Agricultural drought management in Northeast China and Inner Mongolia

中国東北部と内モンゴルにおける農業干ばつの管理

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SUMMARY

Droughts are the world's costliest weather-related natural hazards, causing an average 6–8 billion USD in global losses annually, and collectively affecting more people than any other type of natural disaster (Wilhite, 2000). Agricultural drought is important because it directly influences food security and therefore poses a grave threat to regional economies and society. In this thesis, agricultural drought is defined as "Crop yield damage phenomenon due to water shortage". Three provinces in northeastern China (Heilongjiang, Jilin, and Liaoning) and the Inner Mongolia Autonomous Region were chosen as the study area. Most regions in the continental climate zone have effective accumulated temperature ≥10 °C 1600–3400 ℃ and crops can be only harvested once per year. These important regions rely on rainfed cultivation. Based on a 0.5-degree precipitation dataset from 1961 to 2010, I tested seasonal and yearly precipitation using a coefficient of variation (CV) and linear trend method. I also analyzed the impact of precipitation on province-level crop yield. The results show that: (1) Meteorological drought became serious after the 2000s. Summer drought is a serious threat to farmland water supplies. Precipitation is the dominant control of crop yield fluctuation in Northeast China and Inner Mongolia; (2) there was a decreasing but not significant trend of annual precipitation for most of the latter two regions over 1961–2010; (3) annual precipitation varied greatly in the eastern and western parts of Inner Mongolia, western part of both Jilin Province and Liaoning Province. Owing to a lack of irrigation systems, there is greater drought or flood risk in the rainfed region of the study area.

Agricultural drought is heavily influenced by local factors (e.g., irrigation) and occurs under a certain climate background. Selection of the county is appropriate because it is the basic statistical area for agricultural production in China, and it affects regional food security. Combined with remote sensing and crop model new technologies, this thesis develops multiple methods to understand the relationships of various components with the drought system. I studied agricultural drought

management following the logic of drought occurrence monitoring, drought severity assessment, and drought mitigation practice assessment.

The first question regards the determination of agricultural drought occurrence (Chapter 3). A combination of various drought indices may provide a more comprehensive assessment of drought conditions than a single-index approach. However, this has been challenging because there has been a lack of systematic methods for their combination, use, and evaluation. I assumed that this issue is attributable to complex relationships between short-term rainfall, soil moisture, and crop growth. Therefore, I developed a new decadal time scale (~10 days) conceptual model and evaluated the drought process in a typical rainfed agricultural region, Hailar County in Inner Mongolia. To quantify drought, I used the precipitation-based Standardized Precipitation Index (SPI) and soil moisture-based Crop Moisture Index (CMI), as well as the Normalized Difference Vegetation Index (NDVI). Correlation analysis was done to examine relationships between drought indices during the growing season (May–September) and final yield, using data collected from 2000 to 2010. The results show that:

(1) Yield had positive relationships with the CMI from mid-June to mid-July and with the NDVI anomaly throughout July, but no relationship with the SPI

(2) The relationship between the two drought indices shows that the NDVI anomaly responded to CMI with a lag of one decade, particularly in July.

(3) To examine the feasibility of using these indices for monitoring the drought process at decadal time scale, a detailed drought assessment was carried out for selected drought years. The results confirm that the soil moisture-based and vegetation indices in the late vegetative through early reproductive growth stages can be used to detect agricultural drought in the study area. Therefore, the framework of my conceptual model can be used to support drought monitoring in the rainfed agricultural regions.

The second question regards agricultural drought severity assessment by a crop model (Chapter 4). Conventional assessment methods make it difficult to clarify drought effects on crop yield, because other factors such as technology development also influenced yield, and there was a shortage of long-term yield data. Crop models are a good choice for investigating yield, because they can simulate underlying physiological processes of crop growth and their change in response to environmental stress. Drought affects nearly all climatic regions. One must select a suitable crop model that can be widely used across different climate zones and crop types. To accurately evaluate regional drought intensity, I constructed an assessment framework with three components, namely, crop model calibration and validation, drought index calculation, and index assessment (standard period setting, mean value and agreement assessments with agricultural drought records). I built the assessment based on the Environmental Policy Integrated Climate (EPIC) crop model and tested comparison results by trend analysis. The results show that:

(1) The EPIC model simulated time series of county-level yields well in four spring wheat counties (*RMSE* = 0.556) and five maize counties (*RMSE* = 1.6) in Northeast China and Inner Mongolia.

(2) I calculated a major crop-specific index, i.e. yield reduction caused by water stress (WSYR) within the EPIC crop model, by relating potential and rainfed yields. Using 26 county-level agricultural drought cases, I compared WSYR with two meteorological drought indices, precipitation (P) and aridity index (AI). The results showed that WSYR had better agreement (85%) than either P (65%) or AI (68%).

(3) The temporal trend of the indices over the period 1962–2010 was tested using three approaches. The result from WSYR revealed a significant increase in agricultural drought in drought-prone counties, which was not indicated by P or AI. The increase of average decadal frequency from WSYR of drought years from the 1990s to 2000s was greater than those from P and AI. This study revealed the usefulness of the framework for drought index assessment and possible drought cases for drought classification. The validation and simulation suggest that crop models are useful for drought environment simulation over large regions.

The third question regards the comparison of agricultural drought practices with recovery yield under various drought severities (Chapter 5). Comparing the effects of various agricultural practices on crop yield provides important information related to strategies for mitigating drought. However, quantitative assessment of agricultural practices using common experimental methods requires considerable time and money. I simulated the effects of three practices (supplementary irrigation [SI], sowing date, and crop variety) on wheat and maize yield for dry, normal and wet years in the northeast and Inner Mongolia, based on the EPIC crop model. The results show that:

(1) A single 50-mm SI event was more effective in dry years than wet years for increasing crop yield

(2) A change in sowing date was less effective for increasing yield in dry years than in normal and wet years

(3) For traditional wheat-growing counties, planting the long growing season variety "Yongliang 4" can increase yield more than planting the short growing season variety. For traditional maize-growing counties, the short growing season variety "Dadi" gave better yields than "Zhedan37". However, none of the tested varieties showed significant yield differences based on variety in dry years. Changes in sowing date and variety altered yield less than a single 50-mm SI event, especially in dry years. This suggests that precipitation expressed as dry/wet years should be considered when growing crops. This work shows that the EPIC model can be a useful decision-making tool, in particular for drought mitigation in regions with an annual harvest period.

In summary, agricultural drought refers to water balance within the complex weather-soil-crop-society system in a given region. The agricultural drought management framework considers agricultural drought demands of these system components at different levels. The new drought monitoring framework in Chapter 3 can integrate timely information for agricultural drought early warning for meteorological, agricultural and water resource government departments. The drought severity assessment method in Chapter 4 can be used to identify regional drought years for long-term drought planning of civil departments. The comparison of practices in Chapter 5 can be used to select effective drought mitigation measures from governmental to farmer levels. This suggests consideration of the aforementioned three questions as a whole for drought management. In Northeast China and Inner Mongolia, the crop production system is typically rainfed and has one harvest annually. This may be the most basic regional agriculture-water system, and the investigations in this thesis are expected to provide suggestions for other locations worldwide. Future study should consider the calibration of fixed parameters for the CMI and validation of the crop model, using more cases with crop rotation, technology level, and human activity. Northeast China and Inner Mongolia have widespread water resource shortages, and meteorological drought became serious after 2000. Future agricultural drought studies should consider the regional water supply capacity and its relationship with socioeconomic sustainability.

摘 要

干ばつは、世界的に最も大きな損害をもたらす気象的自然災害である。年平均損失は 6 千万ドルから 8 千万ドルであり、他の自然災害よりも多くの人々に影響を与えている。農業干ばつは、食料安全保障に直接影響を及ぼし、地域経済や社会への重大な脅威をもたらすので、深刻な自然災害である。本論文では、農業干ばつを「水不足による作物収穫量の減少現象」と定義した。中国の東北部 3 省（黒龍江省、吉林省、遼寧省）と内モンゴル自治区を本研究の対象地とした。大陸性気候の多くの地域では、有効積算温度が 1600～3400℃である。それらの地域では、1 年に 1 回収穫が得られる天水栽培に依存する地域であり、春小麦とトウモロコシがその主要作物として栽培されている。中国東北部と内モンゴル自治区の農地における降水量変動の空間的・時間的パターンを 1961～2010 年における 0.5 度降水量データセットを用いて線形傾向法と変動係数（CV）により分析し、以下の結果が得られた。(1) 気象干ばつは 2000 年代以降深刻になった。夏季の干ばつは、農地における水供給に深刻な脅威となっている。降水量は、内モンゴルと中国東北部における作物収量変動を規定している。(2) 1961～2010 年の期間、中国北部のほとんどでは年間降水量の減少傾向が見られた。(3) 年降水量は、内モンゴル西端、内モンゴルと吉林省と遼寧省の境界領域で大きく変化した。灌漑施設が不足していることから、中国東北部と内モンゴル自治区の天水地域では干ばつ危険性があることから、干ばつ管理戦略が必要である。

農業干ばつは、地域的な因子（例えば灌漑施設の有無）によって影響され、気候的な要因によって発生する。中国の行政単位「県」は、農業統計の基本的な統計地域であり、地域の食料安全保障に影響を及ぼす。本研究では、典型的な県において、リモートセンシングと作物モデルを用いて、農業干ばつの新しい管理方法について検討した。農業干ばつの発生モニタリングおよび農業干ばつ強度評価と農業干ばつの被害緩和のための農法の比較を行った。

第一に、干ばつ指標を用いて、農業干ばつのモニタリングを行った。干ばつは、正確に定量化することが複雑な現象であり、短期的な降雨、土壌水分、および作物の成長の間には複雑な関係がある。単一の指標を用いるよりも、様々な干ばつ指標を組み合わせる方が、より統合的な評価を提供する。しかしながら、複数指標を用いた評価は、指標の組み合わせ、使用、および評価のための体系的な方法について十分に検討されていない。そこで本研究では、典型的な天水農業地域である内モンゴルの海拉爾市を対象に干ばつ枠組みの構築を試みた。干ばつを定量化するために、短期間(旬)単位で、標準化降水指数(SPI)、作物水分指標(CMI)、リモートセンシング正規化植生指数(NDVI)偏差、およびエネルギー収量(作物収量の平均カロリー)を計算した。2000～2010 年のデータを用いて干ばつモニタリングを検討したところ以下の結果が得られた。

(1) CMI は 6 月中旬から 7 月中旬、NDVI は 7 月全体に収量との相関が見られた。

(2) CMI は NDVI より 1 旬（10 日間）早く相関係数の最大値が見られた。CMI により約 10 日前に作物生育被害の予測が可能である。

（3）農業干ばつ評価の枠組みを短期間単位で構築できることが明らかになった。この結果から、初期の栄養成長段階の後期における土壌水分指数と植生指数を用いて農業干ばつを検出することができる。

以上のことから、本研究で提案された干ばつ評価の枠組みに基づいて干ばつ災害の早期警戒が可能となることが示唆された。

第二の課題は、作物モデルを活用した天水農業干ばつの強度の評価である。作物モデルは、生理学的プロセスをシミュレーションすることができる。そこで作物生長モデルの校正･検証、干ばつ指数の計算、および指数比較（標準期間設定、平均値チェックと近代における農業干ばつ記録を用いた検証）を行った。地域の干ばつ強度を評価するために、EPIC（The Environmental Policy Integrated Climate）作物生長モデルに基づいて評価を行った。

（1）春小麦が栽培されている４県とトウモロコシが栽培されている５県を対象に EPIC モデルを用いた結果、推定された作物収量は、県統計の実際の収量とほとんど一致した。

（2）EPIC 作物モデルにおける 当該作物の灌漑条件下での推定収量と天水条件下での推定収量の差を灌漑条件下での推定収量で除した値（0～1）（WSYR: Water Stress Yield Reduction）を計算した。各県の近代に発生した 26 回の農業干ばつ記録を使用して、三つの干ばつ指数：降水量（P）と乾燥度指数（AI）と WSYR とを比較した。その結果、WSYR は降水量(65%)または乾燥度指数(68%)のいずれかよりも高い適合百分率（85%）を示すことがわかった。

（3）1962～2010 年の期間、指標の年次変化を三つの指数を用いて分析した。WSYR を用いることで、降水量および乾燥度指数により示すことができなかった農業干ばつの傾向の増加を明らかにすることができた。1990 年代から干ばつの十年平均の頻度については WSYR が P と AI より高かった。

以上のように、本研究で提案した干ばつ評価の枠組みの有用性を明らかにした。本研究で提案された WSYR 指数は、過去の農業干ばつ記録とよく一致することが示された。作物モデルは、広域的な農業干ばつの評価のために有用なツールであることが示された。

第三の課題は、干ばつ被害の緩和のための農法の比較である。さまざまな農法の違いが作物収量に及ぼす影響を比較することは、干ばつ被害を緩和するための戦略において重要な情報を提供する。しかし通常の実験的手法を用いた農法の定量的評価は、多大の時間と費用を必要とする。本研究では、EPIC モデルを用いて、中国東北部と内モンゴル自治区の典型的な県を対象とし、乾燥年、通常年、および多雨年におけるコムギとトウモロコシの収量に対する三つの農法（補助灌漑、播種日および作付け品種の変更）の効果を明らかにし、以下の結果が得られた。

（1）補助灌漑（50mm×１回）は、作物収量の増加について通常年より乾燥年でより効果が高かった。

（2）播種日の変更は、通常年と多雨年に比べて乾燥年では収量増加の効果が低かった。

（3）コムギ生産県では、生育期間の短い品種「竜麦 26」に比べて生育期間の長い品種「永良 4」で、より高い収量が得られた。トウモロコシ生産県では、生育期間の長い品種「哲单 37」よりも、生育期間の 短い品種「大地」で、より高い収量が得られた。しかし乾燥年では、検定されたどのコムギ・トウモロ

コシ品種も収量に関して有意な差が見られなかった。補助灌漑（50mm×１回）は、播種日および作付け品種の変更の効果が大きく、特に乾燥年ではその傾向が顕著だった。

作物の栽培においては、乾燥年・多雨年といった降水量の違いが十分に考慮されるべきであることが示唆される。本研究の結果から、とりわけ一毛作地域における干ばつ緩和において、EPIC モデルが有効な意思定ツールとして役立ち得ることが示された。

以上を要するに、農業干ばつは、特定の地域の気象-土壌-作物-社会の複雑なシステム内の水分バランスに影響される。本研究で提案された新しい干ばつモニタリングフレームワークでは、気象、農業や水資源と関連する政府部門に対してタイムリーな情報を提供することができる。干ばつ強度評価法は、長期的な干ばつ計画のための地域の干ばつ年特定に用いることができる。農法の比較は、政府や農民が効果的な干ばつの緩和策を選択する際に使用することができる。このフレームワークは、農業干ばつに関連するさまざまなレベルの要求を考慮している。調査地域における天水作物生産システムは、年１回収穫として特徴づけられる。今後、CMI のパラメータと技術レベル、輪作などを考慮した作物モデルの検証を行う必要がある。21 世紀の最初の十年で農業干ばつの強度が深刻になった中国東北部と内モンゴルでは、農業干ばつに備えて地域給水能力の向上や適応戦略を検討する必要がある。

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ABBREVIATIONS

A	The assimilation rate
AI	Aridity index
ANOVA	Analysis of variance
APSIM	Agricultural Production System Simulator
AWC	Available water content
B	Biomass produced cumulatively
b	Intercept for the linear trend fitness
BAG	Above-ground biomass
BE	crop parameter for converting energy to biomass
CAFEC	Climatically appropriate for existing conditions
CHT	Changtu County
CMI	Crop moisture index
CV	Coefficient of variation
D	Moisture departure to calculate PDSI
DEP	Deficiency or surplus of water resources
DL	Duolun County
DSH	Dongsheng County
E	Evaporation
EDI	Effective Drought Index
Ep	plant water evaporation rate
EPD	Valid accumulations of precipitation
EPIC	Environmental Policy Integrated Climate
ERGN	Eerguna County
ET	Actual evapotranspiration
ET_x	Maximum evapotranspiration
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization
FHU	A function of crop stage
G	An index of excessive moisture
GF	Gain factor to calculate EVI
H	"return-to-normal" factor to calculate CMI
HI	Harvest index
HIA	Adjusted harvest index
HL	Hailun County
HLR	Hailar County
HUI	Heat unit index
IDL	Interactive Data Language
K	coefficient to calculate D for PDSI
K_y	Yield response factor
L	Water loss to the soil layers
LAI	leaf area index

