheat yield and soil moisture time series were detrended.
Drought Severity Index (scPDSI) was also developed to allow for comparison among regions with highly variable drought conditions \cite{Wells2014}. According to the definitions given in equations 3, 4 and 18 in \cite{Wells2014}, the PDSI and scPDSI of a given month can represent an accumulation of drought over the previous few months while Z index has no inherent memory from the previous months. PDSI has widely been used for drought monitoring during the past few decades and being proven as an effective tool for depicting drought duration and intensity at both regional and global scales \cite{Alley1984, Dai2011, Dai1998, Trenberth2013}. Nonetheless, the applicability of PDSI and scPDSI is often constrained by their fixed timescales. To overcome this shortcoming, probabilistic drought indices, such as the SPI \cite{McKee1993} and the SPEI \cite{Vicente-Serrano2010}, have been developed. The SPI and SPEI define the wetness and dryness periods using either the statistical probability of occurrence for the precipitation or the balance between precipitation and potential evapotranspiration. These indices have commonly been used for drought monitoring, due to their simplicity and possible calculation at different timescales \cite{Begueria2014, Gutman1998}.

Apart from the SPI, all drought indices employed in this work incorporate the atmospheric evaporative demand via estimation of the reference evapotranspiration (ETo). Accordingly, the effective calculation of ETo is important for drought monitoring. The standard method for calculating ETo is the FAO-56 Penman-Monteith equation \cite{Allen1998}, which combines the aerodynamic and radiative components using different climate variables measured at weather stations (e.g., temperature, wind speed, humidity and solar radiation). Previous studies have proven that atmospheric water demand in China is driven not only by the dynamics in the average temperature, but it is mostly controlled by changes in other climatic factors involved in the aerodynamic (e.g., wind speed and relative humidity) and radiative (e.g., solar radiation) components \cite{McVicar2012}.

The FAO-56 Penman-Monteith equation is expressed as,

\[ ETo = \frac{0.408 \Delta (R_n - G) + \gamma \frac{900}{T} \mu_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34 \mu_2)} \]  \hspace{1cm} (1)

where ETo is the reference evapotranspiration (mm day\(^{-1}\)), \(R_n\) is the net radiation at the crop surface (MJ m\(^{-2}\) day\(^{-1}\)), \(G\) is the soil heat flux density (MJ m\(^{-2}\) day\(^{-1}\)), \(T\) is the mean air temperature at 2-m height (°C), \(u_2\) is the wind speed at 2-m height (m s\(^{-1}\)), \(e_s\) is the saturation vapor pressure (kPa), \(e_a\) is the actual vapor pressure (kPa), \(e_s - e_a\) is the saturation vapor pressure deficit (kPa), \(\Delta\) is the slope of the vapor pressure curve (kPa °C\(^{-1}\)) and \(\gamma\) is the psychrometric constant (kPa °C\(^{-1}\)). The reference surface is a hypothetical grass reference crop with an assumed height of 0.12 m, a mixed surface resistance of 70 sm\(^{-1}\) and an albedo of 0.23. In our calculations, monthly average of net solar radiation was estimated using the monthly averages of daily sunshine hours, given close agreement between sunshine duration and surface shortwave radiation \cite{Azorin-Molina2015}. Here, it should be noted that the monthly mean wind speed (\(U\)) was converted before calculation from 10-m to 2-m height (i.e., from \(U_{10}\) to \(U_2\), respectively). This conversion was made following the equation: \(U_2 = 4.87U_{10}/\ln(67.8(10 - 5.42))\).

