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Drought risk assessment of spring maize based on APSIM crop model in Liaoning province, China

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Abstract. Drought risk assessment is a vital part of drought risk management, which plays an important role in drought mitigation. Due to its complexity, drought risk is difficult to define and challenging to quantitatively assess, as the drought impacts associate with many social sectors. This contribution method the issue by quantitatively evaluating the yield loss due to drought as a function of the drought severity indicator in Liaoning province, China for spring maize using logarithmic regression. As crop water deficit is essence to identify agricultural drought, it developed a drought severity indicator using the crop water stress coefficient and duration. The Agricultural Production Systems sIMulator (APSIM) crop model was employed to simulate the spring maize growth to obtain daily water deficit during the growth period (May to September) and yield. The relationship between drought severity frequency and yield loss rate due to drought was established to assess the drought risk of spring maize when drought severity frequency is equal to 20%, 10%, 5% and 2%. The results show that Chaoyang and Fuxin have the highest drought risk in four levels of drought severity frequency whilst the lowest drought risk was identified in Tieling. The central Liaoning province has a moderate drought risk. For a specific drought severity frequency, drought risk increases from east to west in Liaoning province whilst it varies in each city at different drought severities. This method can predict yield loss due to drought for drought early warning. Drought risk maps presents spatial characteristics that can help to agricultural drought mitigation and the development of drought preparedness plan in Liaoning province.

Key words: Drought risk assessment; APSIM crop model; Crop water deficit; Yield loss due to drought

1 Introduction

Drought is slow-onset and one of the most widespread natural hazards. Drought impacts are nonstructural and the occurrence of drought is associated with significant impacts in water resources, environment, energy, and human lives, especially in agricultural production (Wilhite, 2005;Wilhite and Pulwarty, 2018). These characteristics make it particularly challenging to quantify drought risk and capture drought impacts. In China, the average annual yield loss due to drought has increased from 4.35 million tons in the 1950s, to 34.9 million tons in the early twenty-first century (Lv, 2013). Drought affected approximately 60% of the maize sown area during 1990-2007, which resulted in a 20%-30% reduction in production (Jia et al., 2012). The widespread and costly nature of drought has naturally led to an interest in drought risk assessment. Methods to quantify drought risk help decision makers in drought risk management and drought mitigation. It also has a great significance in the theory and practice of quantitative drought risk assessment (Bachmair et al., 2017;Botterill and Hayes, 2012).

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To date, a number of previous studies have evaluated the drought risk of different regions and climates across the world at different spatial scales, most of which focus on agricultural drought risk (Xie et al., 2016). Agriculture is directly affected by the occurrence of drought as it reliable on precipitation, temperature and evapotranspiration, which can decrease the soil moisture (Sruthi and Aslam, 2015). Agricultural drought is defined as water deficit that adverse to plant growth and lead to a decrease in agricultural production (Maracchi, 2000). Soil moisture, plant water deficit and plant growth status are critical indicators to identify agricultural drought. Sites-based, remote sensing-based and simulated data are wildly used in agricultural drought monitoring (Liu et al., 2016). Sridhar et al. (2008) developed a drought index using observed and modelled soil moisture to monitor agricultural drought in Nebraska. Dalezios et al. (2014) used the vegetation health index, which is developed by temperature and normalized difference vegetation index and can reflect crop growth status, to monitor agricultural drought. Most of the agricultural drought indicators ignore the cumulative impacts of drought on crops for a period of time. In this research, an agricultural drought severity indicator (DSI) was established by the maize water stress coefficient and duration during the maize growth period, that modelled by the crop model. DSI is a direct indicator to identify agricultural drought which consider the intensity and cumulative impacts of drought.

From the natural disaster analysis theory, drought risk is combination of the drought hazard and the vulnerability of the sectors (Parry et al., 2007). Drought risk assessment indicators and factors are established to evaluate the drought hazard and vulnerability. He et al. (2013) analyzed the drought hazard, exposure, vulnerability and drought resilience to develop a composite drought risk assessment model, which include standardized precipitation index, irrigation availability and seasonal crop water deficiency. Liu et al. (2013) developed a composite drought risk indicator of maize using factors such as drought occurrence frequency, agrometeorological drought indicators, yield loss, drought affected area and exposure rate of maize to assess the drought risk in Liaoning province. Kim et al. (2015) used the drought risk indicator, developed by frequency and severity of drought, irrigated area, agricultural occupation and population density to assess the drought risk in South Korea. This class of method is based on the analysis of the drought risk theory, reflecting a variety of multifaceted drought risk factors (such as frequency of drought, sown area, effective irrigated area). Nevertheless, factors selected and the weight of factors are inevitably determined subjectively. The results of the drought risk assessment are not comparable in different region.

Since drought impacts are symptoms of vulnerability, it can be used to estimate vulnerability (Blauhut et al., 2015). Bachmair et al. (2014) used correlation analysis to explore the link between drought indicators and drought impacts in Germany. Qualitative and long time series of impact data was collected to evaluate the performance of drought indicators. It emphasize on the occurrences of drought impacts without considering impact severity, duration or spatial extent. Petr et al. (2014) evaluated the drought impact on yield of three major tree species using drought probabilities and vulnerabilities in Britain. Zhang (2004) explored the quantitative relationship between the crop yield loss due to drought and historical climate data to evaluate drought risk in Songliao Plain. It is a critical challenges to match the drought events and the corresponding drought impacts. Lu et al. (2012) developed an agriculture drought risk assessment model using information diffusion theory in county unit in China. It collected drought disaster affected area and the degree of crop affected to

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measure drought impacts. Potopová et al. (2015) explored the drought impacts on crops yield in the Czech Republic. Jia et al. (2011) simulated the crop growth process using EPIC crop model to explore the linkage between drought indicator and reduction in production. EPIC model is less sensitive to crop yield during severe droughts, and it is not good at simulating soil moisture while the crop suffers water stress. Xu et al. (2013) developed a relationship between consecutive rainless days and crop loss to analyze drought risk in east China. Compared to the consecutive rainless days, crop water deficit indicator is a prefer indicator to identify agricultural drought.