Ls	Water loss from surface soil layers to calculate CMI
Lu	Water loss from underlying soil layers to calculate CMI
M	Average percent of field capacity to calculate CMI
m	Slope for the linear trend fitness
MODIS	Moderate-resolution Imaging Spectroradiometer
NA	Nong'an County
NDVI	Normalized Difference Vegetation Index
NDVIA	Normalized Difference Vegetation Index anomaly
P	Precipitation
PA	Precipitation anomaly
PAR	photosynthetic active radiation
PDSI	Palmer Drought Severity Index
PET	Potential Evapotranspiration
PL	Potential water loss to caculate PDSI
PR	Potential recharge to caculate PDSI
PRN	One day’s precipitation needed for a return to normal condition
PRO	Potential runoff to caculate PDSI
R	Recharge
r	Pearson correlation coefficient
R^2	Coefficient of determination
RA	solar radiation
REG	minimum crop stress factor
RMSE	Root mean square deviation
RO	Runoff
RVI	Relative vegetation index
SI	Supplemental irrigation
SL	Soil adjustment factor to calculate EVI
SM	Soil moisture
SMA	Soil moisture anomaly
SPI	Standardized Precipitation Index
Ss	Surface soil moisture
Su	Underlying soil moisture
SWSI	Surface water supply index
SZW	Siziwang County
T_a	Actual transpiration
T_b	base temperature
TG	Soil surface temperature
TGBW	Bare soil surface temperature on wet day
T_o	Optimal temperature
T_p	Potential transpiration
T_S	Plant temperature stress factor
WMO	World Meteorological Organization
WOFOST	World Food Studies
WS	Water stress factor

WSYF	Crop parameter expressing drought sensitivity
WSYR	Water stress yield reduction
X	PDSI value for specific month
Y_a	Actual yields
YI	Yield under fully irrigation
YLD	Amount of the crop removed from the field
YR	Yield under rained condition
Y_x	Maximum yields
ZHLT	Zhalute County
α	Water balance coefficient
ρ_{NIR}	Near-infrared reflectance
ρ_{RED}	Red radiation reflectance
σ	Standard deviation
σ_{PRN}	Standard deviation of the relevant PRN
Ω_s	Scaling factor to adjust for wet days

Chapter 1

General introduction

1.1 The terminology related with agricultural drought

1.1.1 Drought concepts

Drought is recognized as an environmental disaster and has attracted the attention of environmentalists, ecologists, hydrologists, meteorologists, geologists and agricultural scientists. There are variations of definitions of drought. Linseley (Linseley et al., 1959) defined ‘drought as a sustained period of time without significant rainfall’. World Meteorological Organization (WMO, 1986) defines ‘drought means a sustained, extended deficiency in precipitation.’ Gumbel (Gumbel, 1963) defined a ‘drought as the smallest annual value of daily streamflow’. The Food and Agriculture Organization (FAO, 1983) of the United Nations defines drought hazard as ‘the percentage of years when crops fail from the lack of moisture.’ More complete definition is that by the United Nations Convention to Combat Desertification, drought is “naturally occurring phenomenon that exists when precipitation has been significantly below normal recorded levels, causing serious hydrological imbalances that adversely affect land resource production systems.” (UNCCD, 1994)

1.1.2 Drought types

According to Wilhite and Glantz, drought can be divided into 4 types: Meteorological drought, Hydrological drought, Agricultural drought and Socio-economic drought (Wilhite and Glantz, 1985; American Meteorological Society, 2004).

Meteorological drought is defined as a lack of precipitation over a region for a period of time (Mishra and Singh, 2010). It is usually on the basis of the degree of dryness (in comparison to some “normal” or average amount) and the duration of the dry period.

Hydrological drought related to a period with inadequate surface and subsurface water resources for established water uses of a given water resources management system. It is associated with the effects of periods of precipitation (including snowfall) shortfalls on surface or subsurface water supply (i.e., streamflow, reservoir and lake levels, groundwater) (Wilhite and Glantz, 1985).

Socio-economic drought is associated with failure of water resources systems to meet water demands and thus associating droughts with supply of and demand for an economic good (water) (American Meteorological Society, 2004). Socio-economic drought occurs when the demand for an economic good exceeds supply as a result of a weather-related shortfall in water supply.

Agricultural drought links various characteristics of meteorological (or hydrological) drought to agricultural impacts, focusing on precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits, reduced groundwater or reservoir levels, and so forth (Wilhite and Glantz, 1985). Agricultural drought was said to be ‘a period of dry weather of sufficient length and severity to cause at least partial crop failure’ or ‘when soil moisture is depleted so that the yield of plants is reduced considerably’ (Agnew and Anderson 1992). In this thesis, I briefly defined agricultural drought as “crop yield damage phenomenon due to water shortage”.

1.1.3 Aridity, water shortage and drought

There are several similar concepts used when water is insufficient: aridity, water shortage and drought. Aridity is a nature produced permanent imbalance in the water availability characterizing the climatic conditions of a region (WMO, 1975). Water shortage is mainly caused by human induced causes. It means the deficit of water supply to meet the demands and is mainly caused by inappropriate use of water resources or man-made changes (Tsakiris et al., 2013). By comparison, drought is a nature produced but temporary imbalance of water availability caused mainly by low precipitation and thus resulting in lower availability of water resources. When the concept ‘drought’ is used, it refers the relative dry period of water availability compared with normal and wet period.

1.2 Drought in the world

Drought causes an average 6–8 billion ($US) in global losses annually (Wilhite, 2000). Key regions facing droughts are, for instance, Sub-Saharan Africa, the Middle-East and North Africa, South-Eastern Europe, Central Asia, Australia, Brazil, India, USA and China (United Nations International Strategy for Disaster Reduction, 2011). Following the recent IPCC Fifth report (Intergovernmental Panel on Climate Change, 2014), each of the last three decades has been successively warmer at the Earth's surface than any preceding decade since 1850. In the Northern Hemisphere, 1983–2012 was likely the warmest 30-year period of the last 1400 years (medium confidence).The warming intensifies the global hydrological cycle (e.g., Milly et al., 2002). Drought frequency will likely to be increased in dry regions by the end of the 21st century under RCP8.5. The frequency and intensity have likely increased in the Mediterranean and West Africa and likely decreased in central North America and north-west Australia. There is medium confidence that water scarcity in northern China has been exacerbated by decreasing precipitation, doubling population, and expanding water withdrawal from 1951 to 2000.

1.3 Reviews of drought researches

Droughts have significant environmental, agricultural, health, economic and social consequences. There are different researches on drought.

1.3.1 Climate background and drought

Climatic events such as El Niño-Southern Oscillation (ENSO) is a naturally occurring phenomenon that involves fluctuating ocean temperatures in the equatorial La Niña, sometimes informally called "anti-El Niño", is the opposite of El Niño, where the latter corresponds instead to a higher sea surface temperature by a deviation of at least 0.5 ℃, and its effects are often the reverse of those of El Niño. They are well associated with significant climate anomalies such as drought at many places around the globe. Drought was depicted by annual precipitation anomaly, some researches (Waple et al., 2002; Hoerling and Kumar, 2003) show that the 1998-2002 droughts spanned much of the Northern Hemisphere Midlatitudes, with great severity in the regions of the western US, southern Europe, Southwest Asia, eastern Asia and Siberia. Cold sea surface temperatures (SSTs) in the eastern tropical Pacific and warm SSTs in the western tropical Pacific and Indian oceans were remarkably persistent during this period. From aspect of regions, El Niño events caused precipitation shortage across Mexico (Magaña et al., 2003; Cavazos and Hastenrath, 1990), Kalahari Desert of central southern Africa (Nash and Endfield 2008). Variability in thunderstorm and rainfall activity were related with El Niño and La Niña over India (Kulkarni et al., 2013). El Niño can also influence the precipitation in China significantly during its mature phase (Zhang et al., 1999). Climatic event not only may cause shortage of precipitation but also soil moisture and stream flow. Wu found that the roles of remote SST forcing and local soil moisture differ significantly for long-term and short-term droughts in the U.S. Great Plains and Southwest. Dai, et al. (1998) show that the revealed a qualitative agreement between Palmer Drought Severity Index (PDSI) and stream flow, and changes of global drought by using PDSI were closely related to the shift in El Ni˜no-Southern Oscillation (ENSO) towards more warm events since the late 1970s .In Austria, there were a strong relationship exists between stream flow and the El Niño–Southern Oscillation (ENSO) phenomenon (Simpson et al., 1993) and El Niño conditions were often associated with decreased annual flows and La Niña with increased flows in Sri Lanka (Zubair, 2003). Kiem and Franks (2004) investigated multi-decadal variability of drought risk by analyzing the performance of a water storage reservoir in New South Wales, Australia. Abtew and Trimble (2010) evaluated relationships between El Niño–Southern Oscillation (ENSO) indices and South Florida hydrology . Climatic events even can influence global grain yield. Khandekar (1996) found that ENSO event is generally associated with a drought in the Indian monsoon followed by a low grain yield over South Asia and Australia and high grain yield over the north American prairies. In sum, climatic events mainly influence long term drought. The study hotspots concentrate on regions with oceanic climate and are sensitive to these climate events.

1.3.2 Basic characteristics of drought and drought indices

Long term historical drought series can be reconstructed by using proxy data such as literatures (CNMA, 1981; Shen et al., 2007) and tree-ring (Hughes and Brown, 1992; Cook et al., 2007; Fang et al., 2010). The more accurate one is based on scientific instrument data which was started from 100-200 years ago. In the review of drought researches, I focus on the drought based on scientific instrument records.

Drought severity is always defined by different drought indices like below.

(1) Precipitation Anomaly (PA)

$$PA_{i,j} = \frac{P_{i,j} - P_{\mathrm{ave},j}}{P_{\mathrm{ave},j}} \times 100 \qquad (1\text{-}1)$$

where i is year, j is specific decade or month, and $P_{ave,j}$ is the average value for the same decade or month j during multiple years.

(2) Standardized Precipitation Index (*SPI*)

SPI is based on the assumption that precipitation over a period is a random variable distributed according to a gamma probability density function (McKee et al., 1993, 1995). Therefore, it requires a long-term precipitation record to fit the gamma probability density function. The *SPI* is a typical meteorological drought index that considers only precipitation. *SPI* takes into account the stochastic nature of the drought and is therefore a good measure of short- and long-term meteorological drought. It has been accepted by the World Meteorological Organization (WMO) as the reference index to characterize droughts.

(3) Effective Drought Index (*EDI*)

Byun and Wilhite (1999) developed the *EDI* to detect beginning, end, and accumulation stress of drought. The following equations were used for daily EDI calculations:

$$EP_D = \sum_{n=1}^{D}\left[\left(\sum_{m=1}^{n} P_m\right)/ n\right] \tag{1-2}$$

$$DEP = EP - MEP \tag{1-3}$$

$$PRN = DEP \Big/ \sum_{k=1}^{D}\frac{1}{K} \tag{1-4}$$

$$EDI = PRN / \sigma_{PRN} \tag{1-5}$$

Where *EPD* represent the valid accumulations of precipitation from a particular date; *D* is duration of summation begins from 365; P_m is precipitation of m days before. *DEP* shows the deficiency or surplus of water resources for a particular date and place; *MEP* is 30-yr mean of *EP* for each calendar day. In order to reflect the drying effect on the soil from a drought that occurred several years ago, when *DEP* is negative for two consecutive days, "*D*" becomes 366(=365+2-1) and the calculation begins once again; *PRN* is one day's precipitation needed for a return to normal condition; σ_{PRN} is the standard deviation of the relevant *PRN*.

(4) Palmer Drought Severity Index (*PDSI*)

Palmer (1965) introduced the concept of the "climatically appropriate for existing conditions" (CAFEC) value that quantities evapotranspiration, recharge, runoff, loess and precipitation. It considers four surface water fluxes: Evaporation (*E*), recharge to soils (*R*), runoff (*RO*), and water loss to the soil layers (*L*), and their potential values *PE*, *PR*, *PRO,* and *PL,* respectively.

The *PDSI* is calculated using monthly data. For calculation of *ET*, it assumes that soil moisture storage is handled by dividing the soil into two layers and for one dekad when *PET*<P, *ET*= *PET* where *ET* is actual evapotranspiration, *PET* is potential evapotranspiration, *P* is precipitation; if *PET* >*P*, *ET* is the sum of precipitation and water loss from soil layers. The water losses from two layers are as following

$$Ls_i = \min\left[Ss_{i-1}, (PET_{oi} - P_i)\right] \tag{1-6}$$

$$Lu_i = \left[(PET_{\mathrm{oi}} - P_i) - Ls_i\right] Su_{i\text{-}1} / AWC,\ Lu_i \le Su_{i-1} \tag{1-7}$$

where Ls_i and Lu_i is the water loss from surface and underlying soil layers for monthly i; $Ss_{i\text{-}1}$ and $Su_{i\text{-}1}$ are the surface and underlying soil moisture for i-1; *AWC* is available water content.

The CAFEC precipitation ($\hat{P}$) represents the amount of precipitation needed to maintain normal soil moisture level for a given time, α_i, β_i, γ_i, δ_i are water-balance coefficients between surface water fluxes and their potential values for month i. it is defined as

$$\hat{P} = \alpha_i PE + \beta_i PR + \lambda_i PRO - \delta_i PL \qquad (1\text{-}8)$$

The difference between the actual precipitation in a given month and the

computed $\hat{P}$ for the same month is the moisture departure (D=P- $\hat{P}$).

Palmer multiplied D by a climatic characteristic coefficient K to Palmer Moisture Anomaly Index or the Z index ($Z = DK$). x The Z index is used to compute the PDSI value for time t (X_t):

$$X_t = pX_{t\text{-}1} + qZ_i = 0.897X_{t\text{-}1} + Z_t / 3 \qquad (1\text{-}9)$$

$X_{t\text{-}1}$ is the PDSI for the previous month t-1.

PDSI can be slow to respond to developing and diminishing droughts (Hayes et al., 1999). Dai (Dai et al., 1998) revealed a qualitative agreement between PDSI and streamflow.

(5) Crop Moisture Index (*CMI*)

The *CMI* (Palmer, 1968) is based on a subset of the calculations required for the *PDSI* (Palmer, 1965). The origin *CMI* begins with a water balance using historic records of precipitation and temperature. Considering the short-term moisture supply and the moisture demand of the crop, *CMI* is the sum of evapotranspiration deficit and excessive moisture. The equations for these two aspects and *CMI* are as follows:

$$Y_i = 0.67Y_{i\text{-}1} + 1.8\frac{ET_i - (\alpha \times PET_{oi})}{\sqrt{\alpha}} \qquad (1\text{-}10)$$

$$G_i = G_{i\text{-}1} - H_i + (M_i \times R_i) + RO_i \qquad (1\text{-}11)$$

$$CMI_i = Y_i + \qquad (1\text{-}12)$$

Where Y_i is an index of evapotranspiration deficit for dekad i; *ET* is actual evapotranspiration; *PET* is potential evapotranspiration; α is a water balance coefficient; G_i is an index of excessive moisture for dekad i; H is a “return-to-normal” factor; M_i is the average percent of field capacity; R_i is recharge; and RO_i is runoff.

(6) Surface water supply index (*SWSI*)

The surface water supply index (*SWSI*) was primarily developed as a hydrological drought index and it is calculated based on monthly non-exceedance probability from available historical records of reservoir storage, streamflow, snow pack, and precipitation (Shafer and Dezman, 1982). Four inputs are required within SWSI: snowpack, streamflow, precipitation, and reservoir storage. Because it is dependent on the season, SWSI is computed with only snowpack, precipitation, and reservoir storage in winter. During summer months, streamflow replaces snowpack as a component within the *SWSI* equation.

(7) Normalized Difference Vegetation Index (*NDVI*)

NDVI (Rouse et al., 1974) is calculated based on remote-sensing measurements of visible (Red) and near-infrared (NIR) radiation:

$$NDVI = (\rho_{\mathrm{NIR}} - \rho_{\mathrm{RED}})/(\rho_{\mathrm{NIR}} + \rho_{\mathrm{RED}}) \qquad (1\text{-}13)$$

where ρ is spectral reflectance. It is a measure of the greenness or vigor of vegetation. Among the vegetation indices, NDVI is the one most often used and it is an operational, global-based vegetation index, partly due to its ratio properties, which enable the NDVI to cancel out a large proportion of noise in remote-sensing data caused by changing sun angles, topography, clouds or shadow, and atmospheric conditions (Huete and Justice,1999). Stressed vegetation or vegetation with small leaf area has positive but low values of *NDVI* (Kogan, 1994). Therefore, NDVI is often used in research on vegetation dynamics (Zhou, et al., 2009; Duan et al., 2011) and drought spatial monitoring (Kogan and Sullivan, 1993; Kogan, 1994; Kogan, 1997).

(8) Ratio Vegetation Index (*RVI*)

RVI (Birth and McVey, 1968) is calculated by simply dividing the reflectance values of the near infrared band by those of the red band:

$$RVI = \rho_{\mathrm{NIR}} / \rho_{\mathrm{RED}} \qquad (1\text{-}14)$$

. The result clearly captures the contrast between the red and infrared bands for vegetated pixels, with high index values being produced by combinations of low red (because of absorption by chlorophyll) and high infrared (as a result of leaf structure) reflectance.

