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ORIGINAL PAPER

Assessment of agricultural drought in rainfed cereal production areas of northern China

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Abstract Agricultural drought assessment is an important tool for water management in water-scarce regions such as Inner Mongolia and northeastern China. Conventional methods have difficulty of clarifying long-term influences of drought on regional agricultural production. To accurately evaluate regional agricultural drought, we assessed the performance of drought indices by constructing a new assessment framework with three components: crop model calibration and validation, drought index calculation, and index assessment (standard period setting, mean value and agreement assessments). The Environmental Policy Integrated Climate (EPIC) model simulated well of county-level wheat and maize yields in the nine investigated counties. We calculated a major crop-specific index yield reduction caused by water stress (WSYR) in the EPIC crop model, by relating potential and rainfed yields. Using 26 agricultural drought cases, we compared WSYR with two meteorological drought indices: precipitation (P) and aridity index (AI). The results showed that WSYR had greater agreement (85 %) than either the precipitation (65 %) or aridity index (68 %). The temporal trend of the indices over the period 1962–2010 was tested using three approaches. The result via WSYR revealed a significant increase in the trend of agricultural drought in drought-prone counties, which could not be shown by the precipitation and aridity indices. Total number of dry year via WSYR from 1990s to 2000s increases more sharply than via P or AI. As shown by WSYR, the number of dry years in northeastern China and Inner Mongolia is generally increasing, particularly after the 2000s, in the western part of the study area. The study reveals the usefulness of the framework for drought index assessment and indicates the potential of WSYR and possible drought cases for drought classification.

1 Introduction

Drought poses a threat to agriculture, food security, and regional economies in semiarid marginal areas such as Inner Mongolia and northeastern China. The 1980s drought in Ethiopia and Sudan was one of the most devastating natural disasters in human history. In recent history, one of the worst droughts in China was during 2010–2011. Based on evidence from yearly and 5-year average drought indices such as the Palmer Drought Severity Index, Ma and Fu (2006) showed that the frequency of extreme drought has been increasing in the eastern part of northwestern China, central part of northern China, and northeastern China since the 1980s.

Drought impacts on societies are assessed with reference to four drought processes: meteorological, agricultural, hydrological, and socioeconomic. Agricultural drought directly affects household and national food security because it is a period in which insufficient rainfalls or when soil moisture decreases sufficiently to cause water stress in crops. This leads to yield reduction, possibly even crop failure (Agnew and Anderson 1992). In this paper, we therefore defined agricultural drought (hereafter referred to as drought) as an event in which soil moisture is insufficient to support normal crop production, owing to lack of precipitation. Drought indexing may be useful to depict drought impact on regional

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agricultural production. For example, Quiring and Papakyriakou (2003) compared the performance of four drought monitoring indices to predict spring wheat yields in the Canadian prairies. Kogan et al. (2005) modeled maize yields in China using a drought index based on remote-sensing data. However, these indices do not directly measure yield loss. Compared with actual yield, the reduction of potential yield by drought is more meaningful because of its close relationship with reduced water consumption by crops (Doorenbos and Kassam 1979; Sastri et al. 1982).

To classify agricultural drought, long-term reductions of crop yield are widely used as thresholds, e.g., decreases of more than 10 % from mean yields (McQuigg et al. 1973; Wilhite and Neild 1981). This has recently been improved using reductions of potential yield not less than the difference between the mean and standard deviation (Zhao et al. 2011). However, the threshold of agricultural drought may be influenced by the probability distribution of long-term crop yield data. Previous studies showed great variation in yield distribution. For example, Day (1965) studied experimental cotton, corn, and oat yields, finding right skewness in cotton and corn yields and left skewness in oat yields in the Mississippi Delta. Chen and Miranda (2008) also showed right skewness in county-scale cotton yields in Texas. However, Atwood et al. (2002) indicated left skewness for farm and regional yields of barley (Montana and North Dakota), corn and soybean (Illinois and Indiana), cotton (Georgia and Texas), sorghum (Texas), and wheat (Montana and Kansas). Conventional measurement methods have certain disadvantages. For a specific location, the use of different period lengths for depicting the distribution may influence the identification of typical or reduced yields caused by drought. Data of short-term yield observations often lead to incorrect descriptions of the distribution, and longer periods of yield data are also problematic because of technology innovation, such as crop improvement. A suitable reference period length used for the threshold determination must be selected. The identification of drought depends on the interested party (Palmer 1965). Drought cases according to a weather department of the government more or less reflect a consensus of regional agricultural drought and may be used to provide a basis for agreement assessment. Therefore, in this paper, we build a systematic framework to assess agricultural drought.

Crop models are useful for investigating potential yield and yield reduction by constraints such as water and nutrient stresses because they simulate underlying physiological processes of crop growth and development. There are models capable of simulating yields of different types of crops, e.g., the Environmental Policy Integrated Climate (EPIC) (Williams et al. 1989), Decision Support System for Agrotechnology Transfer (DSSAT) (IBSNAT 1989), WOrld FOod STudies (WOFOST) (de Wit 1965), and Agricultural Production Systems sIMulator (APSIM) (McCown et al.

1996), are used to evaluate crop performance at regional scale (e.g., Liu et al. 2007; Jia et al. 2011). Among a number of crop models, EPIC has been widely adopted in China. For example, Wang et al. (2013) successfully used the model to estimate wheat yield observations from agrometeorological stations across China. In Northern China, Li et al. (2004) and Wang et al. (2011) successfully used the model to estimate winter wheat, spring maize, alfalfa, and potato yields and soil moisture at a field scale on the Loess Plateau. Liu et al. (2007) and Jia et al. (2011) demonstrated that at a regional scale, the model fit well the spatial pattern of winter wheat and summer maize yields in 2001 on the North China Plain. These studies suggest that the suitability of EPIC for exploring long-term agricultural drought intensity in northern China.

The principal aim of the present study was to propose a new framework to assess long-term agricultural drought and to demonstrate its validity, based on a case study in northern China. The specific objectives of the study were to (1) verify the validity of the EPIC model at county-level census yield data; (2) verify the advantage of an index of yield reduction caused by water stress (WSYR) over meteorological drought indices in agricultural drought assessment; and (3) show the validity of the framework in a long-term agricultural drought assessment, based on a case study for the period 1962 to 2010.