Building on these previous efforts, this study aims to develop a quantitative drought risk assessment method for spring maize in Liaoning province. Yield loss rate as the drought impacts, which we interpret as a drought risk for four drought severity frequency were analyzed (Blauhut et al., 2015;Jia et al., 2011). The higher yield loss rate for a specific drought severity frequency, the higher of the drought risk. The yield loss was simulated by Agricultural Production Systems sIMulator (APSIM) model which was developed by the Australian Federal Organization of Sciences and the Queensland Government to simulate the processes of agricultural systems (Asseng et al., 1998). Compared to other crop models, APSIM focuses on simulating crop substance supply with an emphasis on the continuous simulation of soil nutrient dynamics (Akponikpè et al., 2010). It is also a mechanistic model which is able to analyze soil water dynamics in arid areas (Holzworth et al., 2014). It therefore has good accuracy for crop water consumption and water stress condition (Gaydon et al., 2017). The application of APSIM has been well documented in many countries and for a wide variety of crops (Keating et al., 2003). In China, the ability of APSIM model to maize, wheat, alfalfa, soybean and grassland in the north, northeast, and southeast China has been verified and has been used to explore the irrigation scheme optimization, climate change impacts, carbon dioxide dynamics and water transport in soil-crop system(Chen et al., 2003;Liu et al., 2012;Wang, 2007;Wei et al., 2015).

The result of research aim to provide guidance for drought management and enhance the ability of drought mitigation. Drought risk map can inform drought situation to decision makers and help to take drought mitigation actions. Specifically, it aims to assess the agricultural drought risk specific to spring maize in Liaoning province, which can provides a methodology for application for other regions of China (and other countries).

2 Materials and Methods

2.1 Study Area

Located in northeast China (shown in Figure 1), Liaoning province, composed of 14 cities, is an important base of high quality spring maize which occupies a large proportion in total maize production and planting area in China (Dong et al., 2015). In 2016, the spring maize sown area was 2.259 million hectares, most of which are rain-fed (Yu et al., 2014), with a total maize yield of 14.66 million tons (Liaoning Province Bureau of Statistical, 2017).

Liaoning province is located in the semi-humid and semi-arid transition zone. Affected by the monsoon climate, the temperature and precipitation distribution is uneven both spatially and temporally. The annual average temperature is between 7-11 °C. The highest temperature is 30 °C whilst the lowest temperature is minus 30 °C.

The average annual precipitation is 550-630mm, and 60%-70% of the precipitation falls during summer (June-August)

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(Chen et al., 2016). Average annual precipitation decrease from east to west in Liaoning province. The average annual precipitation in the eastern Liaoning is over 1000 mm; in the western areas, the average annual precipitation is less than 500 mm, which is the lowest in Liaoning Province; and in the central Liaoning province, the annual average precipitation is about 600 mm.

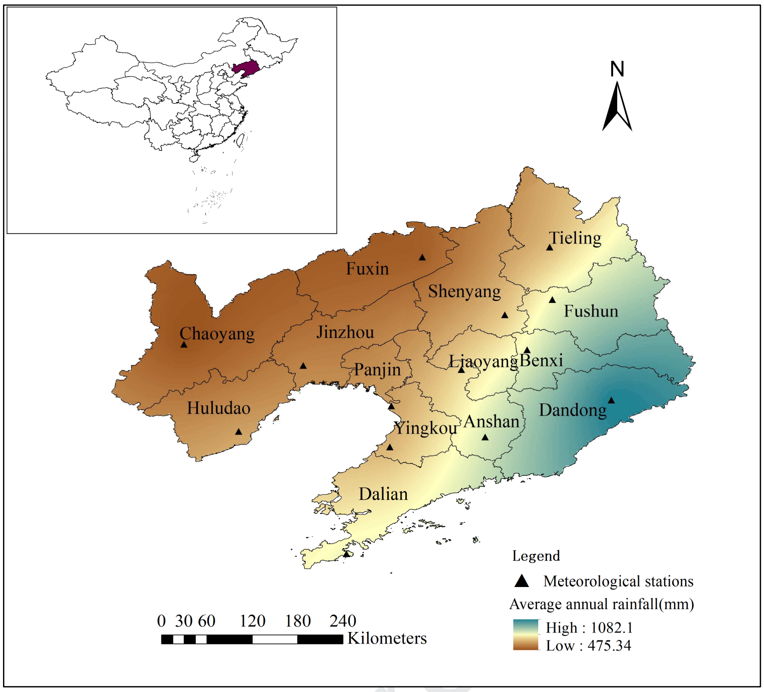

Figure 1: The distribution of meteorological stations and precipitation in Liaoning province, China.

Due to these characteristics, drought occurred frequently in Liaoning province, especially in western areas. Drought occurs more frequent in spring, accounting for more than 70% of the total drought events between 1990 and 2010 (Sun et al., 2012b). From 2000 to 2016, average annual yields loss due to drought is 1.89 million tons. Average annual direct economic losses in agriculture is 4.8 billion yuan and 2.1 million people had temporary difficulty in accessing drinking water due to drought. From the report of the office of State Flood Control and Drought Relief Headquarters, recent severe droughts occurred in 2000, 2001, 2007 and 2009, resulting in a disastrous impacts in agricultural production, economic losses and water supply systems (Zhang, 2009).

2. 2 Data

1. Meteorological data

Daily meteorological data, daily precipitation, minimum temperature, maximum temperature, wind speed, relative humidity and sunshine hours were collected for the period 1961-2013 from China Meteorological Administration (http://data.cma.cn/). Considering the data quality and period of time series, location of stations, data for 14 meteorological stations (shown in Figure 1) in Liaoning province were selected from the China Meteorological Administration (e.g. one in each city). The Penman-Monteith method was employed to calculate the surface radiation and potential evapotranspiration to drive the APSIM model (Monteith, 1965;Schrier et al., 2011).