(9)Enhanced Vegetation Index (*EVI*)

Enhanced Vegetation Index (Huete et al., 1999) is a modified *NDVI* with a soil adjustment factor *SL* and two coefficients *C1* and *C2*, which describe the use of the blue band in correction of the red band for atmospheric aerosol scattering:

$$EVI = GF\left(\rho_{\mathrm{NIR}} - \rho_{\mathrm{RED}}\right) / \left(\rho_{\mathrm{NIR}} + C1\rho_{\mathrm{RED}} - C2\rho_{\mathrm{B}} + SL\right) \qquad (1\text{-}15)$$

The coefficients adopted in the MODIS-EVI algorithm are: *L*=1, *C1* = 6, *C2* = 7.5 and *GF* (gain factor) = 2.5. This *EVI* has improved sensitivity to high biomass regions and reduced atmospheric influence.

Not only severity, drought has lots of other basic characteristics: frequency, duration and spatio-temporal pattern. There are inter-relationship among these characteristics. Typically, there are drought severity–area–frequency (SAF) curves (Mishra and Desai, 2005; Mishra and Singh, 2008), and severity–duration–frequency (SDF) curves (Saghafian et al., 2003) and severity–area–duration (SAD) curves (Grebner and Roesch, 1997). Drought frequency is defined as the number of drought events occurred, drought duration as the number of months in drought conditions, and drought severity as the sum of the integral area below zero of each event. Based on 12 month SPI, Spinoni et al. (2014) found a small global increase in each drought component from 1951 and 2010, but drought frequency decreased in the Northern Hemisphere. The increase in drought frequency, duration, and severity is found to be significant in Africa, Eastern Asia, Mediterranean region, and Southern Australia, while the Americas and Russia show a decrease in each drought component. Sheffield et al. (2009) identified 296 large-scale drought events (greater than 500 000 km2 and longer than 3 months) globally for 1950–2000 based on simulated soil moisture by using severity–area–duration curve. In these curves, drought index is a key point. It is commonly depicted by precipitation or soil moisture.

The overall impact of a drought depends on several factors, severity, frequency, area, and duration which are essential for spatio-temporal analysis or in other words regional drought analysis (Mishra and Singh, 2009). Taking researches in China for example, based on SPI at different time scales as severity index, Zhang et al. (2012) investigated drought spatial and temporal pattern in Xinjiang, and Zhai and Feng (2009) investigated drought pattern in Gansu province. Based on statistics of newspaper reports, Wang et al. (2002) investigated drought spatial and temporal pattern in China. Based on historic drought disaster observation, Hao et al. (2012) assessed drought risk in China.

From above, it can be seen that the definition of drought by different drought indices seriously influences characteristics identification. When considering occurrence of drought, it needs to use suitable drought indices for assessment.

1.3.3 The prediction of drought impact on vegetation

There are some researches which predict yield by using drought indices. Quiring and Papakyriakou (Quiring and Papakyriakou, 2003) compared the performance of four drought monitoring indices and found that indicated that Palmer's Z index is the most appropriate index for measuring agricultural drought in the Canadian prairies to predict spring wheat yields. Mishra and Cherkauer (2010) found crop yields during the period of 1980–2007 were strongly correlated with the occurrence of meteorological drought and maximum daily temperature during the grain filling and reproductive growth period. Potop et al. (2012) found relatively significant negative correlations between the *SPEI* from April to September and the detrended yields of root vegetables ($r = -0.68$), and a linear regression model based on the *SPEI* series explained 59.1% of the variability of the annual detrended yield. Remote sensing technology starting from 1990s provides new ways for yield damage prediction. Kogan et al. (2005) modeled corn yields using a drought index based on remote-sensing data. Mkhabela et al. (2011) and found *NDVI* from the third dekad of June through the third dekad of July could predict grain yield (i.e., barley, canola, field peas, and spring wheat) well in the sub-humid zone. The spatial accumulation of NDVI at the county level in Shandong province of China can predict yield of winter wheat 40 days ahead of harvest time, i.e. at the booting-heading stage of winter wheat (Ren et al., 2008). Liu (Liu et al., 2012) combined the strengths of 1-month, 3-month and 6-month *SPI*, *PDSI* and *Z index* for agricultural drought assessment as related to spring wheat yield. For these researches, the statistics method is usually introduced to judge the precise of yield prediction.

1.3.4 Drought monitoring framework

Svoboda (2000) used the drought monitoring categories method to convert multiple indices into a common standardized form and then incorporated them into an objective single index to evaluate drought intensity. Other assessments have evaluated the impact of drought by assessment of a map of drought conditions at a bi-weekly time scale using the Vegetation Drought Response Index which integrated *NDVI*, *PDSI*, *SPI*, soils, land cover, land use, and the ecological setting (Brown et al., 2008). A multi-index drought model was developed to predict spring wheat yield residuals at six stages based on the monthly *SPI*, *PDSI* and *Z index* (Sun, 2012). The disadvantages are that they did not provide systematic and mechanistic structure. Just like comments from Steinemann and Cavalcanti (2006): A combination of various drought indices may provide a more comprehensive assessment of drought conditions than a single-index approach, but this has been challenging because there has been a lack of systematic methods for their combination, use, and evaluation. It needs to build new logic of drought assessment framework.

1.3.5 Modeling of water stress

Models are generally defined as simplification or abstraction of a real system. The traditional agronomic research methods are not sufficient to meet these increasing needs for agricultural decision making. Models were developed to integrate knowledge about soil, climate, crops, and management for making better decisions. Two types of models are closely related with drought: one is hydrological model, the other is crop model.

The SWAT (Soil&Water Assessment Tool) model (Arnold et al., 1998) is a physically based, semi-distributed and time-continuous hydrological model that operates on a daily time step. It can take into account the processes associated with climate, hydrology, crop growth, agricultural management, nutrients, pesticides, etc. in a large complex watershed. SWAT model is useful tool for water management and drought researches (e.g. Tessema, 2007; Sun and Ren, 2014); The VIC (Variable Infiltration Capacity) model (Liang et al., 1994, 1996) is such a land surface macroscale hydrology model that has been wide used in drought research. It uses a spatial probability distribution function to represent subgrid variability in soil moisture storage capacity. VIC model was widely used to simulate soil moisture drought (e.g. Wu et al., 2009; Wang, et al., 2011a).

A crop model can be described as a quantitative scheme for predicting the growth, development, and yield of a crop, given a set of genetic features and relevant environmental variables (Monteith, 1996). Crop model was born in 1960s and it can simulate crop growth from infancy to maturity (Sinclair and Seligman, 1996). The crop model can even simulate growth details such as pattern of flowering and pollination (Dirk Raes et al., 2012) and when drought causes plant to die (Schultz, 2014). There are some crop models are widely used such as CROPWAT (Doorenbos and Kassam, 1979), EPIC (Williams et al., 1989), CERES (Jones and Kiniry, 1986), WOFOST (de Wit, 1965), APSIM (McCown et al., 1996) and AquaCrop model (Steduto et al., 2009). They have their respective ways to depict water stress and their influences on production. The common point is water use ratio to reduce the photosynthesis.

(1) CROPWAT model

CROPWAT is a decision support tool developed by the Land and Water Development Division of FAO. All calculation procedures used in newest software version CROPWAT 8.0 are based on the two FAO publications of the Irrigation and Drainage Series, namely, No. 56 "Crop Evapotranspiration - Guidelines for computing crop water requirements” (Allen, 1998) and No. 33 titled "Yield response to water"(Doorenbos and Kassam, 1979).

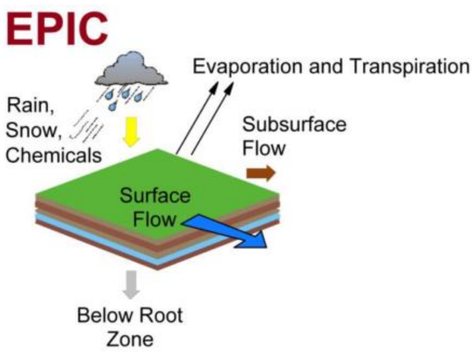
FAO addressed the relationship between crop yield and water use in the late seventies proposing a simple equation where relative yield reduction is related to the corresponding relative reduction in the evapotranspiration (*ET*).

$$\left(1-\frac{Y_{\mathrm{a}}}{Y_x}\right)=K_y\left(1-\frac{ET_a}{ET_x}\right) \tag{1-16}$$

Where Y_x and Y_a are the maximum and actual yields, ET_x and ET_a are the maximum and actual evapotranspiration, and K_y is a yield response factor representing the effect of a reduction in evapotranspiration on yield losses.

(2) EPIC model

The EPIC (Environmental Policy Integrated Climate) model was developed in the USA to investigate the relationship between erosion and soil productivity (Figure 1-1a) and was subsequently enhanced by the further addition of modules to improve the simulation of plant growth (Williams et al., 1989). EPIC model used unified approach for 114 crop types. Moreover, the model was extended to include environmental assessment of pesticides and water quality. WinEPIC6.0 is a user-friendly interface for the EPIC crop simulation model (Figure 1-1b). The Windows interface allows the researcher to provide minimal input data to run EPIC model and customize specific input variables. After preparing the input data into Access database of WinEPIC



(a)

(b)

Figure 1-1 The schematic diagram of EPIC model (a) and profile of WinEPIC model(b)

model, the input data for specific site were well written into the input files and simulation result can be read from output files.

In EPIC model, crop yield is estimated by using the harvest index concept:

$$YLD_j = (B_{AG})(HI_j) \tag{1-17}$$

Where *YLD* is the amount of the crop removed from the field (t/ha), HI is the harvest index, and B_{AG} is the above-ground biomass (t/ha) for crop *j*.

$$HUF_i = \frac{HUI_i}{HUI_i + \exp\left(ah_{j,1} - (ah_{j,2})(HUI_i)\right)} \tag{1-18}$$

HUI is the heat unit index which is calculated by minimum and maximum temperature and $ah_{j,1}$ and $ah_{j,2}$ are parameters of crop *j*.

$$\Delta LAI = (\Delta HUF)(LAI_{mx})\left[1 - \exp\left[5.0(LAI_{i-1} - LAI_{mx})\right]\right]\sqrt{REG_i} \tag{1-19}$$

where LAI is leaf area index, *HUF* is the heat unit factor, and *REG* is the value of the minimum crop stress factor.

$$PAR_i = 0.5(RA)_i\left(1 - \exp(-0.65LAI)\right)_i \tag{1-20}$$

PAR is photosynthetic active radiation (MJ/m^2), *RA* is solar radiation (MJ/m^2), LAI is the leaf area index, and subscript *i* is the day of the year.

$$\Delta B_p = 0.001(BE)_j(PAR)_i \tag{1-21}$$

$\triangle B_p$ is the daily potential increase in biomass (t/ha), *BE* is the crop parameter for converting energy to biomass (kg/MJ)

$$WS_i = \frac{\sum_{l=1}^{M} u_{i,l}}{E_{pi}} \tag{1-22}$$

Where *WS* is the water stress factor, *u* is the water use in layer *l* and E_p is the potential plant water evaporation rate on day *i*.

When precipitation occurs, the bare soil surface temperature (*TG*) usually decreases. The appropriate air temperature for estimating soil surface temperature is near the daily minimum.

$$TGBW_i = T_{mn,i} + \Omega_s \left(T_{mx,i} - T_{mn,i}\right) \tag{1-23}$$

where *TGBW* is the bare soil surface temperature on wet day *i*, and Ω_s is a scaling factor to adjust for wet days.

A 5-day moving average is applied to obtain the final estimate of bare soil surface temperature. If the soil surface is not bare, the soil surface temperature (*TG*) can be affected considerably by the amount of cover which causes lagging the prediction of bare surface temperature.

The plant temperature stress factor is estimated with the equation

$$TS_i = \sin\left(\frac{\pi}{2}\left(\frac{TG - T_{b,j}}{T_{oj} - T_{bj}}\right)\right) \tag{1-24}$$

Where *TS* is the plant temperature stress factor, *TG* is the soil surface temperature and T_b is the base temperature for crop *j*, and T_o is the optimal temperature for crop *j*.

The potential biomass predicted with the equation is adjusted daily with the following equation if any one of five plant stress factors is less than 1.0:

$$\Delta B = \left(\Delta B_p\right)\left(REG\right) \tag{1-25}$$

Where *REG* is the crop growth regulating factor (the lowest value among the estimation for water, temperature, N, P, and aeration stress factors)

$$HIA_i = HIA_{i-1} - HI_j\left(1 - \frac{1}{1 + \left(WSYF\right)\left(FHU\right)\left(0.9 - WS_{\mathrm{i}}\right)}\right) \tag{1-26}$$

Where *HIA* is the adjusted harvest index, *WSYF* is a crop parameter expressing drought sensitivity, *FHU* is a function of crop stage, and *WS* is the water stress factor for day *i*. *FHU* is function of crop stage which is estimated by using the following equations:

$$FHU_i = \sin\left(\frac{\pi}{2}\left(\frac{HUI_i - 0.3}{0.3}\right)\right) \qquad 0.3 \le HUI_i \le 0.9 \qquad (1\text{-}27)$$
$$FHU_i = 0 \qquad HUI_i < 0.3 \text{ or } HUI_i$$

Water stress affects harvest index only between 0.3 and 0.9 of maturity, with the greatest effect occurring at 0.6.

(3) CERES model

The CERES models are comprehensive crop–soil system simulation models which can simulate more than 18 different crops, including maize, wheat, rice, barley, sorghum, millet, soybean, peanut, dry bean, chickpea, cowpea, faba bean, velvet bean, potato, tomato, bell, pepper, cabbage, bahia and brachiaria and bare fallow. The CERES models are currently included in the Decision Support System for Agrotechnology Transfer, Version 4.5 (Hoogenboom, 2010).

The ratio of actual *ET* to potential *ET*, if less than 1.0, indicates that stomatal conductance would have had to be decreased sometimes during the day to prevent plant desiccation. This ratio is typically used in the Plant modules to reduce photosynthesis in proportion to relative decreases in transpiration (Jones et al., 2003).

(4) WOFOST model

The WOFOST (WOrld FOod STudies) permits dynamic simulation of the phenological development from emergence till maturity on the basis of crop genetic properties and environmental conditions (Boogaard, 2011). To be able to deal with the ecological diversity of agriculture, three hierarchical levels of crop growth can be distinguished: potential growth limited growth and reduced growth. Each of these growth levels corresponds to a level of crop production: potential, limited and reduced production.

The effect of water stress to crop is quantified assuming a constant ratio of transpiration to gross assimilation. The assimilation rate *A* is the product of the potential assimilation rate A_p (kg/ha/d) and the ratio of the actual (water-limited) transpiration rate Ta and the potential transpiration rate T_p (both mm/d)

$$A = \frac{T_a}{T_p} \times A_p \tag{1-28}$$

The water-limited production level takes into account the effect of periods of soil moisture deficit on crop growth, and the water-limited yield represents the maximum yield that can be obtained under rain-fed conditions. The yield limiting effect of drought depends on the soil moisture availability as determined by the amounts of rainfall and evapotranspiration, and their distribution over the growing season, by soil type, soil depth and groundwater influence. The difference between potential and water-limited production indicates the production increase that could be achieved by irrigation.

(5) APSIM model

The APSIM (Agricultural Production Systems Simulator) is a modular modelling framework that has been developed by the Agricultural Production Systems Research Unit in Australia (Keating et al. 2003). APSIM was designed at the outset as a farming systems simulator that sought to combine accurate yield estimation in response to management with prediction of the long-term consequences of farming practice on the soil resource (e.g. soil organic matter dynamics, erosion, acidification etc.).

The biomass production (ΔQ) limit by water uptake ($f_{w,\,photo} < 1$, i.e. when $W_u < W_d$), or not (when $f_{w,\,photo} = 1$, i.e. when $W_u = W_d$)

$$\Delta Q_w = \Delta Q_r f_{w,photo} = \Delta Q_r \frac{W_u}{W_d} \tag{1-29}$$

Where W_u is the total daily water uptake from root system, W_d is the water demand of leaf and head parts.

(6) AquaCrop model

AquaCrop model simulates attainable yields of major herbaceous crops as a function of water consumption under rainfed, supplemental, deficit, and full irrigation conditions. The growth engine of AquaCrop is water-driven, in that transpiration is calculated first and translated into biomass using a conservative, crop-specific parameter: the biomass water productivity, normalized for atmospheric evaporative demand and air CO_2 concentration (Steduto et al., 2009).

The AquaCrop model evolved from the equation by separating non-productive soil evaporation (E) from productive crop transpiration (*Ta*) and estimating biomass production directly from actual crop transpiration through a water productivity parameter. The changes lead to the following equation, which is at the core of the AquaCrop growth engine:

$$B = WP \times \sum T_a \tag{1-30}$$

Where *B* is the biomass produced cumulatively (kg per m^2), T_a is the crop transpiration (either mm or m^3 per m^2), with the summation over the time period in which the biomass is produced, and *WP* is the water productivity parameter (either kg of biomass per m^2 and per mm, or kg of biomass per m^3 of water transpired)

For most crops, only part of the biomass produced is partitioned to the harvested organs to give yield (*Y*), and the ratio of yield to biomass is known as harvest index (*HI*), hence:

$$Y = HI \times \tag{1-31}$$

The underlying processes culminating in *B* and in *HI* are largely distinct from each other. Therefore, separation of *Y* into *B* and *HI* makes it possible to consider effects of environmental conditions and stresses on *B* and *HI* separately.