2 Materials and methods

2.1 Description of study area

Northern China experiences several climatic conditions, and hence, dominant crop types vary between these conditions. Three provinces in northeastern China (Heilongjiang, Jilin, and Liaoning) and Inner Mongolia Autonomous Region are typical rainfed regions for maize and spring wheat production. We selected four wheat-growing counties (Hailar, Eerguna, Duolun, and Siziwang) and five maize-growing counties (Hailun, Nong'an, Changtu, Zhalute, and Dongsheng) as samples to evaluate agricultural drought (Table 1). In general, flowering stages, i.e., spring wheat heading and maize tasseling, start from late June to early July and mid to late July, respectively (Zhang et al. 1987). Spring wheat and maize are harvested in August and September, respectively. Total non-irrigated areas of Hailar, Eerguna, Duolun, and Siziwang are large, all greater than 90 % in 1996. Hailun, Nong'an, Changtu, and Zhalute counties are on the plain between the Great Khingan Mountains and Changbai Mountains (China's golden maize belt). Dongsheng is a representative maize belt region on the Ordos Plateau, south of the Yinshan Mountains, where water resources are limited. The total non-irrigated, maize-growing areas are large, e.g., more than 75 % in 1996.

Average growing-season temperatures (1971–2000) in the four wheat-growing counties were from 15 to 16 °C,

Table 1 General information on crops and soils in nine counties of northern China

| County	Main crop type	Cropping calendar[a]	Main soil texture[b]
Siziwang (SZW)	Spring wheat	15 April to 5 August	Sandy loam
Hailar (HLR)	Spring wheat	1 May to 20 August	Sandy loam
Eerguna (ERGN)	Spring wheat	1 May to 20 August	Sandy loam
Duolun (DL)	Spring wheat	1 May to 1 August	Loamy sand
Zhalute (ZHLT)	Maize	15 May to 30 September	Loam
Dongsheng (DSH)	Maize	1 May to 25 September	Clay loam
Nong'an (NA)	Maize	28 April to 25 September	Loam
Changtu (CHT)	Maize	10 April to 25 September	Loam
Hailun (HL)	Maize	1 May to 30 September	Loamy sand

[a] Sowing and harvest dates were obtained from the Chinese agricultural phenology atlas (Zhang et al. 1987) and the Chinese National Agriculture Web site (http://www.xn121.com/)

[b] Main soil texture was determined from FAO soil map (http://www.iiasa.ac.at/Research/LUC/External-World-soil-database/)

colder than the five maize-growing counties (17–21 °C). Annual precipitation of the study area increases from less than 100 mm in the west to more than 600 mm in the east, spanning several aridity zones (Fig. 1). To the west of Siziwang and Dongsheng, there is an arid zone (ratio of multi-year precipitation to potential evapotranspiration (aridity index) < 0.2) where no farming is possible without irrigation (FAO 1989). In contrast, the eastern part of northeastern China is rich in irrigation resources (Gan and Liu 2005). Therefore, the selected counties cover the full range of rainfed regions in northeastern China and Inner Mongolia.
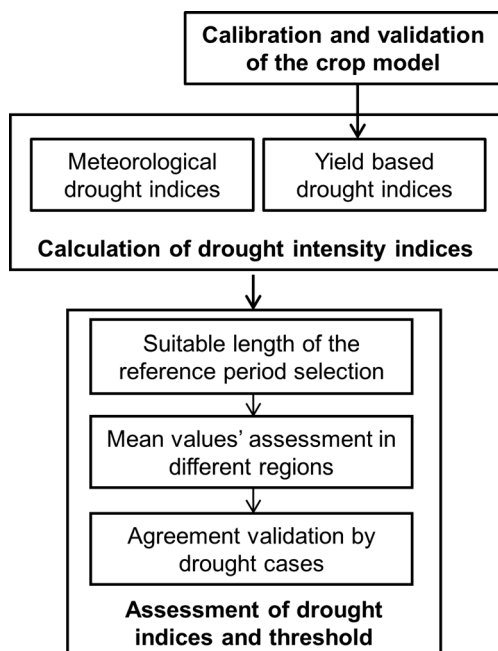
2.2 Agricultural drought assessment framework

To quantitatively assess the agricultural drought index, a new assessment framework with three main parts is proposed (Fig. 2). We calculated and compared a yield-based drought index simulated by a validated crop model and several typical meteorological drought indices. Drought is a temporary feature in the context of climate (WMO 1975). The threshold and drought indices were assessed together, via selection of suitable period length of climate, mean assessment, and agreement validation. Standard period setting must consider standard climate-normal and crop growth years used in model
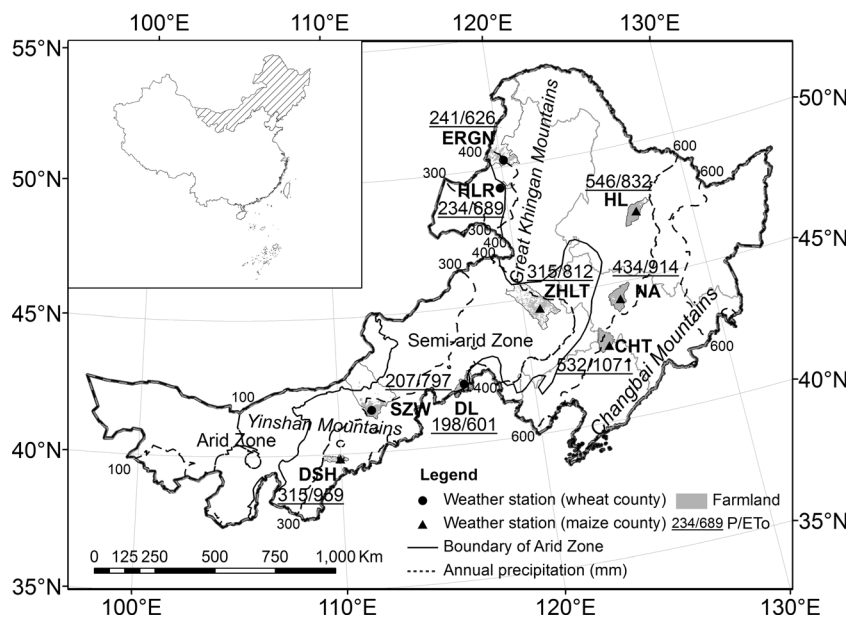
Fig. 1 Locations of nine representative counties in northeastern China and Inner Mongolia Autonomous Region that are dominated by rainfed agriculture. County names: *CHT* Changtu, *DL* Duolun, *DSH* Dongsheng, *ERGN* Eerguna, *HLR* Hailar, *HL* Hailun, *NA* Nong'an, *SZW* Siziwang, *ZHLT* Zhalute. *P/ETo* ratio of precipitation during the growing season to potential evapotranspiration. Annual precipitation isohyet extrapolated from a multiyear average precipitation dataset from the Institute of Agricultural Resources and Regional Planning (IARRP 1999). Aridity zones were extracted from FAO global map of aridity (1961 to 1990; http://www.fao.org/geonetwork/srv/en/metadata.show?id=37040)

**Calibration and validation
of the crop model**

Meteorological drought indices	Yield based drought indices

Calculation of drought intensity indices

Suitable length of the reference period selection

Mean values' assessment in different regions

Agreement validation by drought cases

Assessment of drought indices and threshold

Fig. 2 Methodological framework for agricultural drought assessment in this study

validation. The mean value as a threshold was assessed by comparing their percentiles. The drought indices and thresholds were validated using agricultural drought cases from the literatures.