2. Soil properties data

One major soil type in each city was selected for model simulation. Soil water characteristics, bulk density, and pH in each layer of the soil, were collected from the Chinese soil species for 14 cites in Liaoning province (National Soil Census Office, 1993) and reference (Zhou et al., 2015). The initial relative soil moisture is 80% in each modelling to meet the maize demand at early stage. Take the Jinzhou as an example, water characteristics of the major soil type are shown in Table 1.

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Table 1 Soil properties in Jinzhou, one of city in Liaoning province

Depth (cm)	Bulk Density (g/cc)	Lower limit (mm/mm)	Drained Upper Limit (mm/mm）	Saturated Water Content (mm/mm)
0-10	1.41	0.08	0.24	0.33
10-20	1.39	0.09	0.25	0.34
20-30	1.43	0.08	0.23	0.32
30-50	1.43	0.07	0.23	0.32
50-70	1.45	0.07	0.23	0.32
70-90	1.45	0.07	0.22	0.30
90-110	1.47	0.07	0.22	0.30
110-130	1.47	0.06	0.21	0.29
130-150	1.52	0.06	0.21	0.29
150-170	1.55	0.06	0.21	0.29

3. Crop and filed management data

The agrometeorological and crop growth data are observed in the national agrometeorological station, which measures the crop growth status and field management scheme via a formalized of reports annually. These data then are fed up to the China Meteorological Administration. In this research, field management scheme, phenology, yield structure and biomass accumulation, for 10 agricultural stations were collected from the China Meteorological Administration during 1996 to 2012. Biomass accumulation was measured at 6 different growth period, which was only available in Jinzhou. Stations in Panjin, Dandong and Fushun measured rice's growth during 1996 to 2012 and there is no nation agrometeorological station in Huludao. Then, maize yield data were collected from Liaoning province Statistical Yearbook during 1996-2012 in Panjin, Dandong, Fushun and Huludao (Liaoning Province Bureau of Statistical, 2017).

The spring maize growth period is divided into 10 stages, sowing, emergence, third leaf, seventh leaf, jointing, tasseling, flowering, silking, milk and maturity. The number of days from sowing to flowering and sowing to maturity are applied to model calibration and validation. In 2011, phenology of stages for spring maize in Jinzhou are shown in Table 2. Spring maize was sowed on 3rd May and matured on 26th September. Yield structure was measured before physiological maturity. Table 3 displays the yield structure of spring maize for the agrometeorological station in Jinzhou. The 100-grain weight of maize was 36.83g and theoretical yield was 1119.79g/m^2.

Table 2 Phenology of maize in Jinzhou in 2011

Stages	Sowing	Emergence	Third leaf	Seventh leaf	Jointing	Tasseling	Flowering	Silking	Milk	maturity
Date	3rd May	15th May	21st May	5th June	20th June	19th July	21st July	22nd July	18th Aug.	26th Sep.

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Table 3 Yield structure of maize in Jinzhou in 2011

Yield Structure	Stem diameter	Ear length	Ear diameter	Grain weight per plant	100-grain weight	Theoretical yield	Stem weight	Grain and stem ratio
Value	28mm	31cm	6.1cm	202.43g	36.83g	1070.9g/m^2	1119.8g/m^2	0.96

2.3 APSIM Model

The APSIM model simulates the growth of maize crop in a daily time-step. It is a dynamic model that includes crop module, soil module and field management module (Moot et al., 2015). The crop module of APSIM dominates the key physiological processes, including phenology, organ development, nutrient dynamic, water balance, biomass accumulation and senescence.

Due to the different sowing date and field management scheme every year in every cities, in order to simplify the model simulation, APSIM model was set up with the same sowing parameter (e.g. sowing date, sowing density and sowing depth) and field management scheme (e.g. fertilization) during 1961-2013 in Liaoning province. Field management measures, such as sowing and fertilization scheme, are present in Table 4. Most part of the maize sown area in Liaoning were rain-fed area then the irrigation module is not include in the simulation and fertilization is sufficient to meet the maize's demand. It assumes that the maize yield was only affected by weather before and during the growth period in this research. Other factors, such as technological progress, infrastructure improvement and insects are not taken into consideration (Hong and Wilhite, 2004). In the maize module, the period of each growth stage is dominated by the accumulation of thermal time and is adjusted by other factors, such as light photoperiod and nitrogen, which vary with the growth stages. Yield is associate with two parameters, maximum number of kernel per head and grain filling rate (Asseng et al., 2002).

Table 4 Field management measures in 14 cities during 1961-2013

Parameter		Value	
Initial relative soil moisture		80%	
Sowing date		1st May	
Sowing density		8 plants/m^2	
Row spacing		50cm	
Fertilization	Fertilization date	1st May	22th June
	Fertilization amount	150kg/ha	350kg/ha
	Fertilization type	Urea_N	Urea_N

Note: Urea_N means weight of nitrogen in urea.

The soil water module which is belong to the soil module is a water balance model with daily basis. The water characteristics of the soil are specified in terms of the lower limit, drained upper limit and saturated water content (http://www.apsim.info/). Soil water stress are calculated to simulate the effects of water stress on different maize growth

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processes. Soil water stress ratio is calculated by dividing actual soil water available by the potential soil water supply which is calculated by the difference between lower limit and drained upper limit.

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$$SWSR_i = \left(SW_i - LL_i\right) / \left(DUL_i - LL_i\right) \quad (1)$$

Where $SWSR_i$ is soil water stress ratio in the layer i; SW_i is the soil water in the layer i; LL_i and DUL_i are the lower limit and the drained upper limit in the layer i respectively.

This ratio is used to derive the stress factors for photosynthesis, phenology and leaf-expansion each having different sensitivity to water stress (Muchow, 1989). The maize water stress coefficient in the leaf expansion is equal to soil water stress ratio, which is the most sensitive growth process to water stress for maize. In this research, crop water stress coefficient in leaf expansion of maize is used to represent the daily water stress during maize growth period.