1.3.6 The impact of agricultural drought and drought mitigation assessment

Drought has both a natural and social component (Wilhite, 2000). Drought risk depends on a combination of the physical nature of drought and the degree to which a population or activity is vulnerable to the effects of drought (Shahid and Behrawan, 2008; Kim et al., 2013). With the purpose of synthesis both factors together, there are some assessment work on drought regional properties like drought hazard assessment (Pandey et al., 2012), drought vulnerability assessment (Wang et al., 2013) and drought risk assessment (Wu and Wilhite, 2004; Zhang, 2004; Jia et al., 2012; Zhang, 2014).

There are some other researches on drought response to the drought, such as farmers' response to agricultural drought in paddy field of southern China (Sun et al., 2012), and drought assessment to the 2008-2009 drought in Kenya (Lammert, 2010). Knutson and Hayes (2001) used interviews and qualitative analysis to determine the impacts of and responses to the 1998 to 2000 droughts in South Carolina, United States. The purposes of these researches are for insurance rate making, resource distribution and construction of response system from cases of drought in the past.

Generally, from aspect of drought impact prediction, drought monitoring and management, combinations of different factors currently become trend for drought researches. The framework built and factor identification is important for scientific decision making.

1.4 The impact of drought on crop physiology

Lack of water is the major factor limiting plant productivity. It is a multidimensional stress affecting plants at various levels of their organization (Yordanov et al., 2000). The most obvious effect of even mild stress is to reduce growth. Stomata are sensitive to leaf water status, tending to close with decreases in leaf water potential. Changes in stomata conductance are the main cause of the widely observed decrease of photosynthesis with declining water potential (Boyer, 1976). Water deficits can greatly modify plant development and morphology. Such as the differential sensitivity of roots and shoots leads to large increases in the root to shoot ratio in water stress. Water deficits also increase the abscission of leaves and fruits, particularly after relief of the stress (Jones, 1983). Annuals are not as deeply rooted as perennial grasses and woody forbs or shrubs and trees and therefore cannot tolerate the same degree of moisture deficit. Water deficits also affect the reproductive development. Stress often advances flowering in annuals and delays it in perennials. In wheat, mild deficits can advance flowering by a week but they decrease the number of spikelets and decrease pollen fertility and grain set (Angus and Moncur, 1977).

Crop plants have developed many mechanisms to survive water deficit, including escape, tolerance, and avoidance of and cell dehydration (Turner, 1986). Avoidance of stress includes rapid phenological development, increased stomatal and cuticular resistance, changes in leaf area, orientation and anatomy, among others (Morgan,1984; Jones and Corlett, 1992). These microcosmic researches lay solid basis on understanding the agricultural drought.

1.5 The objectives of the thesis

Drought is considered by many to be the most complex but least understood of all natural hazards, affecting more people than any other hazard (Hagman, 1984; Wilhite, 1992). Agricultural drought refers a complex water–agricultural production system that comprises interactions among meteorology, hydrology, agriculture, and society. The traditional methods such as experiments need to take lots of money and time to get to know the complete information of the whole system. The development of the new technology such as remote sensing and crop model in the recent years is possible to be able to fill the gap of the system knowledge and helpful for the management. Compared with irrigated agriculture, rainfed agriculture system is more sensitive to water shortage. It is significant start point to study the drought in rainfed agricultural system. Wilhite (2000) divided the drought pre-arranged plan into monitoring and early warning, risk and impact assessment, and mitigation and response three primary components. From aspect of drought management, in this thesis, I would like to build more operational framework and validate it with the help of the new technologies. The objectives of the thesis include: (1) the precipitation fluctuation background in the whole northeast China and Inner Mongolia; (2) Before yield damage, indices based agricultural drought monitoring, taking typical rainfed county Hailar County for instance; (3) After yield damage, EPIC model based agricultural drought severity assessment, taking 9 typical counties for instance; (4) Comparison of three agricultural practices under different drought severity, taking 9 typical counties for instance.

My framework for agricultural drought management is following which includes agricultural drought occurrence monitoring, agricultural drought severity assessment and drought mitigation assessment (Figure 1-2). Around the framework, the thesis tried to validate the framework and answer the following questions with three aspects:

a. What is the internal logic among multiple indices in rainfed region with the help of remote sensing technology?
b. How to quantitatively assess agricultural drought intensity by using the crop model?
c. What is the difference in effect of agricultural practices on yield increase under agricultural drought intensities by using the crop model?

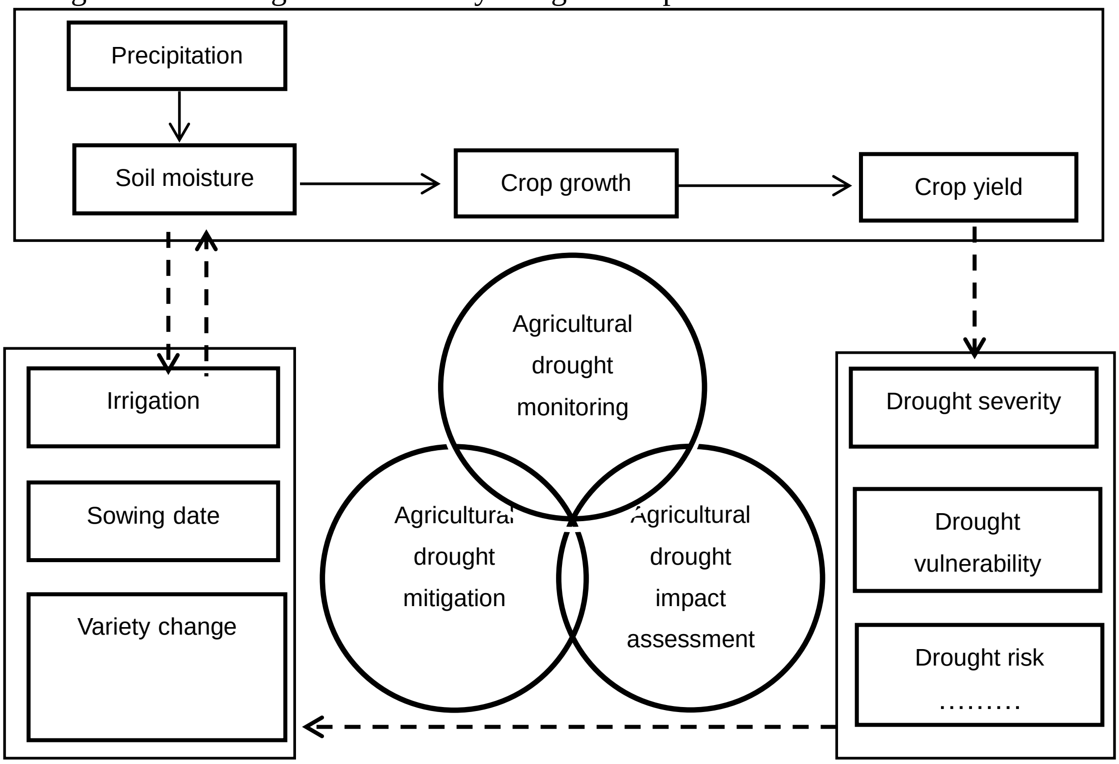


Figure 1-2 The framework of agricultural drought management

After selecting the typical study range, in first questions, I would like to select typical rainfed county to indicate the relationship between precipitation, soil moisture, crop vegetative growth and yield for drought monitoring. For second questions, I would like to model drought impact on yield and assess agricultural drought severity in counties with different climate background. For third questions, I would like to model different drought mitigation measures under different drought severities and assess their effectiveness. These three objectives consists agricultural drought management framework.

1.6 The structure of the thesis

The thesis is composed of five chapters (Figure 1-3) which includes following:

Chapter One, overview of the background of drought in China, basic terminology related with drought, previous drought researches, the equations of drought indices and model methods were shown. And the objective and structure of the thesis were also specific in the chapter.

Chapter Two is temporal-spatial pattern of precipitation variation to check whether the Northeast and Inner Mongolia is the suitable range for my study area. The results include: Temporal pattern of precipitation in farmland from 1961-2010; Spatial pattern of annual precipitation trend and spatial pattern of seasonal precipitation variation. The influence of precipitation functions on agricultural production.

Chapter Three is index-based monitor of agricultural drought in typical rainfed region. I focus on *SPI*, *CMI*, *NDVI* and yield different indices to find the internal logic among these indices in Hailar County, Inner Mongolia. The statistics method was used to link these indices. The results include drought indices in growth period, index and yield relationship and drought indices relationship.

Chapter Four is to accurately evaluate regional drought intensity from aspect of impact on crop yield in 9 typical counties. EPIC model was used in 9 counties of the Northeast China and Inner Mongolia to fill the gap of crop census yield simulation and drought cases were used to validate the drought intensity. The results include model validation, agricultural drought intensity assessment and drought trends.

Chapter Five is to evaluate the effect of three agricultural practices under different drought intensities on crop yield in 9 typical counties of the Northeast China and Inner Mongolia. By using validated EPIC model, I compared the effect of one time irrigation, sowing date change and variety change on yield. The results include the effects of three practices and the comparison among them.

Chapter Six is to summarize previous chapters. It includes organization of the research, significance of the study, main findings and discussions and limitation of the work and highlight for further directions for future research will also be given.

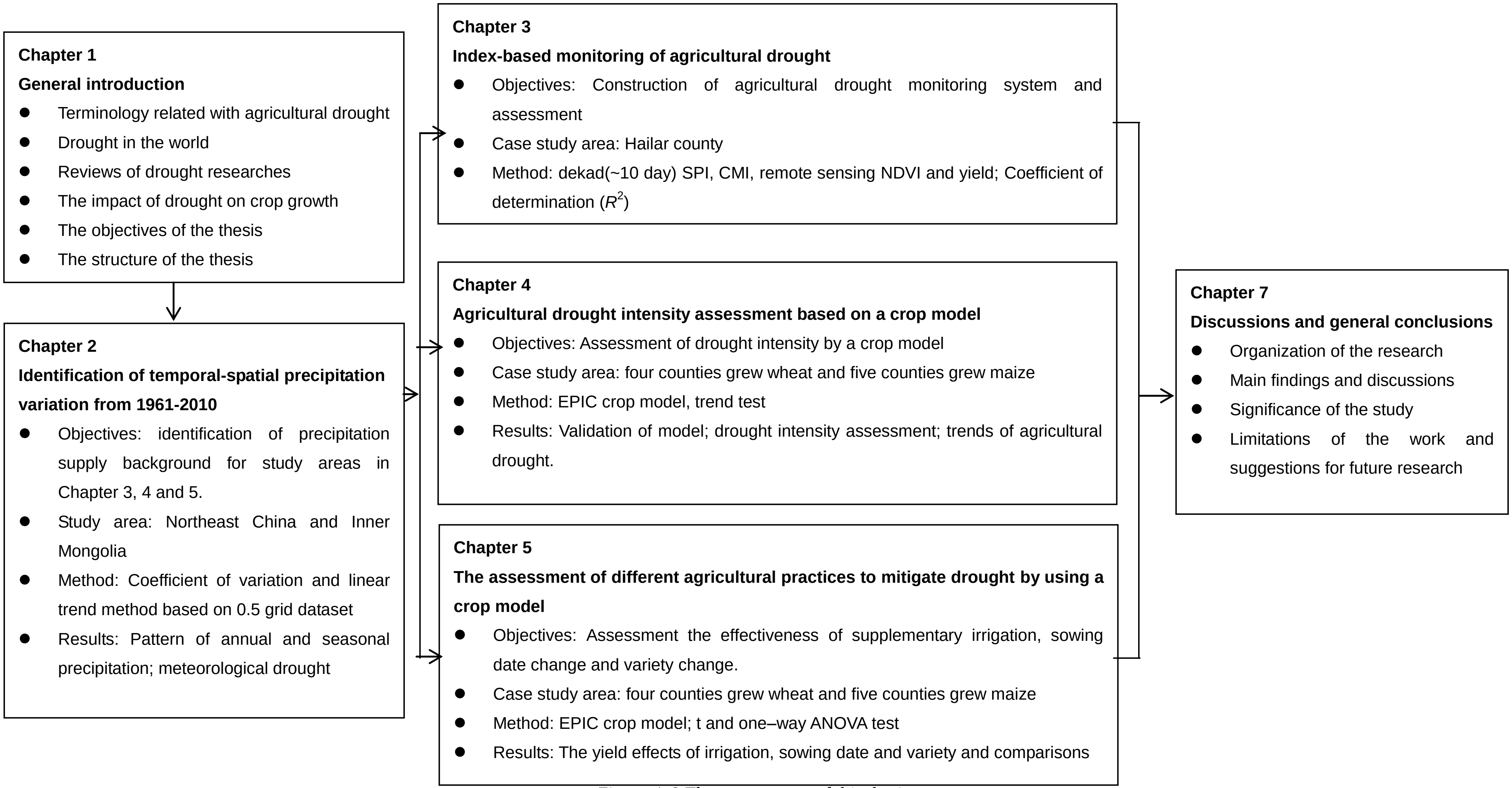


Figure 1-3 The components of this thesis

Chapter 2
Temporal-spatial precipitation variation in Northeast China and Inner Mongolia

2.1 Background

There are meteorological drought, hydrological drought, agricultural drought and so on different types of drought, drought is essentially a meteorological phenomenon (Agnew, 2000). Drought is a temporary period based on climate background (WMO, 1975). The the Northeast and Inner Mongolia is across from arid to humid different climate zones. For rainfed agricultural region, precipitation is only source of water supply. The fluctuation of precipitation may seriously influence the production. Feng and Zheng (1986) examined annual spatial pattern of precipitation variation in China from 1951 to 1980. Ma and Fu (2006) show there is drying trend over Northeast and Inner Mongolia from 1951-2004. Serious drought occurs in Northeast and Inner Mongolia after 2004 such as drought in 2007. In order to consider the precipitation in recent years, as background for agricultural drought, I would like to make the detailed assessment of temporal-spatial variation of precipitation for different season and long term trend.

2.2 Study area

I chose three provinces in the northeast China (Heilongjiang, Jilin, and Liaoning provinces) and the Inner Mongolia Autonomous Region for our research, because these are important regions that rely on rainfed cultivation to produce one harvest per year. The planting area for maize is highest among five crop types. Although the proportion of wheat decreased after 2000, but as a staple food, wheat is still important crop type in the Northeast and Inner Mongolia. From aspect of 60 years planting area, maize and spring wheat can be regarded as two major crop types. The area equipped with irrigation system for normal year (Effective irrigation area) occupies 32% of this farmland (NBSC, 2010). The precipitation increases from less than 100 mm in the west to more than 600 mm in the east, spanning several aridity zones (Figure 2-1).