2.3 Model calibration and validation

We used the WinEPIC6.0 model (http://epicapex.tamu.edu/downloads/model-executables/winepic-6-0/) to simulate yield. The EPIC model is capable of simulating 114 different crop types based on the use of unique parameter values for each crop and therefore represents a useful tool to simulate the impacts of drought in regions with heterogeneous growth and cultivation conditions. This is important because when drought impacts are spread over a large geographic area (Wilhite 1993), multiple crop types must typically be assessed.

WinEPIC6.0 is a user-friendly interface for the EPIC crop simulation model. Model input includes weather and soil data and parameters for field operations, crops, pesticides, and fertilizers. Model output includes daily, monthly, and yearly soil organic C and N, crop stress, soil water, and crop yield (Williams et al. 1989). After preparing input data as a Microsoft Access database file, the model was run for the study areas.

Dry yields were simulated for 6 years (1996–2001) for the eight counties and 15 years for Hailar county (1996–2010). We used default crop parameters for the wheat crop. For maize, the biomass energy ratio (i.e., WA parameter) was changed from 43 to 40 based on model calibration in northern

China by Wang et al. (2011). To analyze long-term (1996–2010) dry yield, Hailar County was selected for its relatively satisfactory continuous data. The Penman–Monteith equation (Monteith 1977) was selected to estimate potential evapotranspiration. Assuming that fertilizer is rationally used, N, P and K fertilizer data were entered as maximum amounts, and the model's "automatic" fertilizer option was used. When fertilizer supply cannot satisfy the demand, the fertilizer is triggered and applied. We assumed that if the model was able to precisely simulate the time series of county-level yield for all nine counties, it would also adequately reflect the impact of drought.

2.4 Drought index assessment and framework validation

The EPIC model was run for the period 1960–2010 based on four assumptions: (1) taking a "no drought" irrigation regime as every 2-day irrigation, to increase soil moisture to field capacity; (2) no soil nutrient deficiencies; (3) the same background soil moisture levels before comparison of rainfed and normally irrigated treatments; and (4) 2 years (1960 and 1961) to spin up the model for balancing the water environment. We found that the difference between simulated yields for a specific year can be ignored when using the 2-year spin up. Starting in 1962, based on 49 years of data on crop growth under rainfed conditions, we applied the full irrigation schedule for individual years from 1962 to 2010 to test the effects of drought in those years. We wrote a program in IDL version 7.0 (Interactive Data Language; http://www.exelisvis.com/) to continually update the input files and run the EPIC model.

Yield loss from drought was estimated as the yield difference between the full irrigation and rainfed scenarios. To quantify the yield loss in percentage, WSYR was calculated as

$$\text{WSYR} = \frac{YI - YR}{YI} \times 100 \tag{1}$$

where YI is the yield under fully irrigated conditions and YR the yield under rainfed conditions.

We selected precipitation (P) and aridity index (AI) as two typical meteorological drought indices. Precipitation during the growth period for each county was calculated. The AI was used to quantify the degree of water stress during the growth period (FAO 1989; UNEP 1992):

$$\text{AI} = \frac{P}{PET} \tag{2}$$

where P is precipitation (mm) and PET is potential evapotranspiration (mm).

The standard World Meteorological Organization climate normal refers to mean values for a period of 30 consecutive years and is updated once per decade (Arguez and Vose 2011). Meteorological data ranges from 1971 to 2000 from

individual stations in the world are more complete and relatively stable (WMO 2011). Given that the range of actual yield data used for validation of the EPIC model was from 1996 to 2001, 1971–2000 was chosen as the standard period.

We compared quantiles and mean values of WSYR in the nine counties and determined the standard threshold for drought intensity. In the *Yearly Charts of Dryness/Wetness in China for the Last 500-year Period* (CIMS 1981), the frequency of normal years is 30–40 %, and two grades of dryness years and of wetness years make up 30–40 % each. For the quantile classes, we assumed that for a given county, the probabilities of recurrence of a WSYR value for wet, normal, and dry years would all be 1/3 for the 30 reference years. Linear interpolation between closest points was used to determine percentiles of means and drought cases of WSYR. To compare two meteorological indices (P and AI) with WSYR, percent agreement of total numbers of drought cases from two sources

was calculated, and the best index was selected with a suitable threshold. The influence of water balance background on the identified threshold was analyzed using the multi-year AI. For validation of the agricultural drought framework, we compared trends of WSYR, P and AI and their frequencies of decadal dry years.

2.5 Data sources and collection

Meteorological data Daily meteorological data from 1960 to 2010 for the nine counties, including precipitation, maximum and minimum temperatures, relative humidity, wind speed, and sunshine hours, were obtained from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/). Solar radiation was estimated from sunshine hours (Angström 1956).