In this study, the calculation of the SPI and SPEI was made using the ‘SPEI’ package developed within R platform \cite{Begueria2014}, and obtained at times scales varying from 1 to 12 months. The Z index, PDSI and scPDSI were calculated with C++ using a modified code of \cite{Wells2014}. In particular, we replaced the potential evapotranspiration from Thornthwaite method with ETo from Penman-Monteith method.
3. Results

3.1. Correlation between winter wheat yield and soil moisture

In Fig. 2, we compare the observed soil moisture at 10-cm depth with five drought indices at Hanting station in Shandong province, Northern China. Results indicate that fluctuations in the SPI, SPEI and Z index at shorter time scales (i.e., 2 months) were similar during May over the period 2000–2013. Also, the temporal evolution of the PDSI and scPDSI concurred with each other. This finding can be expected given that these two indices represent droughts at longer timescales. As depicted in Fig. 2, the evolution of the PDSI and scPDSI showed low intra-annual and inter-annual variations. The 2-month SPI explained larger amount of soil moisture variance at the chosen station ($p < 0.01$), compared to other drought indices. As noted in Fig. 2(f), we found large differences between potential evapotranspiration calculated using the Penman-Monteith method and that of the Thornthwaite method. For the majority of stations, the SPI and SPEI at shorter timescales (i.e., 1–3 months) showed a similar temporal variability to Z index. These three drought indices exhibited a higher correlation with surface soil moisture, relative to the PDSI and scPDSI.

As illustrated in Fig. 3, the response of winter wheat yield to soil moisture differed from one month to another, a generally weak influence of soil moisture on wheat yield for many stations in different months ($r < 0.3$). Fig. 4(a–c) indicates that soil moisture in October–June mainly showed a positive correlation with winter wheat yield. Fig. 4(d–f) reveals that winter wheat yield exhibited
Fig. 6. The best timescale of drought that characterizes the soil moisture at 10-cm depth. Panels (a)-(i) show the timescales of the SPEI that had the highest correlation with soil moisture at 10-cm depth for each month in October-December in the previous year of harvest and January-June in the harvest year, respectively. The color at different stations represents the timescale of the SPEI that had the highest correlation with 10-cm soil moisture. Due to the limited number of effective soil moisture observations for some stations, soil moisture stations with less than 8 observations for a given month during 2000–2013 were not labeled.

Fig. 7 shows that soil moisture at 50-cm depth was strongly impacted by droughts of longer timescales, compared to soil moisture at the surface (i.e., 10-cm and 20-cm depths). As depicted in
Fig. 7. The timescales of the SPEI that can better characterize soil moisture at different depths. Panels (a)–(c) denote the mean timescales from October to June for 10-cm, 20-cm, and 50-cm depths, respectively. Panels (d)–(f) are boxplots of timescales from October to June for 10-cm, 20-cm, and 50-cm depths, respectively.

Fig. 8. Temporal influences of drought on winter wheat yield. Contour plot of correlation between winter wheat yield and the SPI for (a) Hanting station and (d) the 27-station median, winter wheat yield and the SPEI for (b) Hanting station and (e) the 27-station median. Temporal correlation curves between winter wheat yield and drought indices from two-layer bucket model (Z, PDSI, scPDSI) from July in the previous year of harvest to June in the harvest year for (c) Hanting station and (f) the 27-station median. Time series of winter wheat yield and drought indices were detrended.
3.4. Drought indices as indicators of winter wheat yield

Fig. 8(a–c) suggests that shorter timescale (<6 months) of drought in September–February and longer timescale of drought in March–June (>6 months) in Hanting station had higher correlations with winter wheat yield. The SPI and SPEI at a 5-month temporal scale in January showed the best association with winter wheat yield. The Z index in the period from October to January, PDSI in January and scPDSI in June also showed high correlations with winter wheat yield. The multiscalar drought indices (i.e., the SPI and SPEI) achieved better correlations with winter wheat yield than the Z index, PDSI and scPDSI. Fig. 8(d and e) reveals that the median status of the correlation contour plot was similar to the chosen individual station (Fig. 8(a and b)). The SPI and SPEI with shorter timescales (1–5 months) in September–December in the previous year of harvest exhibited a higher correlation with winter wheat yield. Fig. 8(f) suggests that the Z index in September, PDSI and scPDSI in June contribute significantly to variations in winter wheat yield. Both the individual station and the 27-station median agree that the SPI and SPEI showed the highest correlation with winter wheat yield than other climate-based drought indices. Fig. 9 confirms this finding, indicating that the SPI and SPEI had higher absolute correlations with winter wheat yield than the Z, PDSI and scPDSI in most stations. The SPI and SPEI, the PDSI and scPDSI had similar correlations with winter wheat yield.