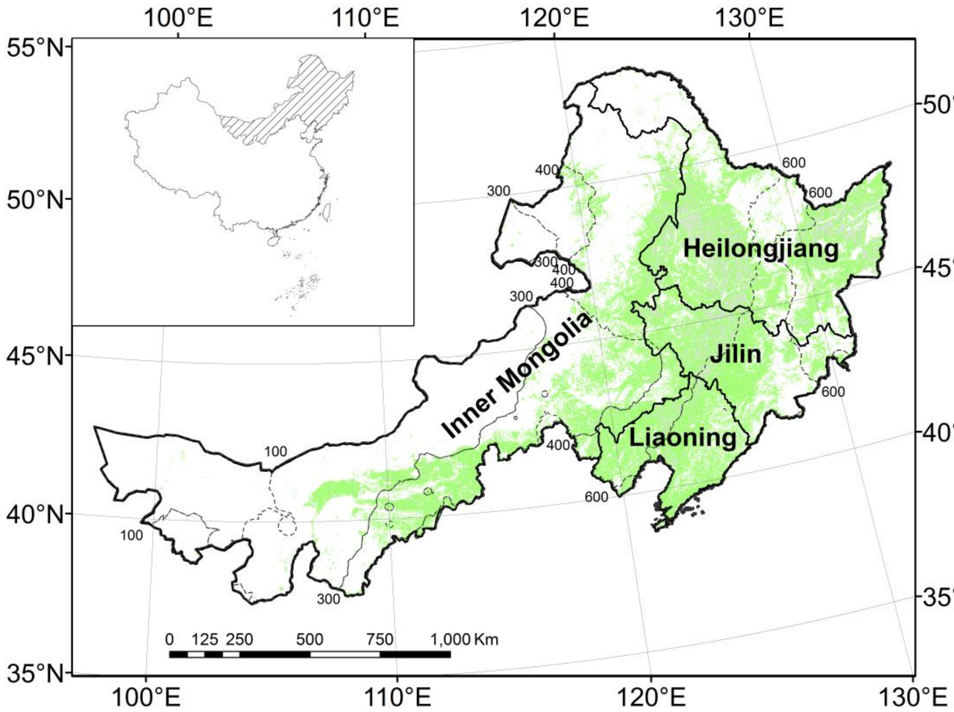


Figure 2-1 Multi-year average precipitation in Northeast China and Inner Mongolia
(Green color is the 1:1 million farmland map in 2000)

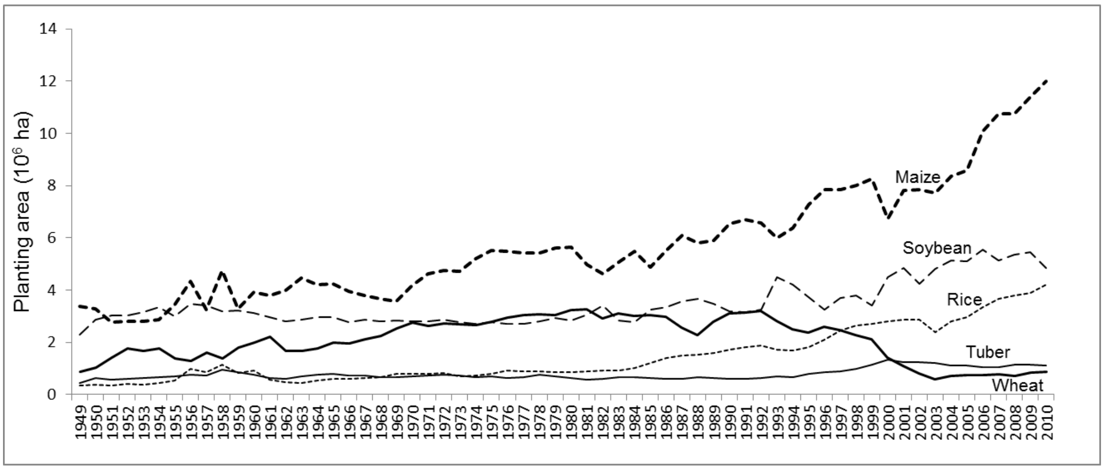


Figure 2-2 The planting area for five major crop types in the study area

2.3 Data and Method

2.3.1 Data

(1) Meteorological data

I downloaded 0.5 degree grid precipitation dataset for China from 1961 to 2010 from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/).

The dataset was created by National Meteorological Information Center based on precipitation measurements in 2472 national weather stations in China. Therefore, the density has better coverage for spatial pattern analysis.

(2) Farmland and land use

Farmland was extracted from a 1-km-scale land-use map of China in 2000. Both of the two subtypes: dryland and paddy include in the map. 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 Web site (http://westdc.westgis.ac.cn). The original dataset was a county-level land-use and cover type dataset (vector format, 1:100,000 scale) created by the Chinese Academy of Sciences. Using the maximum-area method, the datasets were combined and transferred to the final 1-km raster product by Liu et al. (2001).

(3) Crop planting area and production data

Crop planting area and production data for rice, maize, wheat, tuber and soybean from 1961-2010 were downloaded from National Bureau of Statistics of the P.R.C. http://data.stats.gov.cn/. I calculated the average yield for 5 crop types in the whole study area.

(4) Drought areas dataset

The statistical drought area is assessment of drought condition by local government with the purpose of on time drought management. The 'Drought area' is assessed by using respective indices in rainfed region and paddy region. In rainfed region, it means the region area where seeding rate is lower than 80% when soil moisture cannot satisfy the crop water requirement or wilting in crop leaves or soil moisture in 20cm arable layer is lower than 60%. In paddy region, the 'Drought area' means after transplanted period, it cannot provide enough water to rice and cause the wilting of plant. The 'Area suffered by drought' means the drought area with more than 10% damage of crop yield. The 'Area with drought damage' means drought area with more than 30% damage of crop yield. The 'Area with no harvest' means drought area with more than 80% damage of crop yield. The 'Area suffered by drought' includes 'Area with drought damage' and the 'Area with no harvest' (SFCDRH, 2011). The data of areas suffered drought, with drought damage and no harvest three indices from 1961-2010 in Heilongjiang, Jilin, Liaoning and Inner Mongolia were downloaded from http://zzys.agri.gov.cn/zaiqing.aspx.

2.3.2 Method

Continental monsoon climate is main climate type in the Northeast and Inner Mongolia. I defined March to May as spring, June to August as summer, September to November as autumn. The grid data was firstly calculated for each season and each year from 1961-2010. Based on the farmland, the 1961-2010 time series of average annual, spring, summer, autumn precipitation in farmland can be calculated.

In order to show the spatial difference in precipitation variation tendency, I used the linear trend fitness technology to estimate precipitation tendency based on least squares method. The equation of linear trend fitness is following:

$$y = mx + b \qquad (2\text{-}1)$$

x is year, m is slope and b is intercept for the fitness. If m is greater than 0, there is increase tendency; if m is smaller than 0, there is decrease tendency.

I use coefficient of variation (*CV*) to depict variation of seasonal and annual precipitation. The equation of CV is following:

$$CV = \frac{\sigma}{x} = \frac{1}{x}\sqrt{\frac{1}{n-1}\sum\left(x_i - x\right)^2} \qquad (2\text{-}2)$$

Here, σ is standard deviation; n is number of years considered. x_i is precipitation in year i , x is multiple year average precipitation.

I made IDL (Interactive Data Language) program and calculated spatial pattern of *CV* and slope in Northeast China and Inner Mongolia. I also test the significance of slope for each grid using the program.

2.4 Results

2.4.1 Temporal pattern of precipitation and drought from 1961-2010

The precipitation in summer occupied approximately 2/3 of annual precipitation (Figure 2-3a). After 2000 years, there is small increase trend of annual and summer

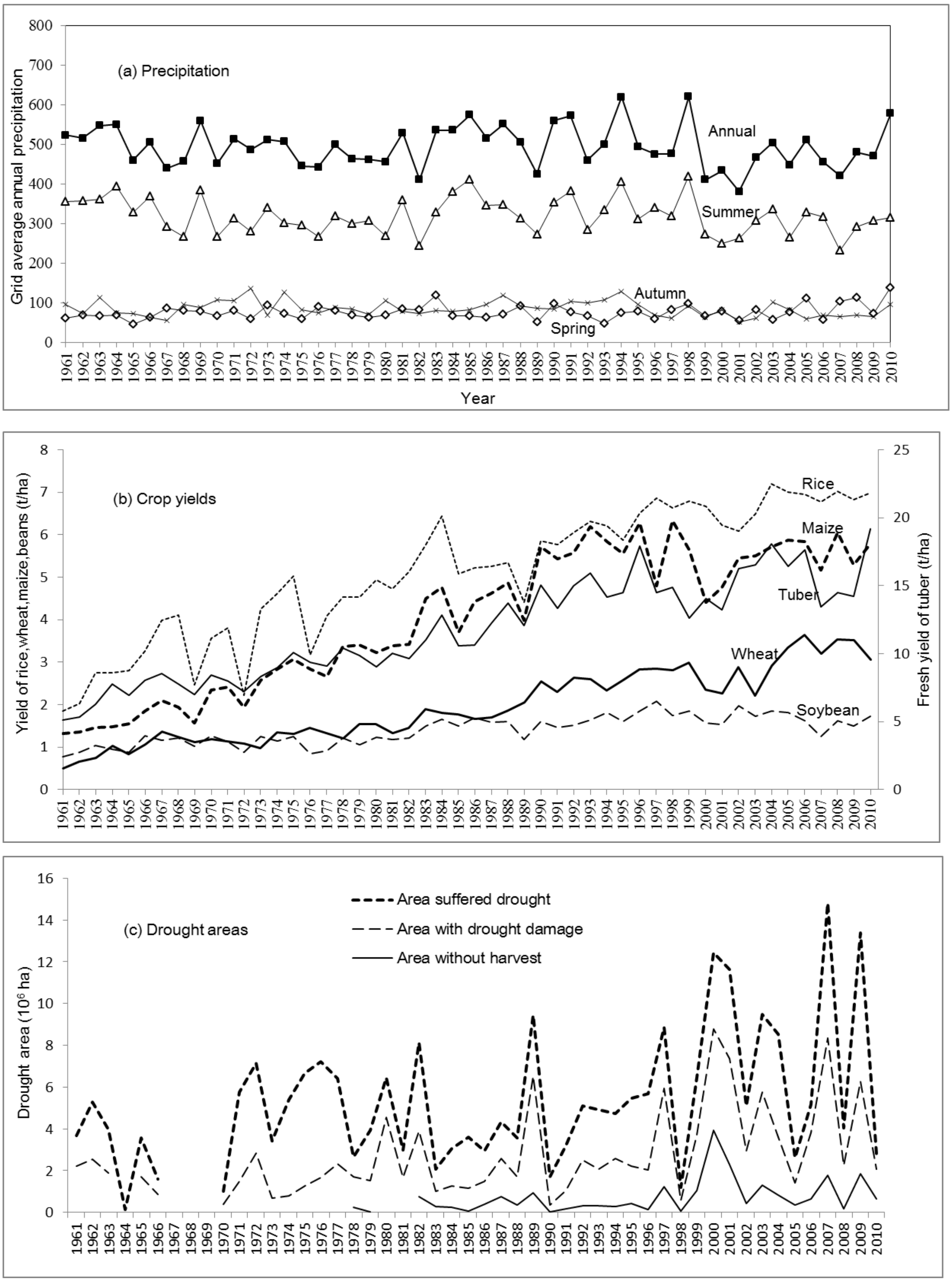


Figure 2-3 The comparison of yearly variations

(a) grid average annual and seasonal precipitation in the farmland and (b) yields of main crop types and (c) drought area in the study area from 1961-2010 precipitation after 2000 years. The decrease trend of summer precipitation is similar to annual precipitation. It shows that summer drought is main meteorological drought in this region. The grid average annual precipitation in the whole farmland shows that amplitude of precipitation fluctuation became larger after 1980s and there is explicit low precipitation stage after 2000. Regional meteorological drought extended in this region in 1982, 1989, 1999-2001, 2007. The yield of crop types even for rice, show explicit decrease due to drought

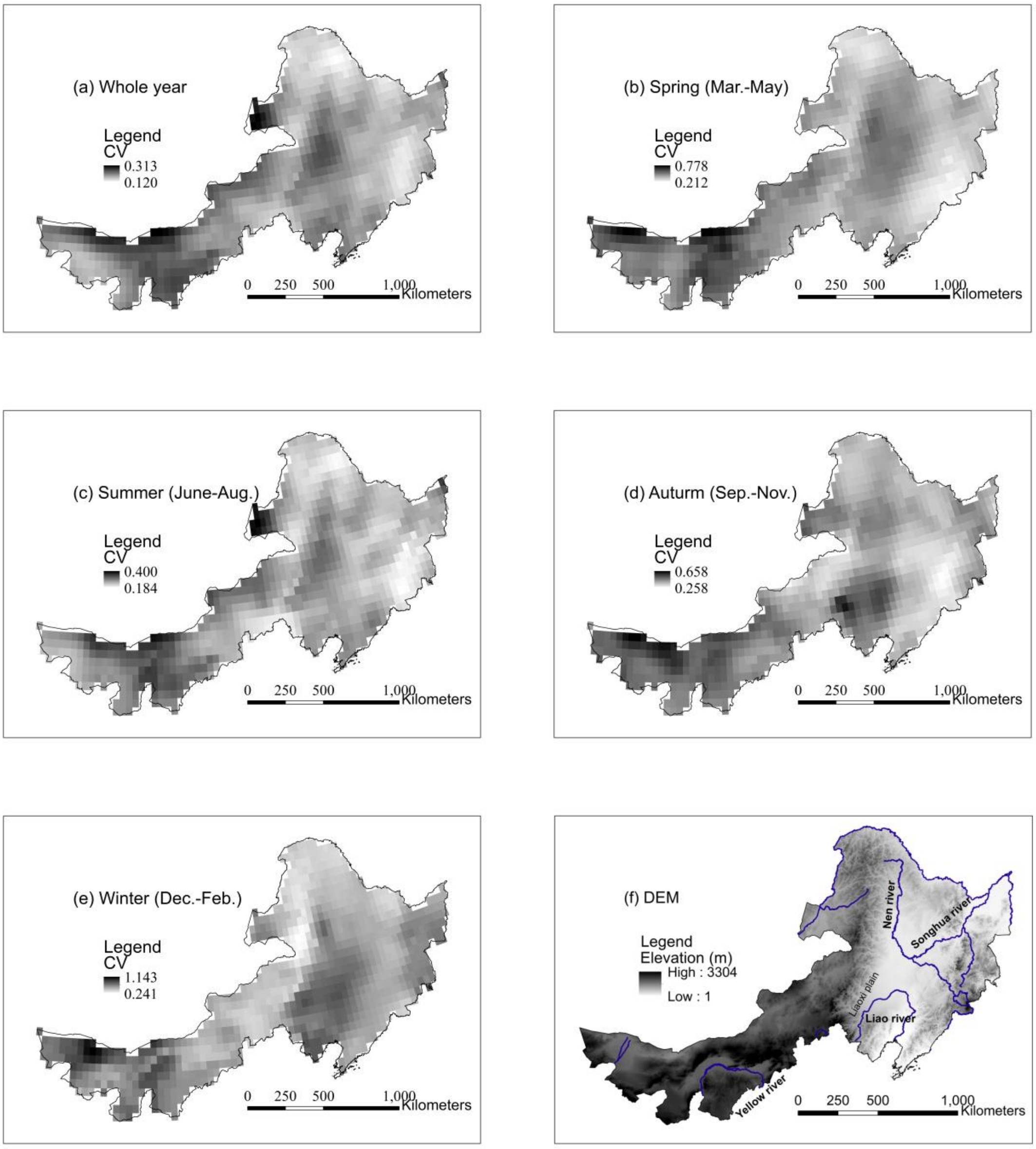


Figure 2-4 Seasonal precipitation variation by coefficient of variation (*CV*) from 1961-2010 (a-e) and DEM and rivers (f) in the study area

(Figure 2-3b). Comparative high yield seems to be kept even in drought years. There is also increase trend of drought area and agricultural drought became serious after 2000 in our study area (Figure 2-3c). It shows that decrease of precipitation is main factor that cause the damage of the crop yields.

2.4.2 Spatial pattern of seasonal precipitation variation

There is higher variation for spring precipitation than other precipitation types (Figure 2-4). Compared with farmland pattern (Figure 2-1), spring precipitation varied seriously in farmland in west part of Heilongjiang, Jilin and west end of Inner Mongolia (Figure 2-4b). Summer precipitation varied seriously in east part, west end of Inner Mongolia, west part of Jilin and Liaoning province (Figure 2-4c).
Autumn precipitation varied seriously in west end of Liaoning and west end of Inner Mongolia (Figure 2-4d). Because summer precipitation occupied majority of annual precipitation, the pattern of summer precipitation variation is similar to that for annual precipitation (Figure 2-4c). After I made the comparison between precipitation variation and DEM (Figure 2-4f), there is very good fitness, the region with serious variation is just on the brink of Mongolia Plateau. The occurrence of precipitation variation is dominated by topography.

2.4.3 Spatial pattern of annual precipitation trend

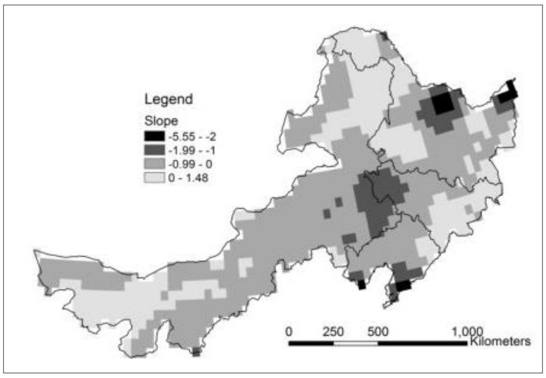


Figure 2-5 Annual precipitation trend by linear trend method (mm per year)

From aspect of 50 years precipitation trend (Figure 2-5), the precipitation decrease in most of the farmland. The more serious trend locates in the west part of Jilin, east part of Inner Mongolia, northern part in Heilongjiang province and southern part in Liaoning province. The increase slope locates in the west part of Heilongjiang province and west part of Inner Mongolia. However, by statistics test, both the decrease and increase trends are not significant.

2.5 Discussion

The precipitation influenced crop yield seriously in the whole region (Figure 2-4). There are some years like 1985 with high precipitation but low yield. It was recorded that Great flood occurred in Liao river in 1985(Zhang et al., 2006) and Liaoning and Jilin provinces suffered most serious flood disasters after 1949 (Li and Men, 2005; Qin, 2008). Totally, drought is main factor that influenced food security in Inner Mongolia and the Northeast China.