Table 2 Agricultural drought cases in nine counties of northern China

County	Year	Description of county-level drought condition
Siziwang	1968	Drought caused seedling emergence difficulty on some farmland (Shen 2008)
	1970	Summer drought caused dry soil layers to 33-cm depth and field crops wilted or died in some cropland (Shen 2008)
	1977	Drought caused hollow kernels during crop-heading and grain-filling period in autumn harvest cropland (Shen 2008)
	1978	Seldom-seen serious drought, causing great damage to agricultural production (Shen 2008)
	1982	Serious crop wilting and death on some cropland (Shen 2008)
	1983	Siziwang and other counties in Ulanqab City suffered serious drought and greatly reduced grain production (Shen 2008)
Hailar	1986	State farms suffered extreme drought, almost no crop harvest (EBCHC 1997)
	1992	Drought caused great agriculture losses (Bai 2008)
	2001	Rare serious drought, causing almost no harvest of wheat, oil rape and beans, and agriculture loss 4.72 million RMB (Bai 2008)
	2003	Most cropland suffered from rare serious drought. There was no harvest on some cropland (Bai 2008)
Eerguna	1979	Dry soil layers to 20-cm depth during April–July (EBCEC 1993)
	1981	Crop suffered great loss from spring drought on State farms (EBCEC 1993)
Duolun	1970	Drought caused incomplete seedling emergence (Shen 2008)
	1972	Drought caused great loss to agriculture (EBCDC 2000)
Dongsheng	1972	One third of total sowing area suffered drought and China returned 2750 t of grain (Shen 2008)
	1986	Field crops wilted, causing low production (EBCDC 1997)
Zhalute	1982	Summer drought caused 10,000 ha unharvested cropland (EBCZC 2001)
Nong'an	1982	100,000 ha cropland suffered drought, owing to high temperature and reduced rainfall (Qin 2008)
	1997	Rare serious drought caused 50–80 % damage to maize and other crop production (Qin 2008)
	2000	Serious drought caused agricultural economic loss of 1.16 billion RMB (Qin 2008)
Changtu	1963	Half of total farmland had difficulty in sowing seed, and autumn drought caused a third of maize to die from dryness (EBCCC 1988)
	1982	Serious drought caused crop wilting over large area (EBCCC 1988)
	1997	Sprouting of field crops dried out in some regions (Li and Meng 2005)
	2000	Average dry soil layer depth to >5 cm and no harvest on some cropland (Li and Meng 2005)
Hailun	1965	Drought caused seedling emergence difficulty, and some farmland required re-sowing (Sun 2007)
	1968	Drought caused seedling emergence difficulty, large area of cropland had to be re-sown, much waste of labor and time (EBCHC 1988)

Fig. 3 Validation of EPIC model for prediction of **a** spring wheat and **b** maize yield in rainfed cultivation, based on actual yield data from nine representative counties between 1996 and 2001, and **c** trend of spring wheat in Hailar county between 1996 and 2010. *Diagonal line* represents y = x. *n* is sample number. County names: *SZW* Siziwang, *HLR* Hailar, *ERGN* Eerguna, *DL* Duolun, *ZHLT* Zhalute, *DSH* Dongsheng, *NA* Nong'an, *CHT* Changtu, *HL* Hailun. *Double asterisks* (**) denote significant trend at 1 % probability level
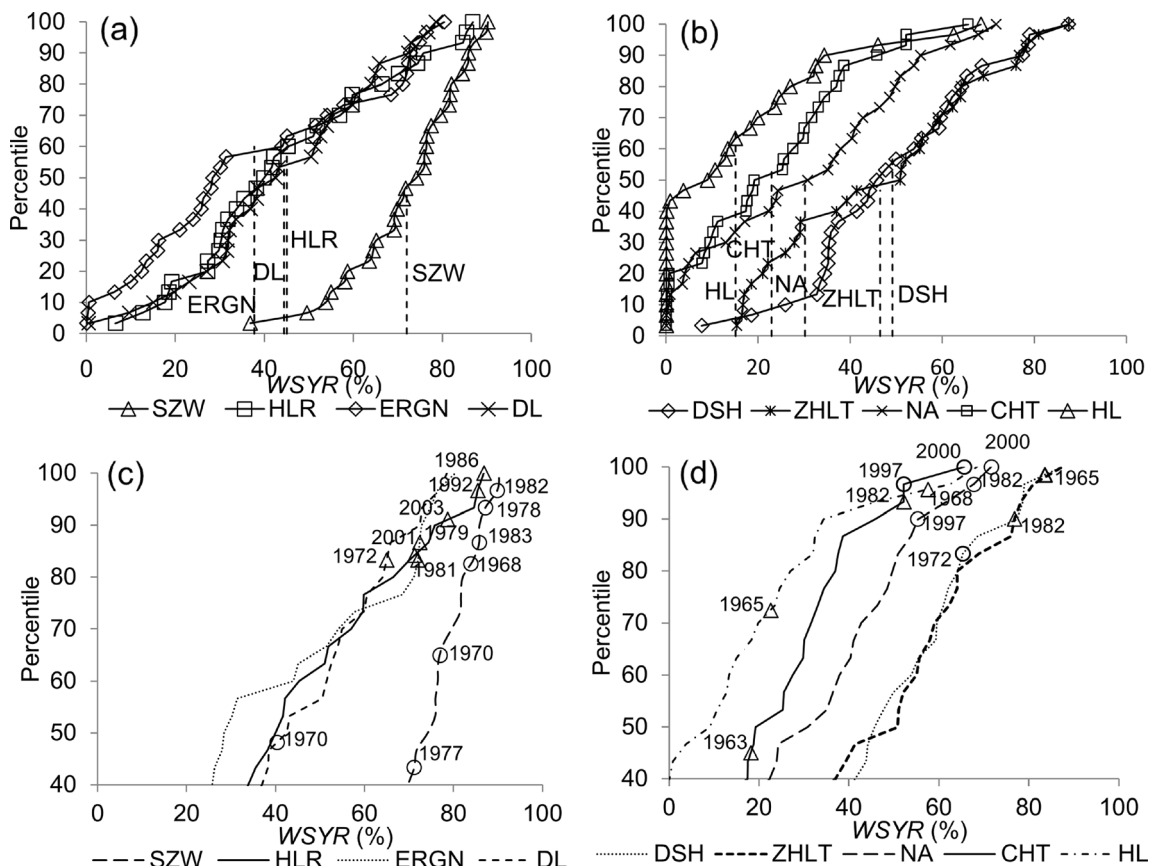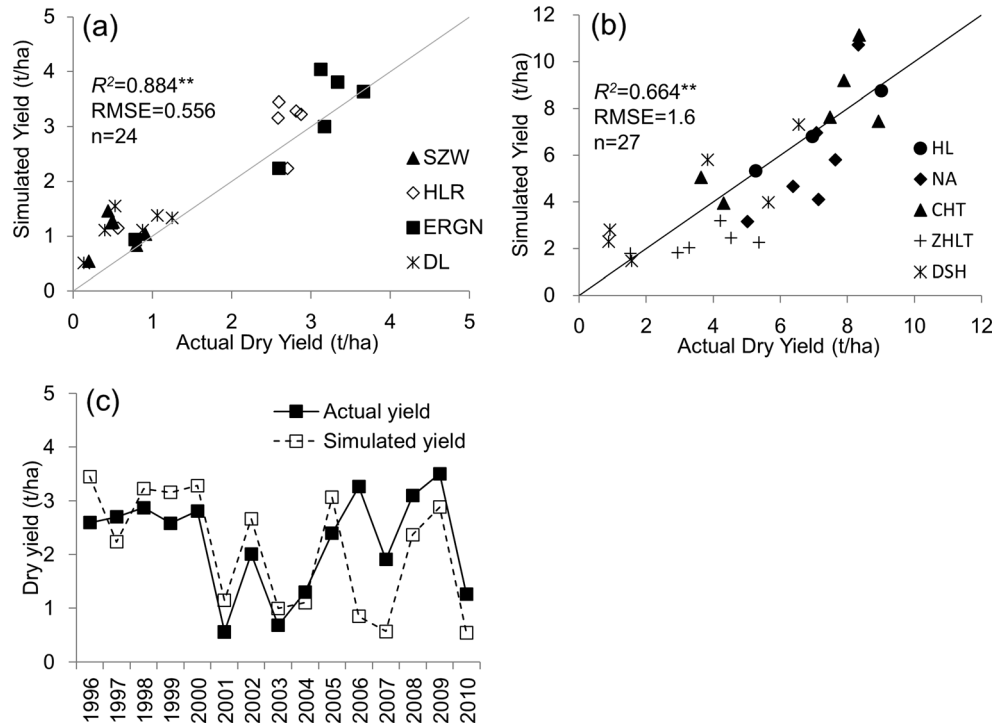
Fig. 4 Percentiles of mean WSYR in **a** four counties that grew spring wheat and **b** five counties that grew maize from 1971 to 2000; percentiles of drought cases in **c** counties growing wheat and **d** counties growing maize. *Dashed line* is mean for the three-decade period. County names: *SZW* Siziwang, *HLR* Hailar, *ERGN* Eerguna, *DL* Duolun, *ZHLT* Zhalute, *DSH* Dongsheng, *NA* Nong'an, *CHT* Changtu, *HL* Hailun. *Triangle* (△) indicates drought cases from local chorographies, and *circle* (○) indicates cases from meteorological disaster compilation books