2.4 Model Calibration and Validation

In this study, APSIM model was developed in city unit. Maize yield, phenology and biomass accumulation are used to calibrate and validate the parameter of APSIM. Data during 1996 to 2005 were used to calibrate the model, whilst data during 2006-2012 were applied for model validation. After parameterizing the model, it was used to simulate the water deficit during spring maize growth period and the impact of drought on maize yield. Parameters were calibrated for different maize varieties, including the thermal time of growth stages, photoperiod slope, grain filling rate and maximum number of kernels.

The following statistics are used to evaluate the performance of the APSIM model in each city. Root mean square error (RMSE, Equation 2) and normalized root mean square error (NRMSE, Equation 3) reflects the difference between the simulated and measured values, where lower values indicate less residual variance. The coefficient of determination (R^2, Equation 4) reflects the consistency between the simulated value and the measured value which is the closer to 1, the higher consistency.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - S_i)^2}{N}} \quad (2)$$

$$NRMSE = \frac{RMSE}{O} \quad (3)$$

$$R^2 = \left(\frac{\sum(O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum(O_i - \bar{O})^2 \sum(S_i - \bar{S})^2}}\right)^2 \quad (4)$$

Where S_i is the simulated value; O_i is the measured value; $\bar{O}$ is the average of the measured values; $\bar{S}$ is the average simulated value; n is the number of samples.

2.5 Drought Severity Indicator

The intensity and duration of water stress of maize during the growth period are the two direct factors to identify agricultural drought. They are therefore used to develop the drought severity indicator (DSI, Equation 5), which directly reflects agricultural drought during the maize growth period.

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$$DSI_{yj} = \frac{\sum_{i=1}^{n}(1-WS_i) - \min DSI}{\max DSI - \min DSI} \quad (5)$$

Where DSI_{yi} is the drought severity indicator of the j station in year y, WS_i is the maize water stress coefficient for day i, n is the number of water stress days during growth period, maxDSI and minDSI is the maximum and minimum values of $\sum_{i=1}^{n}(1-WS_i)$ for all years at all stations respectively.

The calculation of drought severity frequency is similar to the flood frequency. It is related to the return periods of the drought, for example, the frequency of a drought with 50-year return period is 2%. It is calculated as follows:

$$P(X \geq x(m)) = \frac{m}{n+1} \times 100\% \quad (6)$$

Where X is the annual DSI, $x(m)$ is the m-th largest value of X; and n is the total number of years.

2.6 Yield Loss due to drought

Since it assumes maize yield was only affected by weather, the difference between potential yield and simulated yield is used as yield loss due to drought (ignore the impact of flooding). There are several methods to calculate the potential yield. Automatic irrigation can be applied in the APSIM model, that is, if water stress occurs, the model will automatically irrigate to meet the crop's water demand. Simulated maize yield without water stress can present potential yield. The second method is to select a typical year with no flood and no drought occurred in this year, and precipitation is suitable for maize growth. The simulated yield of typical year is used as potential yield. The third method, it take the average of daily meteorological data to drive the crop model to simulate the potential yield. In this research, maximum simulated yield during 1961-2013 was selected as potential yield. The yield loss rate due to drought is calculated as follows:

$$R_{loss} = \frac{Y_m - Y_s}{Y_m} \quad (7)$$

Where R_{loss} is the yield loss rate due to drought; Y_m is potential yield; and Y_s is simulated yield in each year.

3. Results

3.1 APSIM Model Calibration and Validation

The evaluation results of the model for yield during 1996 to 2005 are shown in Table 5. The R^2 of each city is over 0.6 in Liaoning province. The highest R^2 were identified in Anshan and Jinzhou, where R^2 were 0.89 and 0.87, respectively. The average NRMSE of yield is 13.5%, and the highest NRMSE occurred in Fuxin and Huludao. The NRMSE of each city is less than 30% in Liaoning province. These results indicate that APSIM model is satisfactory in simulating spring maize in Liaoning province.

Table 5 The model evaluation results in Liaoning province

City	NRMSE(%)	R^2	City	NRMSE(%)	R^2

Shenyang	10.1	0.79	Yingkou	10.2	0.62
Dalian	12.7	0.81	Fuxin	22.3	0.85
Anshan	8.1	0.89	Liaoyang	11.2	0.66
Fushun	15.3	0.74	Panjin	9.2	0.75
Benxi	9.8	0.73	Tieling	14.4	0.69
Dandong	8.7	0.80	Chaoyang	20.1	0.85
Jinzhou	13.1	0.87	Huludao	23.4	0.70

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Simulated yield from the APSIM model and the measured (or statistical) yield during 1996-2005 in 14 cities of Liaoning are displayed in Figure 2. The results shows that the simulated yield basically falls near the 1:1 line, which illustrates that there is a high consistency between simulated yield and measured (or statistical) yield. APSIM model has a good ability to simulate the maize yield in Liaoning province.