3.5. The influence of recent drought trend on winter wheat yield trend

Our results indicate that drought conditions in September–December of the previous year of harvest can influence winter wheat yield more than drought conditions during January–June period of the harvest year. Whereas, the month by month analysis suggested that the SPEI trend in March–June during the harvest year showed a statistically significant positive (p < 0.05) association with winter wheat yield for the selected 27 stations (Fig. 10).

4. Discussion

Recent studies have indicated that different gauge- or model-based gridded climatic datasets can influence ETo calculations (Trenberth et al., 2013; Wang et al., 2014a). Over China, a range of studies has also discussed the uncertainties associated with precipitation and soil moisture data derived from interpolated climatic grids (Zhao andCongbin, 2006), reanalysis data (Li et al., 2005) and space-based data (Han et al., 2015). Alternatively, this study employs in situ climatic data to accurately assess soil moisture and drought indices, as indicators of winter wheat drought threat in Northern China.

Winter wheat yield can be impacted by vertical variations as well as seasonal changes of soil moisture. This study reveals that 50-cm soil moisture tends to influence winter wheat yield more than soil moisture at 10-cm and 20-cm depths. This response can probably be attributed to the memory effect of soil in deeper layers (Wang et al., 2015). More specifically, droughts at longer timescales can affect soil moisture in deeper layers more than in the surface layers. The low influence by evapotranspiration and smaller water
mobility in deeper soil layer compared to that in the surface soil layers are key factors for maintaining adequate water supply of winter wheat at 50-cm soil depth. This work also demonstrates that soil moisture in the months preceding winter wheat harvest (i.e., October–December) showed relatively higher correlations with wheat yield than soil moisture in other months. This finding can be explained by the notion that soil moisture in March–June period, which is the winter wheat fast growing period after dormancy in winter, can be influenced easily by droughts of longer timescales. As such, soil moisture conditions associated with winter wheat field can partially be determined by soil moisture during autumn and winter in the previous year. Earlier work confirmed this finding, suggesting that water conditions a few months prior to the harvest could contribute significantly to crop yield (Austin et al., 1998; Vicente-Serrano et al., 2012; Vicente-Serrano et al., 2006).

Soil moisture and ETo are two key indicators for agricultural drought monitoring (Narasimhan and Srinivasan, 2005; Zhang et al., 2004). Previous studies have confirmed the complex interactions between soil moisture and evapotranspiration in cultivated areas (Anothai et al., 2013; Wetzel and Chang, 1987). Our study demonstrates that 50-cm soil moisture in October–December showed a stronger association with winter wheat yield than 10-cm and 20-cm soil moisture. This finding may be related to the fact that the relatively higher soil moisture at 50-cm depth in previous year can meet winter wheat water demand in the fast growing period of the harvest year, particularly when the surface layers suffer from water shortage. In June, soil moisture at 10-cm depth correlated better with winter wheat yield, compared to soil moisture at deeper depths. This finding can be related to the surface water shortage caused by higher ETo and accordingly the lower soil moisture at 10-cm layer during this month. Overall, winter wheat yield variations over Northern China are sensitive to a wide range of factors, including: soil moisture and ETo conditions, soil depths and timescales of drought. As such, any crop model should account for the possible influences of these factors on winter wheat yield in the region. Our findings can enhance current understanding of the impacts of climatic change on winter wheat yield in China, which benefits a wide range of disciplines (e.g., agriculture, ecology, meteorology etc).