Annual precipitation varied seriously in southeast part of Inner Mongolia west part of Jilin and Liaoning province. The result is similar to precipitation variation regionalization by empirical orthogonal function method (Gong et al., 2007) which revealed that drought was frequent in Liaoxi plain and hilly region of southeast part of Inner Mongolia due to typography. Both multi-year 400mm and 600mm precipitation line are closely across this narrow region (Figure 2-1). Large precipitation gradient is possibly one reason for both the serious variation of precipitation and increase trend of the precipitation in this region. Annual precipitation varied seriously in west end of Inner Mongolia. There is less precipitation in the west end of Inner Mongolia (Figure 2-1), the variation of precipitation is possibly due to unstable water supply.

2.6 Conclusion

The research reveals that the meteorological droughts became serious after 2000s in the Northeast China and Inner Mongolia. I made accurate identification of the temporal-spatial pattern of precipitation variation and its impact in Northeast China and Inner Mongolia. It shows that (1) Precipitation in summer occupied approximately 2/3 of the annual precipitation. Summer drought seriously influences whole year variation in farmland. The meteorological drought heavily influenced yield damage in the whole region. (2) Annual precipitation varied seriously in east part, west end of Inner Mongolia, west part of Jilin and Liaoning province. (3) There is decrease but not significant trend of precipitation for whole Northeast China and Inner Mongolia from 1961-2010. Due to lack of irrigation system, there is higher drought risk in the rainfed region in the Northeast China and Inner Mongolia. It requires different strategies for drought preparation.

Chapter 3
Index-based agricultural drought monitoring in Hailar County, Inner Mongolia

3.1 Background

Drought assessment is related with evaluation of the status of the entire water cycle. A combination of various drought indices may provide a more comprehensive assessment of drought conditions than a single-index approach, but this has been challenging because there has been a lack of systematic methods for their combination, use, and evaluation (Steinemann and Cavalcanti, 2006). With regard to drought occurrence, the onset of an agricultural drought may lag that of a meteorological drought, depending on the prior moisture status of the surface soil layers (Heim, 2002). Agricultural drought is a slow-onset "creeping phenomenon" (Tannehill, 1947), and there appears to be an inherent temporal relationship between shortage of rainfall and yield damage. In addition, according to the agricultural drought definition, agricultural drought occurs when vegetation suffers from a water deficit. The definition is likely to describe drought occurrence process. Therefore, to accurately identify the features of agricultural drought in a specific region, it is necessary to examine the underlying drought process.

Numerous drought indices have been developed to simplify the identification of agricultural drought, and these indices can be divided into three groups. The first group is precipitation-based indices, such as precipitation anomaly and the Standardized Precipitation Index (*SPI*) (McKee et al., 1993, 1995). The second group is soil moisture–based indices, such as the Palmer Drought Severity Index (*PDSI*) (Palmer, 1965) and Crop Moisture Index (*CMI*) (Palmer, 1968). The third group is vegetation-based indices, including the Ratio Vegetation Index (*RVI*) (Jordan, 1969), Normalized Difference Vegetation Index (*NDVI*) (Rouse et al., 1974), and Enhanced Vegetation Index (*EVI*) (Huete et al., 1999).

The relationship between moisture shortage and crop growth is the key link in the agricultural drought process. Previous studies have revealed that remotely sensed *NDVI* has a time-lag relationship with rainfall (Nicholson and Farrar, 1994; Wang et al., 2001; Ji and Peters, 2003). From this viewpoint, drought is a temporary feature in the context of climatic variability (WMO, 1975). Therefore, the *NDVI* anomaly (*NDVIA*) is a more accurate index of drought than the *NDVI*. In addition to rainfall, however, meteorological factors such as temperature and wind speed also influence the water shortage of crops. Thus, it is more reasonable to assume that the *NDVIA* and water deficit reflect agricultural drought. Previous drought studies showed great variation in the relationship between moisture shortage and satellite-derived drought indices. For example, Bayarjargal et al. (2006) found no agreement between the spatial extent of satellite-derived drought indices and monthly *PDSI*. Quiring and Ganesh (2010) reported that monthly relative *NDVI* change index (vegetation condition index) is most strongly correlated with prolonged moisture stress, including 6-month *SPI*, 9-month *SPI*, and *PDSI*, and less sensitive to short-term precipitation deficiencies than to long-term ones. Can *NDVI* change and *in situ* drought indices at shorter time scales provide detailed information indicating the vegetation response to water deficit? The temporal scale of a dekad (~10day) is often used in agricultural studies. In this study, short-term 10-day vegetation variation was used to assess the ability of several indices to describe the agricultural drought process.

The overall goal of this study is to assess the agricultural drought process based on a conceptual model that synthesizes meteorological information, remote-sensing dynamic monitoring, and observational data. We then examined the relationships among indices and the temporal interaction of factors on a short time scale during the drought process. The specific objectives are to: (1) clarify trends of 10-day scale SPI, *CMI*, and *NDVI* during the crop growing period; (2) examine the relationships between drought indices and crop yield; (3) evaluate the temporal relationships among the drought indices, mainly focusing on water shortage accumulation and time lag; and (4) assess agricultural drought over a long-term period.

3.2 Study area

The study area is Hailar County (total area 1440 km^2), which lies in the transitional zone between low mountains and the hilly region along the western slope of the Greater Khingan Mountains and Hulunbuir high plain in Inner Mongolia, China (Figure 3-1). The elevation ranges from 603 to 777 m a.s.l.. Flat terrain is the county's main geomorphic unit. Chestnut soil is the main soil type, and the soil texture is loamy sand and loam (USDA classification, FAO soil map). Hailar County is in the semi-arid region (aridity index = 0.46) of China. As an agriculture–pasture transitional zone, this region is strongly influenced by the East Asian summer monsoon and frequently suffers from extreme climatic conditions, such as limited precipitation and low temperature. Based on measurements recorded at the Hailar weather station (49°13′ N, 119°45′ E) of the Chinese Meteorological Administration (1971–2010), average annual precipitation is 348 mm. About two-thirds of the annual precipitation occurs from June to August, and there is a significant increase in rainfall (i.e., the rainy season) from late June to late August. In cold winters, the monthly temperature in January falls to –25.8 ℃. The whole county lies within the permafrost region, with 4–5 months of continuous snow cover each year (Jin et al., 2000, Li and Mi, 1983), and there is a short growing period (May to September).

Hailar County is located in the northeastern part of the farming-pastoral ecotone of Northeast China and Inner Mongolia, and grassland and farmland are the two main land use types (Figure 3-2). In 2009, 97% of the farmland was un-irrigated. Large areas of homogeneous cultivated plots exist in Hailar County (Figure 3-2), which is favorable for monitoring crop growth based on moderate-resolution remote-sensing technology. Spring wheat (*Triticum aestivum L.*) was the main crop type, occupying 74% of the farmland, in 1998. In 2010, the proportion of spring wheat fell to 36%, whereas barley (*Hordeum vulgare L.*) and potato (*Solanum tuberosum L.*) increased to18% and 30%, respectively; oil rape accounted for 10%, vegetables accounted for 5%, and soybeans, watermelon, and maize occupied the remaining 1%. Thus, grain crops play an important role in the agricultural production of Hailar County.

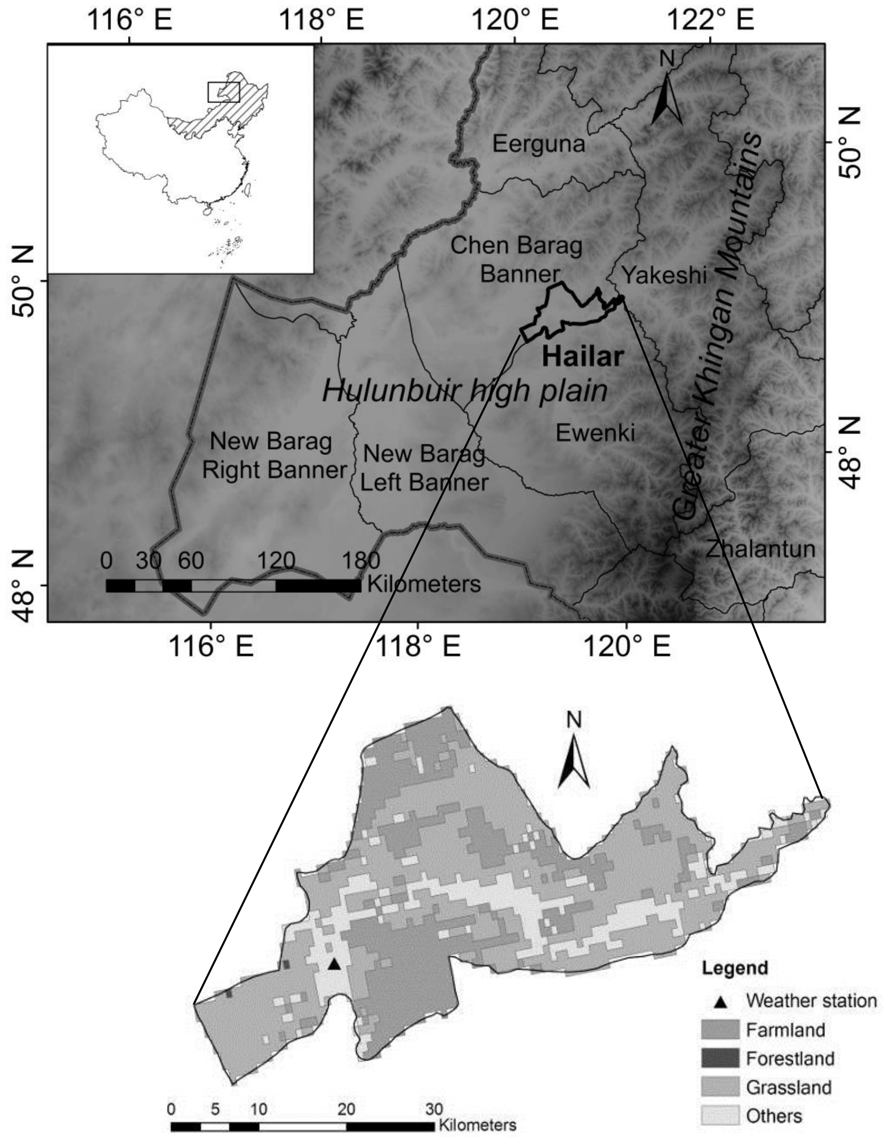


Figure 3-1 The location of Hailar County in China and distribution of land-use types
(Land-use information from 1-km grid land-use map of China in 2000)

a. Spring wheat

b. Barley

Figure 3-2 Spring wheat (a) and barley (b) plots in Hailar county (August, 2012)

3.3 Conceptual model of the agricultural drought process

The agricultural drought process refers to the water balance within the weather–soil–crop agricultural production system. Crop growth can be divided into vegetative growth and reproductive growth stages. For a few crop types, yield is closely related to vegetative growth, such as crude fiber crops and leaf vegetables. For most crops, however, such as wheat, maize, and beans, the yield is closely related to reproductive growth. When drought occurs, leaves wither; thus, drought conditions affect these two categories of crops differently. For the former crop types, the yield will be closely correlated with vegetation damage. For the latter types, the damage of vegetation will influence yield via a reduction in the nutrition supply.

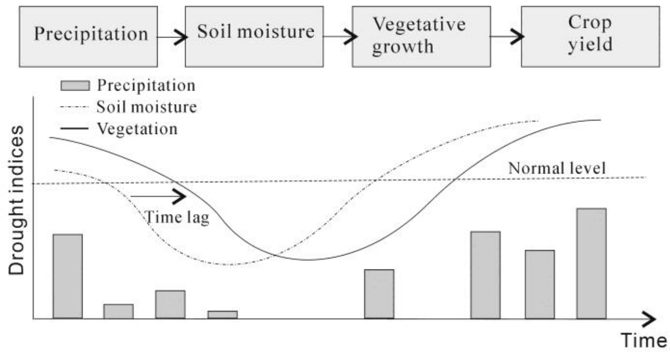


Figure 3-3 Schematic diagram of the drought process during the crop growing period in a rainfed agricultural region

The key link during the drought process can be simplified as a temporal sequence of precipitation, soil moisture, vegetative growth, and yield. In rainfed agricultural regions, precipitation is the main water source, and yield is the final outcome of the drought process. During the generation of water stress, there is a time lag in the effect of soil moisture on vegetation vigor (Figure 3-3). Following this framework, I use 10-day scale *SPI*, *CMI*, *NDVIA*, and yield as input for an assessment of the agricultural drought process.

3.4 Data and Method

3.4.1 Data

(1) Daily meteorological data, including precipitation, temperature, relative humidity,

wind speed, and hours of sunshine, from the Hailar weather station (1951–2010) were downloaded from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/).

(2) MODIS daily 500-m products (MOD09GA h25v4) from May to September for the years 2000 to 2010 (for a total of 1641 products) were downloaded from the U.S. Geological Survey's website (https://lpdaac.usgs.gov/). One product provides bands 1–2 in a daily gridded L2G product that includes 500-m reflectance values in the absence of atmospheric scattering or absorption.

(3) A land-use map of China in 2000 (1:1,000,000, 1-km grid, WESTDC) 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 (http://westdc.westgis.ac.cn). The original dataset is a county-level land-cover dataset (vector format, scale: 1:100,000) from the Chinese Academy of Sciences. Using the maximum area method, the datasets were combined and transferred to the final 1-km raster product (Liu et al., 2001).

(4) The water content in Hailar County available for farmland was calculated using an area-weighted method using the available water content records noted on a 1:1,000,000 scale soil map of China provided by the Chinese Academy of Sciences (downloaded from FAO Harmonized World Soil Database v 1.2, http://www.iiasa.ac.at/Research/LUC/External-World-soil-database/).

(5) Crop planting area and yield data from 2000 to 2010 were collected from the Hailar Statistics Bureau. Although the meaning of crop yield varies across species, the most important aspect is the food energy. Yield energy analysis can measure total agricultural output of the farmland as well as the environmental contribution to crop production. The coefficients of the food energy obtained from the main crops in Hailar were taken from Shu (2008). The values are 16.3×10^6 J/kg for wheat and barley grain, 20.9×10^6 J/kg for soybeans, 16.3×10^6 J/kg for maize, 4×10^6 J/kg for fresh potato, 26.3×10^6 J/kg for oil rape, 2.5×10^6 J/kg for vegetables, and 1.1×10^6 J/kg for melon. Then, using the sowing area and production data for these eight types of crops during 2000–2010, the yield energy per unit area was estimated for Hailar

County.

3.4.2 Method

1) *SPI*

Using the 10-day data from 1951 to 2010, I calculated the 10-day *SPI* by using the method of McKee (McKee et al., 1993, 1995) for monthly data. To account for the antecedent rainfall of *SPI* in the effect on other factors, *SPI* was calculated with the simple averaging method using the following equation:

$$SPI_{i,j} = \frac{\sum_{k=j-i}^{j} SPI_j}{i} \tag{3-1}$$

where i is the total number of the 10 days considered, and j is ascending time serial number of 10-day *SPI*.

2) *CMI*

The C++ package for computing *CMI* (scPDSI, version 2.0) was downloaded from http://greenleaf.unl.edu/downloads/scPDSI.zip. The original method for computing potential evapotranspiration (*PET*) is based on the weekly Thornthwaite method (Thornthwaite 1948). To obtain the 10-day estimation of *PET*, the Penman–Monteith FAO 56 (PMF-56) model was introduced to modify the program (Allen et al., 1998). The PMF-56 model is recommended as the sole method for determining *PET* and it has been widely accepted as superior to other methods in China (Cai et al., 2007). To estimate 10-day *PET*, the daily temperature, humidity, wind speed, and hours of sunshine data were used to calculate daily *PET* and summed for 10-day period *CMI* values from 1951 to 2010.

3) *NDVI* anomaly

In this study, MOD09GA bands 1 and 2, a band quality map, and a 1-km reflectance state map from each daily MODIS product (h25v4) were used. Bands 1–3 were first used for computing daily *NDVI* images according to Rouse (Rouse et al., 1974). In the band quality map and resized 500-m reflectance state map, pixels with ideal quality and clear pixels were labeled and merged together. Then, the 10-day synthesized *NDVI* as well as corresponding synthesis quality maps were produced based on daily images following the maximum-value composite procedure (Holben, 1986). Finally, for each index, with the help of the quality map, the noise was removed from the images. Due to a lack of images for vegetation indices from 15 June to 1 July 2001, there is no value for the third dekad of June 2001.

The farmland map of Hailar County was extracted from the land-use map of China. The farmland *NDVI* series was built using the MODIS dataset and a farmland mask. Because the area of Hailar County is small, the spatial differences of drought across the county were not considered here. Considering the farmland of the county as a whole, the *NDVIA* was calculated with the following equation:

$$NDVIA_{i,j} = \frac{NDVI_{i,j} - NDVI_{ave,j}}{NDVI_{ave,j}} \times 100 \qquad (3\text{-}2)$$

where i is year, j is dekad, and $NDVI_{\mathrm{ave},j}$ is the average value for the same dekad j during 2000–2010. Because the county was considered to be one harvest region, the average value was computed using all the records in the same dekad.