Soil properties Soil depth, sand content, silt content, bulk density, pH, organic carbon (C) content, and calcium carbonate fraction satisfy the minimum soil input data requirements of EPIC (Liu et al. 2007). These seven soil parameters were calculated using an area-weighted method, based on a 1:1,000,000 scale soil map of China from the Harmonized World Soil Database (FAO/IIASA/ISRIC/ISS-CAS/JRC 2009).

Farmland map Farmland locations were acquired from a 1 km-scale land-use map of China in 2000 (Liu et al. 2001). The map was downloaded from the Environmental and Ecological Science Data Center for West China, National Natural Science Foundation of China, and Data-sharing Network of Earth System Science website (http://westdc.westgis.ac.cn).

Agricultural data Time-series datasets of county-level yield and sowing area from 1996 to 2001 were collected for all counties. Exceptions were Hailun county, for which data were only available for 1996, 2000, and 2001, and Hailar, for which data were available for 1996–2010. These data were from the Thematic Database for Human-Earth System (http://www.data.

ac.cn/), China Black Soil Ecology Database (http://www.blackland.csdb.cn/page/lssc.vpage), the County Level Crop Database (http://202.127.42.157/moazzys/nongqing_xm.aspx), Inner Mongolia Autonomous Region Rural Socio-economic Yearbooks (IMRPSST 1998; Zhen 1999; Zhen 2000; Zhen 2001; Zhen 2002), and Local Chronicles of Hailar County (Bai 2008). Assuming that yields of maize and spring wheat have water contents of 15 and 12 %, respectively (default values in the EPIC model), the dry yield of these grains were estimated. Average county-level nitrogen (N), phosphorus (P), and potassium (K) fertilizer and compound fertilizer data in 1996 were procured from the Thematic Database for Human-Earth System.

Historical records of agricultural drought Agricultural drought cases were culled from county-level chorographies and meteorological disaster compilation books. The chorographies, recording environmental, societal, economic, and important affairs within counties, were edited by local governments. The disaster compilation books were written by province-level meteorological bureaus. Both records complement each other. Records of drought descriptions are complex because of diverse

Fig. 5 Dry years in time series of WSYR, precipitation (P) and aridity index (AI) from 1962 to 2010 in **a** four counties that grew spring wheat, and **b** five counties that grew maize. County names: *SZW* Siziwang, *HLR* Hailar, *ERGN* Eerguna, *DL* Duolun, *ZHLT* Zhalute, *DSH* Dongsheng, *NA* Nong'an, *CHT* Changtu, *HL* Hailun. *Solid symbols* signify years with identified drought cases.

(a) Spring wheat region   (b) Maize region
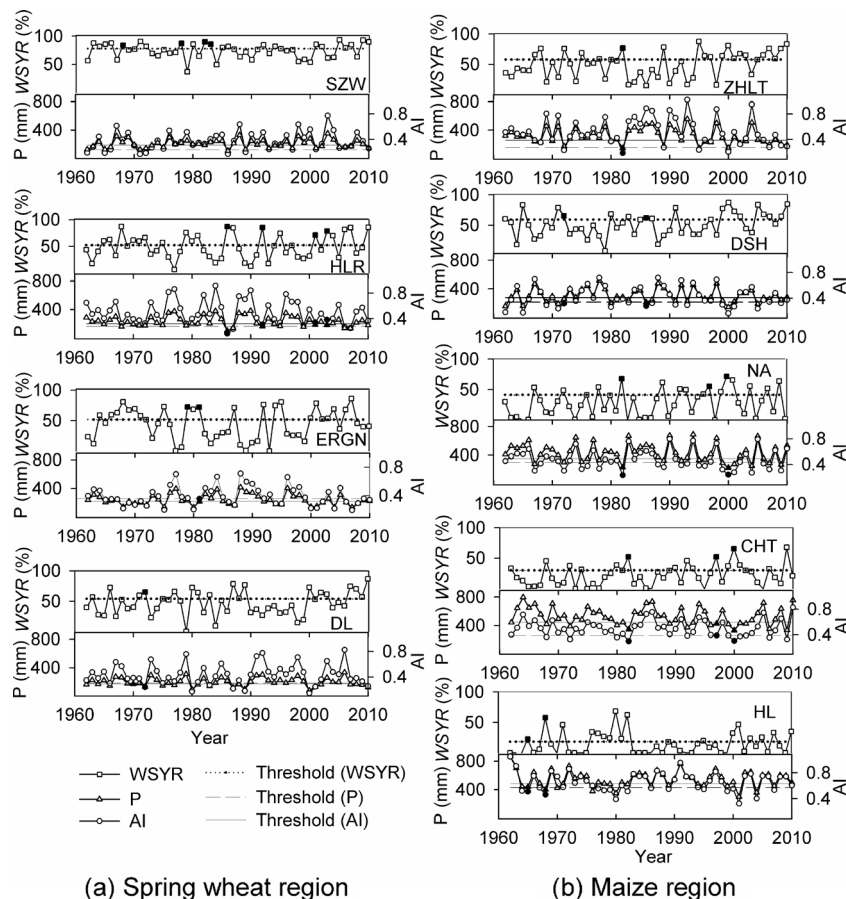
Table 3 Threshold of water stress yield reduction (WSYR) for classifying agricultural drought intensity in nine counties of northern China for the period 1971–2000