Our findings suggest that climate-based drought indices can reflect winter wheat drought conditions during the growing season and thus enhance agricultural drought monitoring over the study region. With the availability of climate data, drought indices can significantly contribute to assessment of crop drought threat, especially in the presence of sparse soil moisture observations and/or ambiguity of crop model outputs. Thus, climate-based drought indices can provide a solid base for crop disaster monitoring in agricultural lands (Piao et al., 2010; Potop, 2011; Wang et al., 2014b). Given their consideration of the changing timescale of drought,
the multiscalar drought indices (e.g., SPI and SPEI) perform better than drought indices that rely on two-layer bucket model (e.g., the PDSI). Previous studies have confirmed the usefulness of multiscalar drought indices for agricultural drought monitoring (e.g., Sims et al., 2002; Wang et al., 2015). Nonetheless, our findings suggest that the SPEI can achieve better correlation for both individual station observation and stations median than the SPI. This finding concurs with earlier works, which suggest a superior performance of the SPEI over other drought indices for monitoring ecological, hydrological and agricultural droughts in many regions (e.g., McEvoy et al., 2012; Scaini et al., 2014; Törnros and Menzel, 2013; Vicente-Serrano et al., 2012). Taken together, the SPEI can be recommended for winter wheat drought monitoring in Northern China. However, the optimum timescale for SPEI varies from one site to another. Therefore, further investigation to determine the most appropriate timescale for each particular region in China is needed.

Despite their advantages for agricultural drought monitoring, particular attention has to be paid when using climate-based drought indices as indicators for winter wheat yield. This is because variations in wheat yield can also be linked to some anthropogenic forces, such as irrigation, fertilization etc. (Brisson et al., 2003; Lobell et al., 2011). Hlavinka et al. (2009) found that the Z index can only explain 51% of winter wheat yield variations in Czech republic. Our study mainly assesses the performance of climate-based drought indices and soil moisture in monitoring winter wheat drought. As such, further research can be made using other crop types, which are prone to drought threat. This investigation can be applied at a small cropland scale in China, allowing for a detailed assessment of the effectiveness of drought indices for monitoring agricultural droughts.

5. Conclusion

To assess changes in winter wheat drought over Northern China, this study employed five climate-based drought indices: the SPI, SPEI, Z index, PDSI and scPDSI, besides soil moisture observations. Overall, the investigated drought indicators perform well in monitoring winter wheat drought threat in the study domain. Some conclusions can be drawn from our research.

i Soil moisture at 50-cm depth showed better correlations with winter wheat yield during the growing season (October-June), compared to 10-cm and 20-cm soil moisture. In addition, soil moisture at 50-cm depth was largely influenced by droughts at longer timescales, with respect to soil moisture at lower depths.

ii Soil moisture at 0–50 cm depth positively influenced winter wheat yield during October and November of the preceding year of harvest, while ET0 negatively influenced winter wheat yield in the same period. A similar response was also found between soil moisture in surface layers (i.e., 10-cm and 20-cm) and ET0 during June of harvest year.

iii Climate-based drought indices are advantageous when climatic observations are reasonably distributed over space and time, providing valuable information for winter wheat drought monitoring and assessment. Over Northern China, the SPI and SPEI calculated at shorter timescales (i.e., 1–5 months) in the previous year of harvest showed stronger influence on winter wheat yield. These indices can achieve higher correlations with winter wheat yield than other drought indices (e.g., PDSI and scPDSI). Nonetheless, The SPEI can achieve the highest correlation with winter wheat yield than other climate-based drought indices. The SPEI trend in March-June has significant positive influence on winter wheat yield trend ($r > 0.4$, $p < 0.05$).

Acknowledgements

The authors are grateful for station-based climatic data, soil moisture and winter wheat yield data by Data Sharing Infrastructure of China Meteorology Agency. The research was funded by the National Sci-Tech Support Plan (2012BADB0B00103): the development of agricultural disaster warning information system and network by the 863 Project (2013AA10230103): remote sensing of crop information with satellites and ground observations. The authors acknowledge Dr. Santiago Begueria and Dr. Steve Goddard for their help with calculation of drought indices. Thank Mr Craig C. Dremann for his help in language check.

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