3.5 Results

3.5.1 Seasonal trends of drought indices

The average *NDVI* began to increase in early May and exceeded 0.3 in late May, when the average dekad temperature was higher than 0 ℃; at this point, crop growth accelerated until the curve reached a peak in mid-July (Figure 3-4a). After that, the *NDVI* decreased sharply until late September, when the average dekad temperature again decreased to 0 ℃. With regard to local crop phenology, the sowing stage for spring wheat and barley in Hailer County is late April and harvest occurs in late August. The growing period of oil rape is from early May to late August, and that for potato is from early May to mid-September. Due to the short growing period in Hailar County, when the temperature reaches its peak in July, most of the crops are just reaching the flowering stage. From 2000 to 2010, the low values of SPI were in late May, late June, and from late July to early August, showing the periods when precipitation was lower than the 60-year average one (Figure 3-4b). The shortage of rainfall frequently reduced the ability of the CMI value to return to normal, such that the CMI value showed a decreasing tendency during the growing period. These low-value periods in late June and late July span the elongation–heading and milky periods of spring wheat and barley, thus producing a high risk of yield reduction.

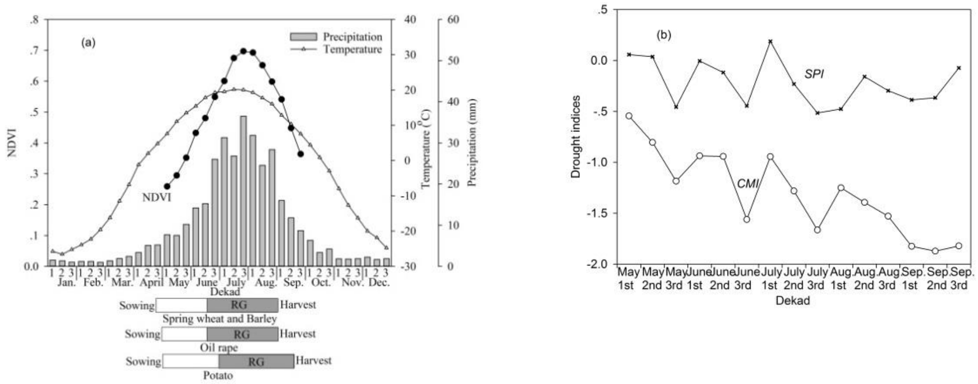


Figure 3-4 The average decadal *NDVI* (a) and *SPI* and *CMI* (b) from 2000 to 2010 during the growing period

Panel (a) also shows the median temperature and average precipitation during 1951–2010 and crop phenology. Phenology information (Sowing, harvest and reproductive growth (RG) period) was obtained from Zhang (Zhang et al., 1987) and local monograph by Wang and Zhao (Wang and Zhao, 2006) and interviews with staff of the Hailar Agricultural and Animal Husbandry Bureau.

3.5.2 Relationships of drought indices with crop yield

The key period for 10-day *CMI* was from the second dekad in June to the second dekad in July (Table 3-1). The key period for *NDVIA* is from the first to the third dekad in July. There was clear seasonality in the relationship between yield and these indices. In addition, there were time lags between the sensitive period identified by *CMI* and those based on *NDVIA*. My analyses revealed no clear sensitive dekad for SPI during June–July. However, with regard to cumulative average *SPI* values, there was a significant correlation with yield energy in May–June, May–July, May–August, and May–September, as was the case for *CMI* (Table 3-2). Thus, a longer period of precipitation accumulation has a greater effect on the energy yield than does a short period. For the *SPI*, the R^2 values were highest for May–June and then decreased. For the multi-dekad average of *CMI* and *NDVIA*, the R^2 values were highest for May–July and then decreased.

Table 3-1 The coefficient of determination (R^2) between dekad-scale indices and crop energy yield anomaly in Hailar County during 2000–2010 (n = 11)

Index	May			June			July			August			September		
	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
SPI	0.006	0.039	0.069	0.028	0.217	0.327	0.136	0.019	0.014	0.455*	0.051	0.023	0.008	0.022	0.007
CMI	0.002	0.003	0.035	0.139	0.814**	0.630**	0.526*	0.638**	0.160	0.012	0.027	0.081	0.602**	0.002	0.003
NDVIA	0.204	0.24	0.000	0.097	0.087	0.249	0.723**	0.665**	0.647**	0.176	0.042	0.157	0.244	0.072	0.029

Note: 1st, 2nd, and 3rd refer to the three dekads within each month. For NDVIA, n=10 in the 3rd dekad of June.

* Statistically significant at the 0.05 level.

** Statistically significant at the 0.01 level.

Table 3-2 The coefficient of determination (R^2) between multi-dekad average values of indices and crop energy yield anomaly in Hailar County during 2000–2010 (n = 11)

Index	May	May–June	May–July	May–August	May–September
SPI	0.023	0.587**	0.388*	0.588**	0.538*
CMI	0.006	0.523*	0.638*	0.623*	0.602**
NDVIA	0.073	0.136	0.403*	0.356	0.205

* Statistically significant at the 0.05 level.

** Statistically significant at the 0.01 level.

3.5.3 Temporal relationships between drought indices

The R^2 between *CMI* and average *SPI* was higher than that between average *SPI* and *NDVIA*. The strongest correlation for *CMI* was with the average SPI of four dekads (Figure 3-5a). The strongest correlation for the *NDVIA* was with average *SPI* of six dekads (Figure 3-5b). Thus, a precipitation shortage within a particular dekad does not directly influence the *CMI* and vegetation; rather, this occurs through a cumulative process.

When considering the correlation between *CMI* and the performance of the *NDVIA* from May to September over the 2000–2010 study periods, the strongest correlation existed with a 1-dekad time lag (Figure 3-6a). By considering the relationship between these indices for each month separately, the maximum R^2 ranged from 0.319 (May) to 0.619 (July). The highest correlations between these indices occurred in July and showed a 1-dekad time lag (Figure 3-6b).

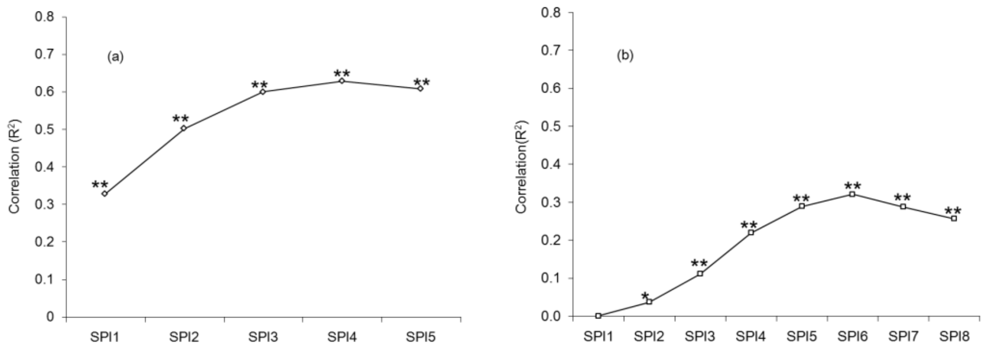


Figure 3-5 The coefficient of determination (R^2) between multi-dekad accumulated *SPI* and *CMI* (n=165) (a) and *SPI* and *NDVIA* (n=164) (b) during May to September from 2000 to 2010 in Hailar County.

The x-axes denote the number of dekads for *SPI*, with, for example, 2 indicating 2 dekads (1 antecedent dekad)

* Statistically significant at the 0.05 level; ** statistically significant at the 0.01 level.

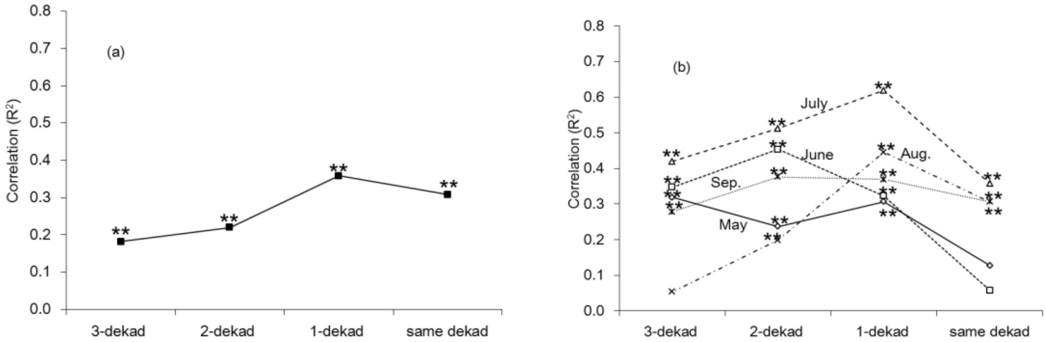


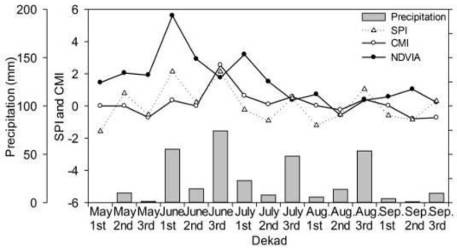
Figure 3-6 The coefficient of determination (R^2) between *CMI* and *NDVIA* over the entire growing period (a) and in individual months (May to September) from 2000 to 2010 in Hailar County (b).

The x-axes denote the time lag of *NDVIA* compared with *CMI*. In panel (a), n=164 and In panel (b), n = 33 for most of the month and n = 32 for June.

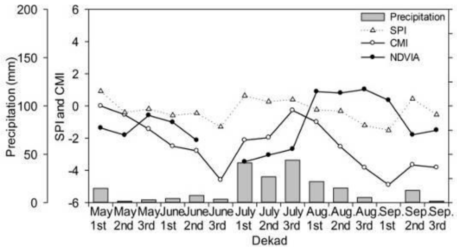
* Statistically significant at the 0.05 level; ** statistically significant at the 0.01 level.

3.5.4 Drought assessment

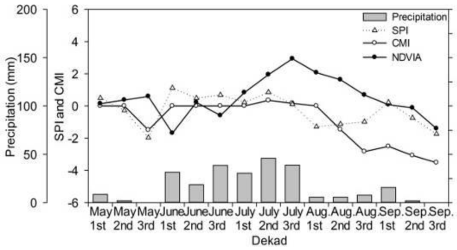
During 2000–2010, yield was heavily reduced in 2001, 2003, 2004 and 2007. For each of these drought years, as assessed by *SPI*, *CMI*, and *NDVIA*, there was a time lag between *CMI* and *NDVIA* (Figure 3-7). The year 2003 had the most serious yield reduction, with the yields of spring wheat, oil rape, and potato all fallen to nearly



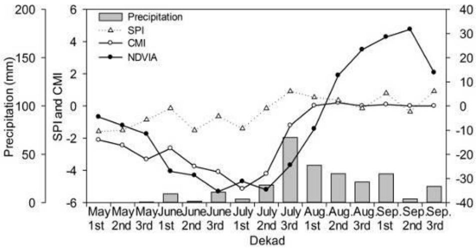
2000 (5.64)



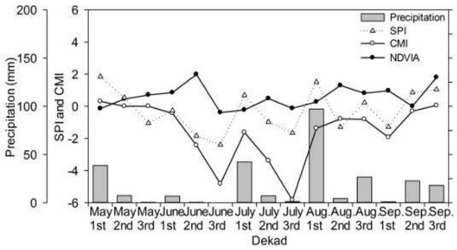
2001 (2.07)



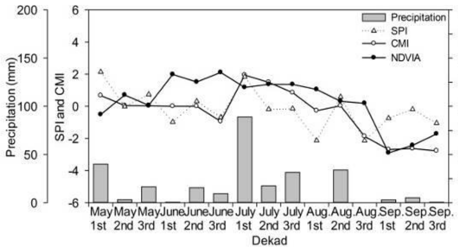
2002 (4.15)



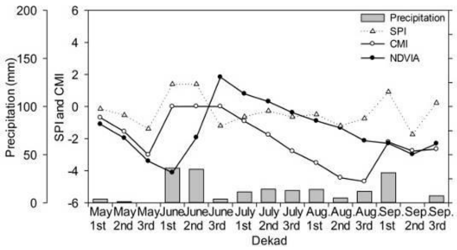
2003 (1.28)



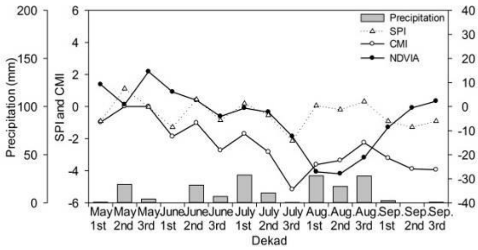
2004 (2.56)



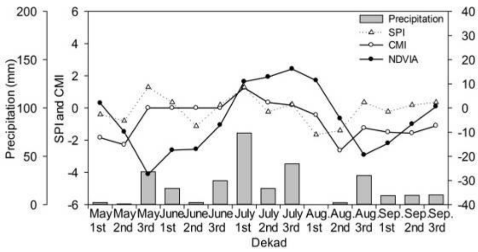
2005 (5.25)



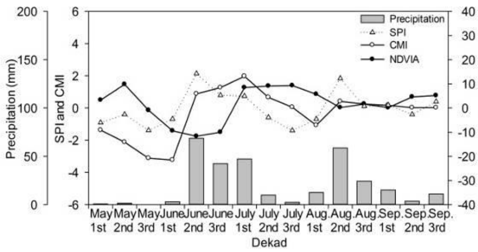
2006 (4.12)



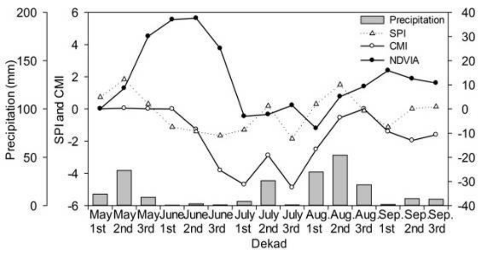
2007 (3.12)



2008 (6.08)



2009 (6.43)



2010 (4.15)

Figure 3-7 Drought process as depicted by precipitation, SPI, CMI, and NDVIA from 2000 to 2010 in Hailar County.
On the *x*-axes, values in parentheses represent the total crop yield energy ($\times 10^7$ kJ/ha).

lowest values during these 11 years (Figure 3-8). The *CMI* value in the first dekad of May was less than –2, indicating that there was a lack of soil moisture before the growing season. After sowing, from early May to early July, the SPI values were continuously less than 0. This long-term precipitation shortage caused a gradual decrease in *CMI* until mid-July, when the soil moisture began to recover. Although the *SPI* value seemed to return to normal in early June, this short-term precipitation did not change the decreasing trend in *CMI* and mitigate the drought conditions. The shortage of water ultimately caused a continuous decrease in the *NDVIA*. Because there was a 1-dekad time lag between *CMI* and *NDVIA*, the vegetation recovery began in late July. *SPI* was close to or higher than 0 from mid-July to early August, so the *CMI* value increased and returned to normal. The recovery of soil moisture also prompted the recovery of *NDVI*. The vegetation condition returned to normal in mid-August. However, this recovery period occurred too late in the growing season. Therefore, the yield was heavily reduced due to this spring and summer drought.

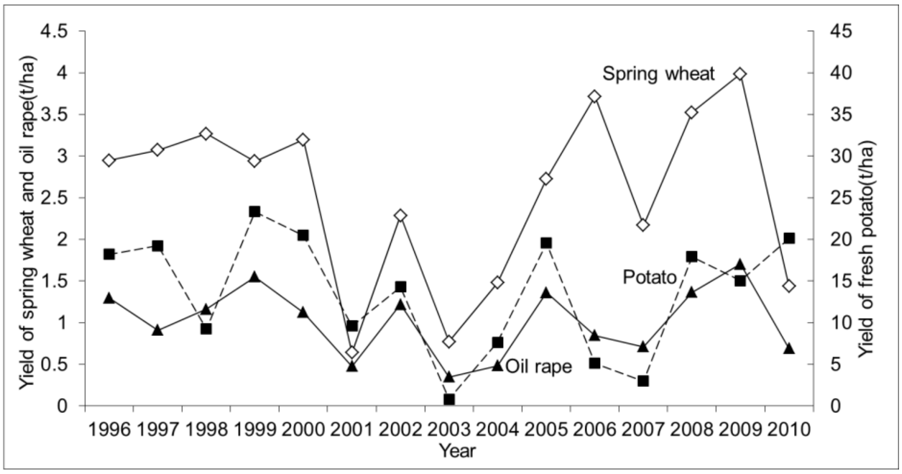


Figure 3-8 Yields of spring wheat, potato and oil rape from 1996 to 2010 in Hailar County

In contrast, the serious period of drought in 2007 was in summer and autumn. The precipitation in mid and late May provided good moisture conditions during the crop seeding period. The *NDVIA* showed that the growth condition was even better than normal. However, there was a series of dekads after mid-June when precipitation was lower than normal, particularly the dekad in late July, with only 0.4 mm precipitation. *CMI* showed that water stress rose to the most serious point in late July. Due to this water stress, *NDVIA* decreased sharply and fell to the lowest point in mid-August. Although the precipitation in August returned to normal, the *NDVIA* recovered to normal levels in mid-September. By that point the crops had already passed through the flowering stage, and the yield suffered great damage.