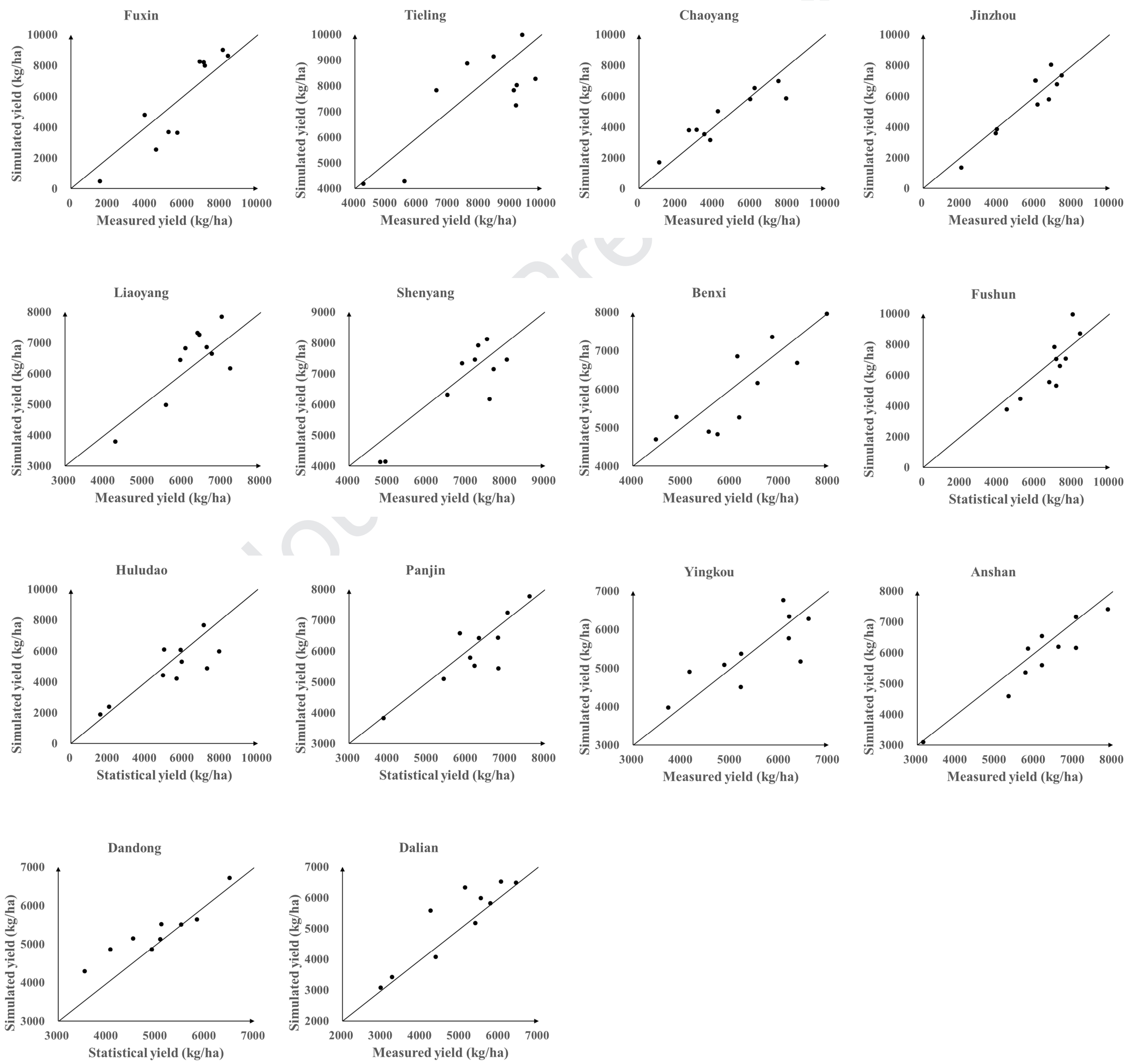

Figure 2: Simulated yield and measured (or statistical) yield during 1996-2005 in 14 cities of Liaoning province

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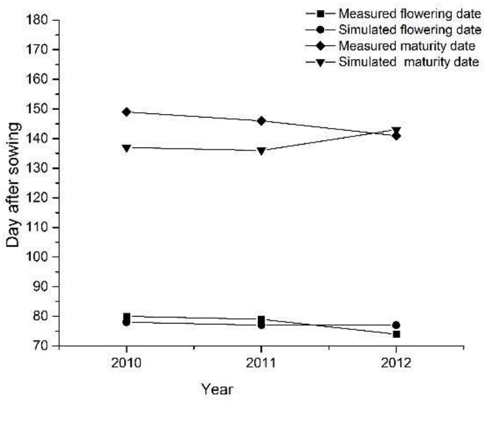
APSIM was calibrated for the local field conditions and cultivars in city unit based on the available data from 2001–2012, which means that there was a set of parameter calibration result in each city of Liaoning province. Considering the availability of maize biomass accumulation data and the R^2 of the measured yield and simulated yield, Jinzhou was therefore selected to further demonstrate APSIM model's performance. The model parameter calibration results for Jinzhou are presented in Table 5.

Table 5 Calibration results of spring maize in Jinzhou

Parameter		Description	Value
Growth Stages parameters	est_days_endjuv_to_init	Number of days from the end juvenile to initial flowering (d)	20
	tt_emerg_to_endjuv	Thermal time from emergence to end juvenile (□)	160
	tt_flower_to_maturity	Thermal time from flowering to end maturity (□)	850
	photoperiod_crit	Light photoperiod (h)	9.8
	tt_flower_to_start_grain	Thermal time from flowering to start grain (□)	80
Yield structural	head_grain_no_max	Maximum number of corns per plant (kernel/head)	450
	grain_gth_rate	Grain filling rate(mg/grain/day)	9.5

Measured phenology (number of days from sowing to flowering and maturity) and the corresponding simulated phenology during 2010-2012 in Jinzhou are displayed in Figure 3. The measured average number of days from sowing to flowering is 78 days, whilst the average number of days of maize growth period is 137 days. The average error between measured and simulated number of days from sowing to flowering is 0.4 days, whilst the average error of the simulated number of days from sowing to maturity is 6.6 days during 2010-2012 in Jinzhou.



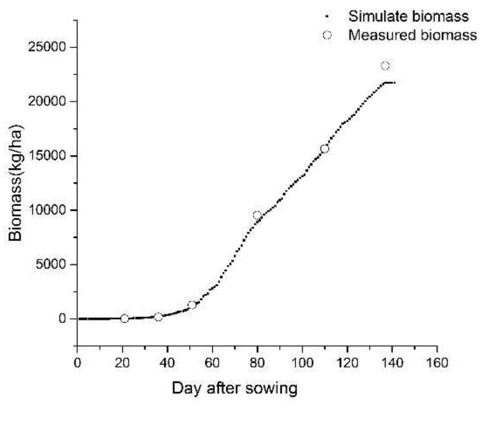


Figure 3: Phenology during 2010-2012 in Jinzhou **Figure 4: Comparison of biomass in 2011 in Jinzhou**

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The measured biomass accumulation in 2011 in Jinzhou is shown in Figure 4. The average relative error of the simulated biomass accumulation is 6.8% with the measured biomass accumulation at six growth period. The model validation results elucidate that the APSIM model has good performance for simulating spring maize in Jinzhou, as well as other cities in Liaoning province.