Class	Percentile	WSYR (%) in spring wheat counties				WSYR (%) in maize counties				
		Siziwang	Hailar	Eerguna	Duolun	Zhalute	Dongsheng	Nong'an	Changtu	Hailun
Wet	0–33.3	0–69.2	0–30.7	0–21.0	0–32.2	0–29.1	0–35.9	0–14.9	0–10.2	0–0.0
Normal	33.3–66.7	69.2–77.5	30.7–51.9	21.0–51.5	32.2–54.1	29.1–57.9	35.9–59.3	14.9–41.1	10.2–30.0	0.0–18.3
Dry	66.7–100	77.5–100	51.9–100	51.5–100	54.1–100	57.9–100	59.3–100	41.1–100	30.0–100	18.3–100

Threshold values were determined by the same (one-third) percentile

understandings by different people. We selected only drought cases for which the records clearly show agriculture damage (Table 2).

2.6 Statistical analysis

The coefficient of determination (R^2) and root-mean-square error (RMSE) were used to evaluate goodness of fit of the EPIC model. For analyzing 49-year temporal trends of yearly drought impacts with the WSYR, P, and AI methods, the following statistical methods were used: (1) simple linear trend fitting using SPSS software; (2) Mann–Kendall test (Mann 1945; Kendall 1975; Yue et al. 2002) using U.S. Geological Survey software (http://pubs.usgs.gov/sir/2005/5275/downloads); and (3) the Pettitt (1979) test, which identifies a change point in a time series using an IDL language program, following the calculation method presented in Zhang et al. (2009).

3 Results and discussion

3.1 Crop model performance

Both R^2 and RMSE confirmed that simulated yields fit actual yields well for the nine counties over 1996–2001 (Fig. 3a, b). For a given county, the scatter plot approximately followed the line y = x. Based on these results, the EPIC model was able to simulate county-level yield for counties in which spring wheat and maize were the main crops. The trends of actual and simulated yields from 1996 to 2010 in Hailar fit well with each other (Fig. 3c). Previous research has shown similar good agreement between EPIC-simulated yields and national yield data of wheat, maize, and rice in the world (Liu et al. 2007; Liu 2009). These support the choice of EPIC to simulate the effects of drought in the study area. Cooter et al. (2012) found that EPIC-simulated fertilizer rates agreed well with the spatial pattern of reported national-scale fertilizer application in the USA. The favorable simulation of fertilizer rate further supports EPIC model use for regional yield estimation.

EPIC is a plot-based model and has limited consideration of certain environmental factors like river flow. Figure 3b shows two points indicating that simulated maize yields (10.7 t/ha in Nong'an and 11.1 t/ha in Changtu) were substantially higher than actual yields. These lower actual yields were recorded in 1998, when there was serious summer flooding in the Songhuajiang and Liao river basins, causing tremendous crop damage (SCIO 1998; MWR 1998). Thus, there must be careful consideration of EPIC use in simulating drought impact on yield for regions with frequent flooding. County-level yield modeled by EPIC may be also biased, owing to the lack of background information. In the present study, it was assumed that meteorological conditions, crop cultivars, and fertilizer application within the counties were homogeneous. However, the rainfall distribution could vary within the counties, and farmers might use different cultivars. In northern China, wheat and maize are the two major grain crops, and both can be cultivated without rotation for many years. It was reasonable to simulate maize and wheat continuous cultivation as a mono-cropping system for 49 years in the study area, but some studies show that crop rotation or intercropping improves soil properties (Dick 1984) and soil moisture (Benson
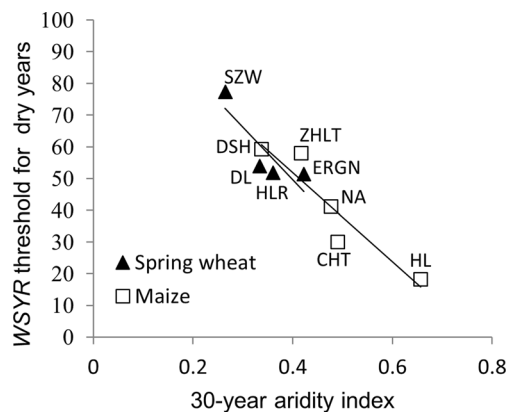
Fig. 6 Relationship between aridity index (ratio of precipitation to potential evapotranspiration) from 1971 to 2000, and drought threshold based on WSYR. County names: *SZW* Siziwang, *HLR* Hailar, *ERGN* Eerguna, *DL* Duolun, *ZHLT* Zhalute, *DSH* Dongsheng, *NA* Nong'an, *CHT* Changtu, *HL* Hailun

1985), and hence crop yield. There has been significant technology improvement in the study region. Consequently, actual yield was consistently higher than simulated yield during the last third of the study period (2006–2010) in Hailar (Fig. 3c). Therefore, simulation bias could be reduced by considering additional information.