3.2 The Linkage between Yield Loss rate and Drought Severity Frequency

Maize yield loss due to drought was calculated in each city of Liaoning province from 1961 to 2013. The results show that the annual average yield loss of maize in Liaoning province during 1961-2013 is 2236 kg/ha. The most serious yield loss occurred in Chaoyang and Fuxin that both located in west Liaoning province, with yield loss of 3900 kg/ha and 3412 kg/ha per year, respectively. There is little drought impact on yield in northern part of Liaoning province, especially in Tieling, which has a 427 kg/ha yield reduction per year. In the central and south part of Liaoning Province, there is a moderate severity of drought impact on maize yield.

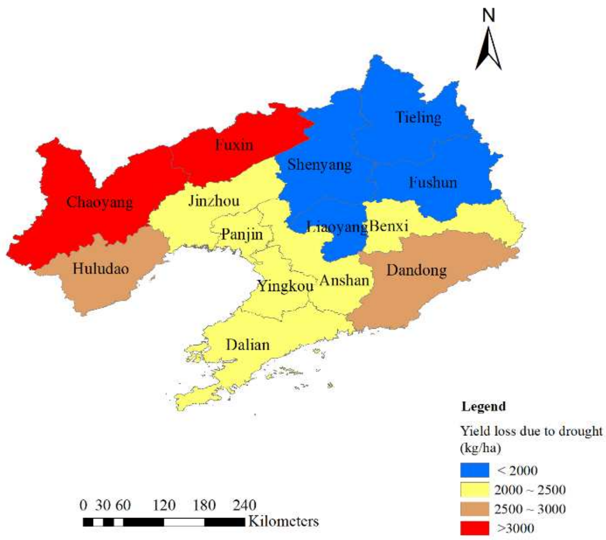

Figure 5: Simulated average annual yield loss due to drought during 1961-2013

The results of the model show that sum of daily maize water stress coefficient in each year is above 0 in Liaoning province, which illustrates that even in years with adequate precipitation, soil water supply may not meet the maize demand every day. The relationship between maize yield loss rate and DSI frequency was developed to assess the drought risk in Liaoning province in four different DSI frequency levels (20%, 10%, 5% and 2%). Since the drought risk is a combination of drought hazard and vulnerability (yield loss rate is used as an index to evaluate vulnerability), the more severe of drought impact on yield loss for a specific DSI frequency, the higher of drought risk.

Figure 6 presents the linkage between yield loss rate and DSI frequency in 14 cities of Liaoning. The logarithmic function was employed to describe the linkage and the R^2 of all cities was greater than 0.6, indicating that the function satisfactorily well in explaining the relationship between DSI frequency and yield loss rate due to drought in Liaoning province. From a visual inspection, it can be found that yield loss rate in Tieling is least sensitive to DSI frequency, whilst yield loss rate in Chaoyang and Fuxin are most sensitive to DSI frequency.

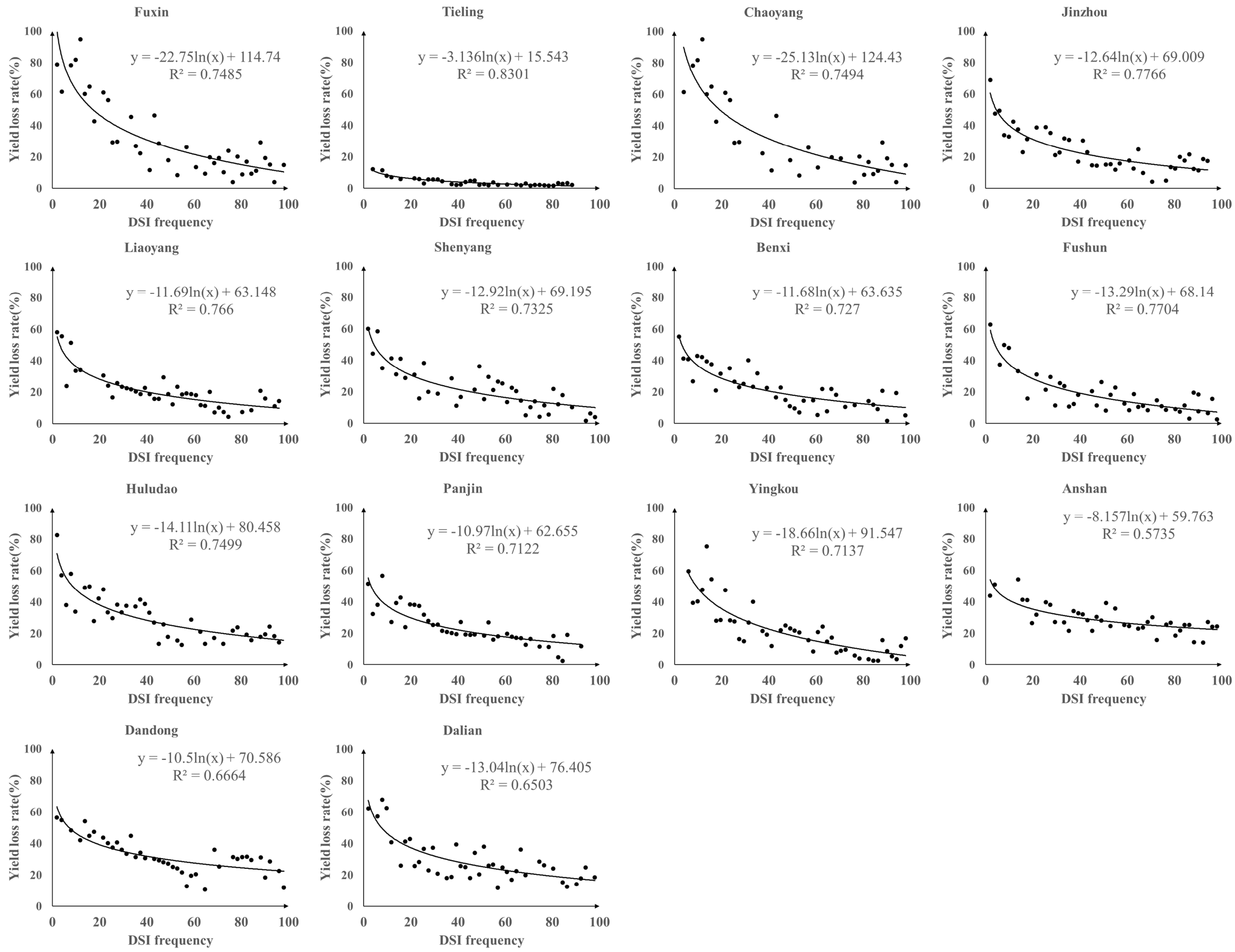

Figure 6: Linkage between DSI frequency and yield loss rate in 14 cities of Liaoning province

The fitted logarithmic function in each city was employed to calculate the yield loss rate (as an index for drought risk) in four drought severity frequency, 20%, 10%, 5% and 2%. Drought risk was identified in four grades and Table 6 presents the threshold of yield loss rate at each grade in four different DSI frequency. The thresholds are vary in four drought severity levels, the more severe of drought the higher thresholds of the yield loss rate.

Table 6 Threshold of yield loss rate (r) grades at four different DSI frequency

Drought risk grades	20%	10%	5%	2%
□	r<15%	r<20%	r<30%	r<40%
□	15%≤r<20%	20%≤r<30%	30%≤r<40%	40%≤r<50%
□	20%≤r<25%	30%≤r<40%	40%≤r<50%	50%≤r<60%
□	25%≤r	40%≤r	50%≤r	60%≤r

The yield loss rate of maize in different cities with the DSI frequency at 20%, 10%, 5% and 2% is shown in Figure 7. There is a higher drought risk in western Liaoning province than the east. The highest drought risk were identified in Chaoyang and Fuxin in four DSI frequency levels, both located in the west of Liaoning province, whilst the lowest drought risk is identified in Tieling in different drought severities frequency. Drought risk varies for each levels of DSI frequency

(20%, 10%, 5% and 2%) in central Liaoning province. Generally, there is a moderate drought risk in central of Liaoning

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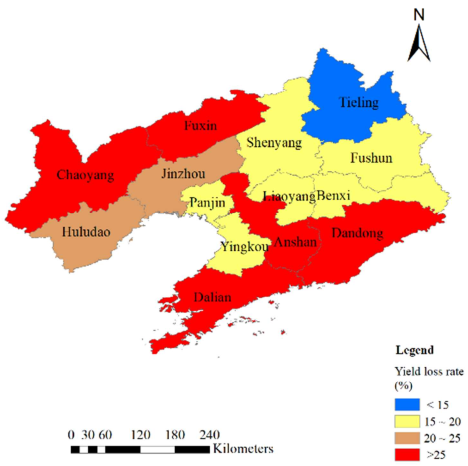
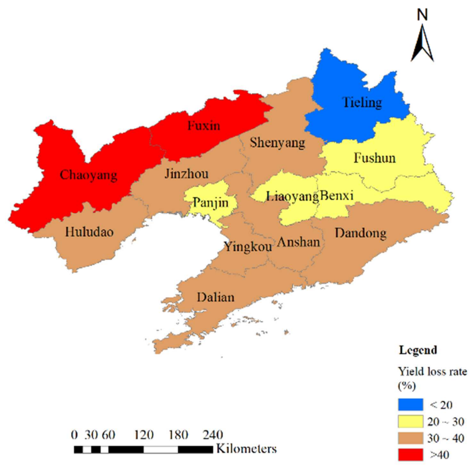
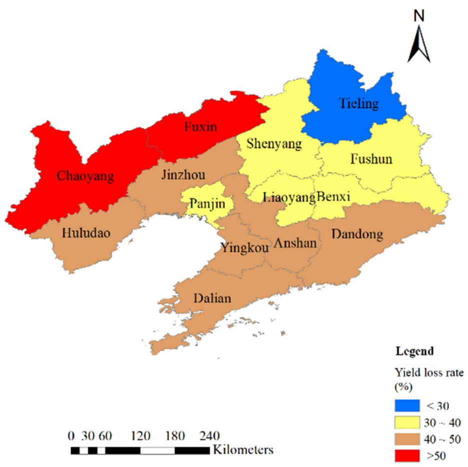
province. When DSI frequency is 20%, there is a higher drought risk in Dandong, Dalian and Anshan than other DSI frequency levels. A higher drought risk is identified in Yingkou when DSI is 2% compared to other drought frequency levels. Drought risk varies from different DSI frequency in Shenyang, Dandong, Yingkou and Dalian. Generally, drought risk decreased from west to east in Liaoning province. Drought risk distribution for spring maize is consistent with the simulated average yield loss due to drought in Liaoning province.



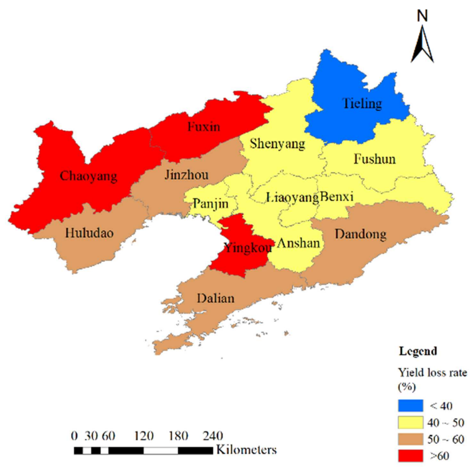
(a) Drought frequency is equal to 20%



(b) Drought frequency is equal to 10%



(c) Drought frequency is equal to 5%



(d) Drought frequency is equal to 2%

Figure 7: Yield loss rate of maize at four DSI frequency (20%, 10%, 5% and 2%) in Liaoning province

4. Discussion

Based on multiple source data: meteorological data, soil properties, maize growth process data and field management scheme, this study developed a quantitative method for drought risk assessment for spring maize in Liaoning province. Drought severity indicator was developed to identify the agricultural drought which considers both agricultural drought intensity and duration. APSIM model, which has a good ability in simulating water dynamic and crop water stress was applied to simulate the maize water stress and yield in Liaoning province (Song et al., 2010). APSIM model is driven by daily meteorological data to simulate maize growth and daily crop water

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stress while some other studies are based on monthly data during the growing season (Dennett and Elston, 1980;Luo et al., 1994;Sun et al., 2012a) that ignored the water stress events less than a month. However, a few days of water stress in critical growth stages can lead to a serious yield loss. Water stress of maize during growth period is a vital index to identify agricultural drought, whilst yield loss directly response to agricultural drought impact. Therefore, these two factors were selected to access agricultural drought risk specific to spring maize in Liaoning province.