3.2 Agricultural drought indices assessment

Taking 1971–2000 as the reference period in the wheat-growing counties, the percentile for mean WSYR was less than 50 % in Siziwang (47 %) and greater than 50 % in Hailar (60 %), Eerguna (58 %) and Duolun (54 %) (Fig. 4a). In the maize-growing counties, the percentile for the mean was lowest for Zhalute (48 %), intermediate for Dongsheng

(56 %) and Nong'an (50 %), and highest for Hailun (63 %) (Fig. 4b). Overall, drought years identified by mean values tended to be underestimated for relatively wet counties and overestimated for drier ones. The average WSYR in Siziwang was greater than that in Hailar, and that in Dongsheng was greater than in Hailun (Fig. 4a, b). These indicate that low-rainfall areas had greater yield reductions than high-rainfall areas. Similarly, Liu et al. (2012) used the APSIM-Maize model to simulate a gap between actual rainfed and potential maize yields, with a range between 0.4 and 63 % in three provinces in northeastern China. They found that the gap was large at locations with low precipitation, but greatly decreased in regions of higher precipitation. Our results indicate that crops suffered from frequent serious yield reductions in the west

Table 4 Linear trend slope, Mann–Kendall, and Pettitt tests for WSYR (%), precipitation (P) (mm) and aridity index (AI) for nine investigated counties during 1962–2010

County	Index	Linear trend slope (10 year^{-1a})	Mann–Kendall test (Z)	Pettitt test		
				Change point	K_T[b]	Shift
Siziwang	WSYR	−0.010	−0.353	2004	−136	Upward
	P	3.30	0.629	1975	−128	Upward
	AI	0.012	1.276	1975	−178	Upward
Hailar	WSYR	2.07	0.646	2000	−156	Upward
	P	−6.28	−0.922	1998	156	Downward
	AI	−0.009	−0.940	1998	153	Downward
Eerguna	WSYR	0.38	0.284	1999	−138	Upward
	P	−4.10	−0.784	1999	186	Downward
	AI	0.005	−0.629	1999	174	Downward
Duolun	WSYR	2.52	1.302	1999	−228	Upward
	P	−1.07	−0.233	1999	114	Downward
	AI	0.003	0.129	1989	−130	Upward
Zhalute	WSYR	4.54*	2.129*	1994	−304**	Upward
	P	−13.3	−1.508	1994	258*	Downward
	AI	−0.009	−1.052	1994	216	Downward
Dongsheng	WSYR	3.90*	2.026*	1998	−278*	Upward
	P	−3.0	−0.336	1998	138	Downward
	AI	−0.002	−0.207	1998	134	Downward
Nong'an	WSYR	4.13	1.845	1987	−218	Upward
	P	−15.53	−1.405	1994	127	Downward
	AI	−0.004	−0.776	1994	172	Downward
Changtu	WSYR	3.35	1.621	1986	−205	Upward
	P	−17.82	−1.457	1988	168	Downward
	AI	0.000	−0.672	1995	129	Downward
Hailun	WSYR	0.40	1.019	1975	−166	Upward
	P	−6.0	−0.129	1982	−94	Upward
	AI	−0.01	−0.422	1982	−98	Upward

[a] 10 year^{-1}—every 10 years

[b] K_T—maximum sum of signed rank between intervals before and after change point

*0.05 significance level; **0.01 significance level

possibly because of a substantial soil moisture decrease from southeast to northwest in China (Zhang et al. 2008). Thus, mean values do not serve for a suitable threshold in our study area.

A total of 26 drought cases were recorded in the chorographies and disaster compilation books (Table 2). These records are consistent with high values of WSYR in both the wheat- and maize-growing counties. Most of the drought cases (21 of the 26, or 81 %) had WSYR percentiles higher than 80 % (Fig. 4c, d). The exceptions were a few cases in both the wheat (1970 and 1977 in Siziwang and 1970 in Duolun) and maize counties (1965 in Hailun and 1963 in Changtu). These exceptions could be explained by disagreements between of drought case records and of model outputs. The drought case of 1977 in Siziwang, which was recorded in the disaster compilation books, is described as having impacts on autumn harvest crops such as sunflowers. However, the present model simulated WSYR of spring wheat. The drought cases of 1970 in Duolun, 1963 in Changtu, and 1965 in Hailun are described as the result of failure of seedling emergence and re-sowing of crops, but the model could not simulate such scenarios. Compared with means, medians are less sensitive to the existence of extreme values (Kozak et al. 2008) such that quantile

classification, an extension of the approach based on the median, improves the determination of drought thresholds. By setting the threshold percentile at 66.7 % (Fig. 4c, d), there was agreement for 22 of the 26 drought cases, or 85 % (Table 2), with a high WSYR. Using the same threshold percentile, agreements using P were 16 of the 26 cases (65 %) and that of AI were 17 of the 26 cases (68 %). The agreement using WSYR is greater than that of P or AI. For example, drought years 1978, 1982, and 1983 in Siziwang, 1979 in Eerguna, and 1997 in Nong'an were identified by WSYR but not by P or AI (Fig. 5). It reveals that crop-specific index i.e., WSYR is superior to the meteorological indices for agricultural drought identification. Thus, for simplicity, the one-third probability of WSYR was used to classify agricultural drought.