The relationship between yield loss rate and DSI frequency was established to evaluate the drought risk in Liaoning province. There is a higher drought risk in western Liaoning province than the eastern area. Some of the drought risk assessment results are consistent with Shan et al. (2012), they found that there is a serious maize yield loss in western Liaoning province and the probability of the occurrence for severe drought or extremely drought is more than 45% in western Liaoning province. 30% of the sites with high-risk in Liaoning Province are mainly distributed in western Liaoning.

The above results are also in general agreement with Dan et al. (2011). Their results shows that eastern Liaoning province has a lower drought risk than western and drought risk increase from the east to the west. In Wang et al. (2015), their study focus on specific growth stages of maize and found that high drought risk are identified in the western part of Liaoning.

In eastern Liaoning, the rain-fed maize is less affected by drought, since it has more precipitation compared to the western region. Chaoyang and Fuxin have less precipitation than other cities with an average annual precipitation only 450mm-550mm, which can't meet the water demand of spring maize. Additional, per capita water resources of Chaoyang and Fuxin is less than 500 m^3, indicted there is a serious water resource shortages (Ban et al., 2010). In Tieling, the per capita water resources is 850 m^3, it is even higher than the per capita water resources in Liaoning province (Gong and Ning, 2009). The meteorological drought index (ratio of annual water surface evaporation to annual rainfall) gradually increases from east to west. The meteorological drought index in Chaoyang and Fuxin is more than 2.0, which makes it the most serious drought region in Liaoning province (Wang et al., 2014).

The climate, land surface conditions and natural environment result in a higher agricultural drought risk in the western Liaoning province than the east. According to the historical drought record, drought mostly occurs in spring in the western Liaoning province which has a serious impact on spring maize growth since water shortage at the seedling stage of maize can easily lead to a decrease in yield (Liang et al., 2008). Drought risk is related not only to climatic factors but also to conditions of the surface cover (Zhang, 2004). Parts of area in western Liaoning province is covered with hilly and mountainous, where the soil is barren, soil erosion and soil desertification occur frequently. It result in that drought occurred more easily in western Liaoning province.

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5. Conclusion

Drought impact on maize yield in four drought severity levels were interpret as agricultural drought risk in this research which is involve to the definition that drought risk is a combination of drought hazard and vulnerability. The APSIM model was applied to simulate maize yield loss due to drought. Calibration and validation show that APSIM model satisfactorily well to simulate spring maize yield in Liaoning province, with R^2 of all 14 cities were greater than 0.6. The result shows that there is a serious agricultural drought impact on maize yield in Liaoning province, with an average annual simulated yield loss during 1961-2013 of 2236 kg/ha, especially in Chaoyang and Fuxin, which are both located in western Liaoning, with annual average yield loss of 3900 kg/ha and 3412 kg/ha respectively. There is little drought impact on yield in Tieling, which is located in the northern Liaoning province.

Drought severity indicator was developed with maize water stress coefficient and duration, which directly reflect agricultural drought. The relationship between DSI frequency and yield loss rate was established to explore the drought risk in 14 cities in Liaoning province. The logarithmic function was established to explain relationship between DSI frequency and yield loss rate. The R^2 of all 14 cities were greater than 0.6, elucidating that the function can explain the linkage well. Drought risk maps shows that the western Liaoning province has a higher drought risk than the east. Drought risk varies at different DSI frequency levels in central region of Liaoning province. Chaoyang and Fuxin have the highest drought risk in four DSI frequency levels, while Tieling has the lowest risk in four DSI frequency. A higher drought risk was identified in Yingkou when DSI frequency is 2% than other drought severity levels. There is a moderate drought risk in central Liaoning province. Drought risk decreased from west to east in four DSI frequency, which is similar with the distribution of simulated yield loss due to drought during 1961-2013 in Liaoning province.

With the same fertilization and sowing scheme, this research assumed drought is the only factor affecting maize yield. However, maize yield was affected by multiple factors, flooding, pests and other diseases and yield has increased in the past decades because of the technological progress, fertilizer application and other factors. Actually, for farmers, the sowing date and fertilization scheme of maize changes every year in each city due to the weather condition. Sum of the daily crop water stress in each year was applied to calculate DSI, it ignore the fact that different growth stages of maize have different sensitivity to water stress. For example, the drought impact on yield of water stress occurred in emergence is different when the same severity of water stress occurred in silking. One major soil type is selected in each city, but it doesn’t match the soil type at the agrometeorological station. More experiment need to be done to measure soil data at agrometeorological station in the further study.

Since the main crop in Liaoning province is rain-fed maize, agricultural technology measures, such as inhibiting evaporation, maintaining water, and improving water use efficiency, can be taken to improve drought resilience. This method is able to predict maize yield loss due to drought for drought early warning and can provides guidance

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for drought preparedness, drought relief materials allocation and drought mitigation plans for decision makers. It also provides information for the optimization of industrial planting structures for farmers, and critical information for drought insurance premiums and subsidies. Since APSIM model has applicability in many countries and for a wide variety of crops and similar data can be collected in other regions, this methodology can be developed and expand to other regions in China (and other counties).

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Competing interests

The authors declare they have no conflict of interest.

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