When the one-third probability for the dry class (drought) was used to categorize a specific WSYR threshold for each county (Table 3), Siziwang had the highest threshold (77.5 % WSYR), and Hailar, Eerguna, and Duolun had lower ones (51.5–54.1 % WSYR) for the wheat-growing counties. For the maize-growing counties, Hailun had the lowest threshold (18.3 % WSYR), while Zhalute and Dongsheng had higher thresholds (57.9–
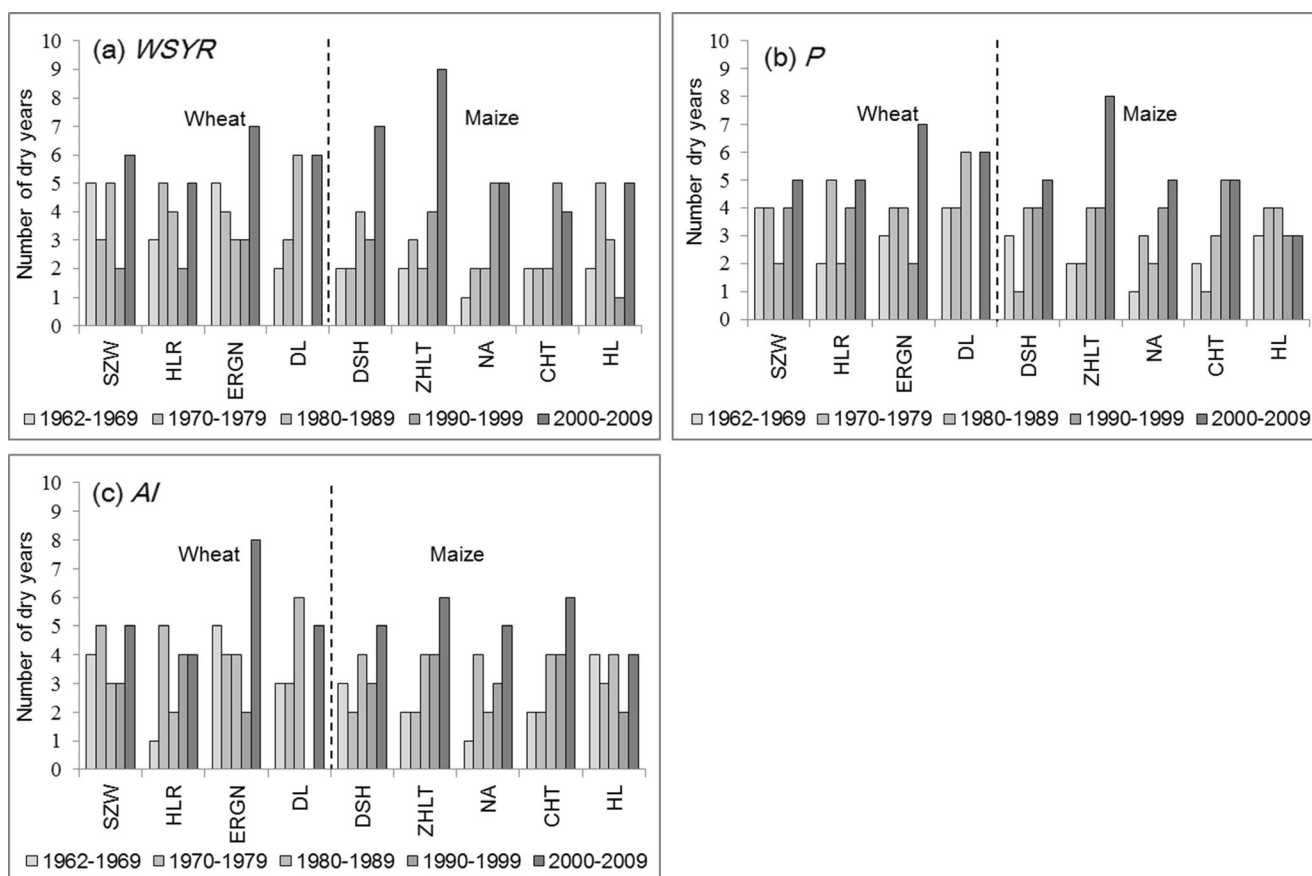
Fig. 7 Number of dry years from 1960s to 2000s in nine counties, via a WSYR, b precipitation, c aridity index. County names: *SZW* Siziwang, *HLR* Hailar, *ERGN*, Eerguna, *DL* Duolun, *ZHLT* Zhalute, *DSH* Dongsheng, *NA* Nong'an, *CHT* Changtu, *HL* Hailun. There are 1962 to 1969 8 years for 1960s

59.3 % WSYR), and Nong'an and Changtu intermediate thresholds (30.0–41.1 % WSYR). Although the Food and Agriculture Organization (FAO) yield response factor to water deficit shows that maize is more sensitive (1.5) than spring wheat (0.65) during the crop development, the sensitivity during the entire season of spring wheat (1.15) is close to that of maize (1.25) (Doorenbos and Kassam 1979). The WSYR threshold declined from 77.2 to 18.3 % with increased 30-year AI from 0.26 to 0.66 (Fig. 6). Thus, aridity has a strong influence on the classification of the drought intensity.

3.3 Validation of the assessment framework

Linear regression analysis and the Z-value of the Mann–Kendall test showed an increasing trend of WSYR from 1962 to 2010 in all counties, except for a decrease in Siziwang. The Pettitt test indicates upward shifts of WSYR. All tests also show a decreasing trend of P and AI in all counties, except for an increasing trend in Siziwang. The Pettitt test reveals upward shifts of P and AI in Siziwang and Hailun (Table 4). Among the nine counties, the trends and shifts of WSYR in Zhalute and Dongsheng were statistically significant. The shift of the time series of P in Zhalute was also significant, and the change point in 1994 was the same as that of the WSYR. But the significance level of shift is lower than that of WSYR. It reveals that the precipitation and aridity index may underestimate the severity trend of agricultural drought in serious counties.

The number of dry years classified by WSYR (Fig. 7a) for each decade shows that there are more dry years in the 2000s than other decades for maize-growing counties (Zhalute and Dongsheng). Maize-growing counties except Hailun had greater number of dry years in the 1990s and 2000s than in the 1970s and 1980s, but the numbers were not as high as those for Zhalute and Dongsheng. All the four wheat-growing counties had fewer numbers of dry years in the 1990s than other decades, and no increase in number per decade was found in those counties. Using only maize WSYR to assess agricultural drought, the number of dry years increased in the five maize-growing counties, so the number of agricultural drought has been increasing in northeastern China and Inner Mongolia. This is supported by the study of Chen et al. (2011). They reported that the drought area where there was yield reduction greater than 10 % from mean yield during 2001–2008 was higher than that of 1980–2000 in Heilongjiang and Jilin provinces and Inner Mongolia, but not in Liaoning Province. The number of dry years identified by P in the 2000s was smaller than that in the 1990s in Hailun County (Fig. 7b). In all five counties, the number of dry years identified by the AI in the

2000s was greater than that in the 1990s (Fig. 7c). The total number of dry years via WSYR for nine counties was 25 in the 1990s and 54 in the 2000s. The total number of dry years via P was 30 in the 1990s and 49 in the 2000s. Total number of dry years via AI was 25 in the 1990s and 48 in the 2000s. The increase of dry year number from the 1990s to 2000s via WSYR was greater than those via P and AI.

4 Conclusions

Following the proposed drought assessment framework, the performance of agricultural drought indices were quantified and compared in a rainfed region of northern China. First of all, the EPIC model was validated reasonably well to be used for estimating yield loss from drought. The crop-specific index (i.e., WSYR), which is calculated using the crop model, was then compared with meteorological drought indicators (i.e., P and AI). By cross-checking these indices against the historical records of drought events, it was found that the crop-specific index was more accurate in representing agricultural drought than the meteorological drought indicators. The present study further shows that the long-term trend of agricultural drought from the crop-specific index agreed to a great extent with the result that was previously reported on drought in the region, while the meteorological drought indicators might underestimate the severity of agricultural drought. Therefore, as demonstrated here, a drought assessment framework based on crop model simulation can be valid for quantifying the impact of drought on yield, classifying the intensity of agricultural drought, and thereby analyzing the trend of regional drought.

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