For the other two years, the year 2001, although there is better precipitation in early May, the continuing low precipitation made the *CMI* decrease from middle May to late June. *NDVIA* start to decrease due to water stress from early June. In July, the precipitation returned to normal, *CMI* slowly returned in late July. *NDVIA* recovered to 0 in early August. Precipitation began to continue decrease from late August, *NDVIA* undertook early senescence in middle September due to water shortage.

For the year 2004, the precipitation continually decreased beginning from middle June, *NDVIA* fell starting from late June. Because the precipitation in early July is higher than normal and there was quick recover of *CMI*. *NDVIA* recovered to higher point in middle July. After that, *CMI* started to decrease in middle July, *NDVIA* deceased in late July. The precipitation in early August brought sharp increase of *CMI* and after that *NDVIA* increased in middle August. CMI decreased in early September and *NDVIA* decreased in middle September after several dry spell, there was an 85.5mm precipitation event on Aug. 1st, 2004. The growth period was nearly the milk ripe stage for wheat and barley, the stem was fragile. It is possible that heavy rainfall also caused the early falling of the fringe and making the low yield.

3.6 Discussion

3.6.1 Recent trends of climate and agricultural drought in Hailar County

In Chapter 2, it can be seen that, since 2000, there is a low precipitation stage (Figure 2-5). In addition, the decrease in precipitation influenced the moisture balance and further caused water stress to crops. Because the water deficit occurs during the key reproductive growth period (flowering time) of crops, the energy yield has suffered greatly from the water deficit. These findings suggest that in semi-arid regions such as Hailar County, the dry and warm climate trends that have occurred during the growing season over the past dekads mean that meteorological drought has easily transformed into agricultural drought.

3.6.2 Critical growth stages related with yield reduction

The majority of the crops in Hailar County are grains, such as spring wheat and barley, whose yield is closely related with reproductive growth. My results showed that vegetation vigor as measured by *NDVI* best reflects yield energy in July (Table 3-1). Deng et al. (2011) studied spring wheat in northern Hailar County and Chen Barag Banner (adjacent to Hailar County) by comparing the actual yield and *NDVI* in 2009/7/29 30-m image from the Chinese HJJZ satellite; they found an extremely significant correlation between this index and yield. Likewise, a study conducted in the Canadian prairies showed that MODIS *NDVI* from the third dekad of June through the third dekad of July could predict grain yield (i.e., barley, canola, field peas, and spring wheat) well in the sub-humid zone (Mkhabela et al., 2011). The Canadian prairies and Hailar County share a similar crop planting structure and growing season (May–August).

Research on crop physiology has shown that for cereal crops, the uppermost leaves (i.e., the flag leaves) are an important source of carbohydrate production. The flag leaves, which emerge during the tillering stage, make up approximately 75% of the effective leaf area that contributes to grain filling (Miller, 1999). The characteristics of flag leaves reflect photosynthetic activity and are considered to be some of the greatest components in determining grain yield potential (Hirota et al., 1990). In Hailar County, the grain-filling stage for spring wheat is in mid-July. Thus, it is possible that vegetation indices in July detect the growth condition of flag leaves and therefore perform well in monitoring yield damage.

The key water stress period identified by dekad-scale *CMI* can be validated by research on crop water requirements. According to experiments on spring wheat in northern China, based on actual measurements and the soil water balance equation, water consumption of spring wheat reached a peak during the jointing to milky period, which accounted for 47.5% of the total water consumption (Li et al., 2003). The jointing to milky period for spring wheat in Hailar County is from late June to late July. Perhaps the unbalanced state between the water supply and water consumption by spring wheat during this period is what allowed *CMI* in mid to late June to provide the best forecast of yield. The key period identified by *CMI* is a little earlier than that identified by *NDVIA* (Table 3-1). The significant time lag between *CMI* and *NDVIA* in July (Figure 3-6) suggests that the influence of dekad-level water stress on the ability of flag leaves to produce carbohydrates around the grain-filling period (mid-July) is a significant agricultural drought process that causes yield damage of spring wheat in Hailar County.

3.6.3 Time lags between water deficit and *NDVI*

SPI was originally calculated at the monthly scale (McKee et al., 1993). Because 1-month SPI reflects relatively short-term conditions, its application relates closely with short-term soil moisture and crop stress, especially during the growing season. In this study, the cumulative period from *SPI* to *CMI* was about 4 dekads seems to show more accurate relationship result (Figure 3-4a). My findings show that dekad-scale *CMI* can bridge the gap between short-term vegetation change and water deficit as depicted by an *in situ* meteorological dataset. In May, June, and September, the time lag between *CMI* and *NDVI* was longer than that in July and August, during the growing period (Figure 3-6). The measurement of soil moisture at Ewenki, Eerguna, and Zhalantun experiment stations (near Hailar County) showed that in spring, after snow melt, there is a period of significant soil moisture loss from early April to early June due to strong wind (Wang and Zhao, 2006). Thus, CMI may perform poorly in depicting the soil moisture balance influenced by snow melt and strong wind in spring.

The average time lag between *CMI* and *NDVI* was 1 dekad during the growing period, and my findings suggest that *CMI* could be used to track the change of dekad-scale crop *NDVI* in similar rainfed agricultural regions. In a previous study, Zipporah (2011) investigated the temporal aspects of drought in Africa based on *NDVI* and Owe's AMSR-E soil moisture dataset, using correlation analysis and a distributed lag model(Dominic et al., 2002). The results showed that a 10-day lag between soil moisture and *NDVI* was the dominant pattern in grassland, cropland, and shrubland. Gu et al. (2008) evaluated the temporal relationship between soil moisture data and *NDVI* at 10 homogeneous grassland sites; at 7 of the sites there was a 1- to 2-week time lag in the *NDVI* response to soil moisture variation in the 5- and 25-cm layers. Thus, my finding that the response time of crop vegetation to soil moisture is 1 dekad is comparable with the results of previous studies.

3.6.4 Feasibility of *SPI*, *CMI*, and *NDVI* for monitoring agricultural drought

The detailed assessment of the agricultural droughts in 2003 and 2007 showed that *SPI*, *CMI*, and *NDVI* can depict the processes underlying a serious drought at the dekad time scale during the growing season. Based on these three indices, it is possible to judge the likelihood of drought developing and to assess the possible yield damage. Dekad-scale *SPI* can be regarded as the earliest indicator of the drought's impact on crops. The relationship between *CMI* and *NDVIA* displays a significant time lag. In this study, the 10-day synthesized *NDVI* values were produced using the maximum-value composite method (Holben, 1986) to reduce noise. Therefore, although dekad-scale *NDVI* is not a direct measure of crop growth, the results of this study suggest that *NDVI* provides sufficient information to reflect the response of crops to drought at the dekad time scale.

3.7 Conclusion

The findings indicate that the agricultural drought assessment model is suitable for regions where crop yield is closely related to conditions during the reproductive growth stage. In the assessment of 2001, 2003, 2004 and 2007 drought years based on the conceptual model, we were able to track the drought process in Hailar County. I found that meteorological drought during 2000–2010 was easily transformed into agricultural drought in the county. In this region where grain crops, including spring wheat and barley, are the main crop types, soil moisture–based and vegetation indices during the late vegetative to early reproductive growth stages (*CMI* in June and *NDVIA* in July, respectively) could be used to detect agricultural drought. The most frequent average time lag between *CMI* and *NDVI* was 1 dekad, especially in July. The results of this 11-year assessment at the dekad time scale in Hailar County fit the conceptual model of the agricultural drought process well. My findings suggest that when synthesizing multiple indices to identify drought features at a short time scale, the underlying drought process needs to be considered. Future research of the drought process should consider the calibration of fixed parameters for *CMI* using cases of drought lasting for longer time periods, the effects of snow melt and strong wind on soil moisture in spring, and the role of human activity in the drought process. In regions with a dry and warm climate, such as that of Hailar County, longer term or more sustainable measures, such as adjusting the cultivation calendar or crop planting structure, may be necessary to prevent damage from agricultural drought in the future.

Chapter 4
Agricultural drought severity assessment based on a crop model

4.1 Introduction

Drought poses a great threat to agriculture, food security and regional economies in semiarid marginal areas such as Inner Mongolia and the 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 the Northeast and Inner Mongolia, 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 rain falls 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 chapter, I 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 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% over mean yields (McQuigg et al., 1973; Wilhite and Neild, 1982). 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 groups (Palmer, 1965). Drought cases according to 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 chapter, I 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. Models able to simulate yields of different types of crops, e.g., the EPIC (Environmental Policy Integrated Climate) (Williams et al., 1989), DSSAT (Decision Support System for Agrotechnology Transfer) (IBSNAT, 1989), WOFOST (WOrld FOod STudies) (de

Wit, 1965), and APSIM (Agricultural Production Systems sIMulator) (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. Li et al. (2004) and Wang et al. (2011b) 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 regional scale, the model fit well the spatial pattern of winter wheat and summer maize yields in 2001 on the North China Plain. Loess Plateau and North China Plain adhere to Inner Mongolia. They suggest that the suitability of EPIC for exploring long-term agricultural drought intensity in Northeast China and Inner Mongolia.

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 Northeast China and Inner Mongolia. The specific objectives of the study were to: (1) verify the validity of the EPIC model by 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.

4.2 Materials and methods

4.2.1 Description of study area

The Northeast China and Inner Mongolia spans 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 (Figure 4-1). 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. The total non-irrigated, maize-growing areas are large, e.g. all greater than 75% 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 planting region on the Ordos Plateau south of the Yinshan Mountains, where water resources are limited.

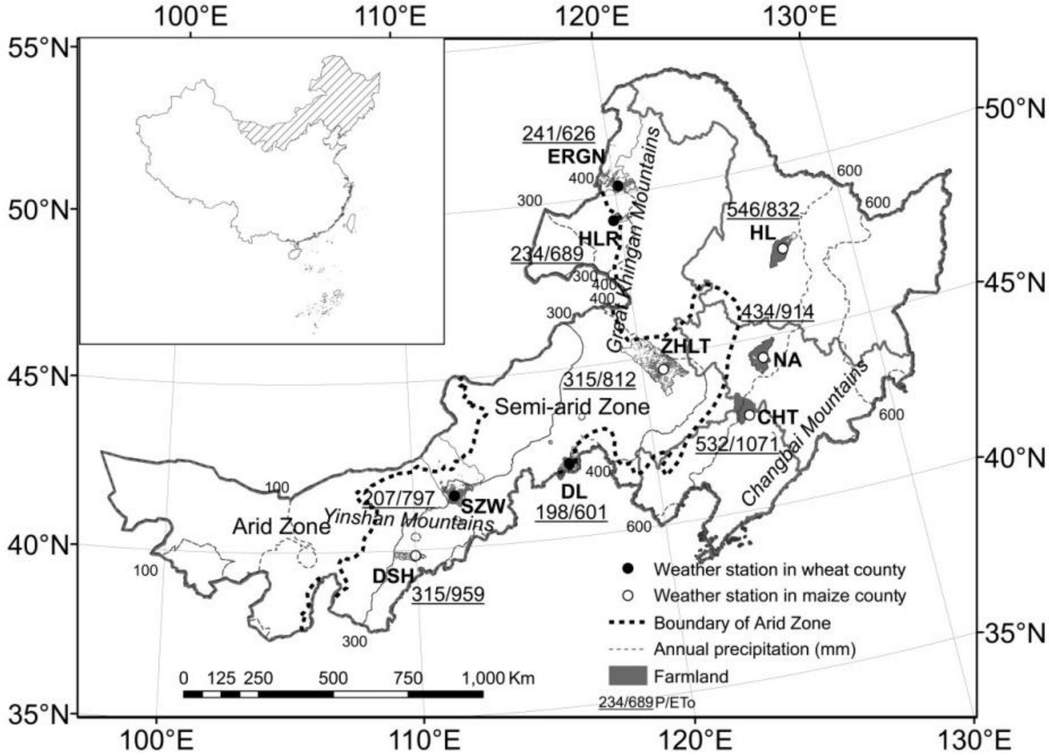


Figure 4-1 Locations of nine representative counties dominated by rainfed agriculture

County names: CHT, Changtu; DL, Duolun; DSH, Dongsheng; ERGN, Eerguna; HLR, Hailar; HL, Hailun; NA, Nong'an; SZW, Siziwang; ZHLT, Zhalute. P/PET: ratio of precipitation during the growing season to potential evapotranspiration. Annual precipitation isohyet extrapolated from a multiyear average precipitation dataset from 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).

Average growing-season temperatures (1971–2000) in the four wheat-growing counties were from 15– 16 ℃, colder than the range 17–21 ℃ in the five maize-growing counties. 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 (Figure 4-1). 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 main range of rainfed regions in Northeast China and Inner Mongolia.

Table 4-1 General information on crops and soils in the typical nine counties

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/).

4.2.2 Agricultural drought assessment framework

To quantitatively assess the agricultural drought an index, a new assessment framework including three main parts is proposed (Figure 4-2). We calculated and compared a yield-based drought index simulated by a validated crop model and 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, mean assessment, and agreement validation. Standard period setting must consider standard climate-normal and crop growth years used in model validation. The mean value as a threshold were assessed by comparing their percentiles. The drought indices and thresholds were validated using agricultural drought cases from the literatures.

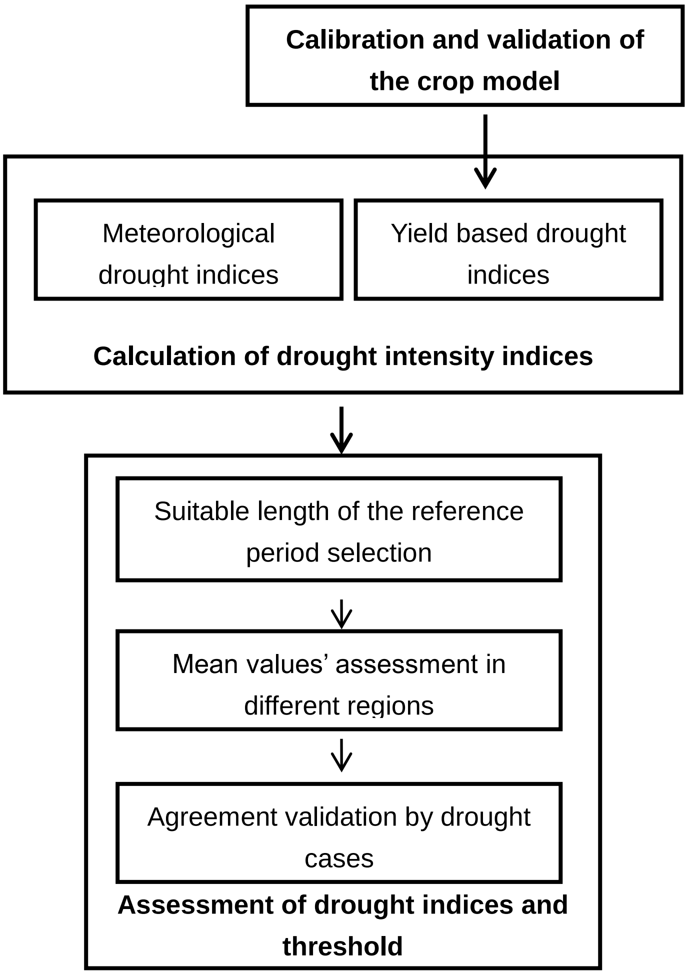


Figure 4-2 Methodological framework for agricultural drought assessment in this study.

4.2.3 Model calibration and validation

WinEPIC6.0 model (http://epicapex.tamu.edu/downloads/model-executables/winepic-6-0/) was used to simulate yield. The EPIC model can be used to simulate 114 crops 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 six 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. (2011b). 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.

4.2.4 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 drive 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

$$WSYR = \frac{YI - YR}{YI} \times 100, \qquad (4\text{-}1)$$

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 based on the daily data. The *AI* was used to quantify the degree of water stress during the growth period (FAO, 1989; UNEP, 1992):

$$AI = \frac{P}{PET}, \qquad (4\text{-}2)$$

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 dekad (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%, 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.

4.2.5 Soil moisture simulation

Surface soil moisture is sensitive to environments change. *CMI* in chapter 3 was regarded as soil moisture index. In this chapter, the 20cm depth soil moisture was used to be representative as 0-30cm tillage layer to validate the previous assumption. The daily 20cm soil moisture from 1962 and 2010 in 9 counties was simulated by using EPIC model. We calculated 10-day soil moisture anomaly (*SMA*) based on soil moisture following equation below:

$$SMA_{i,j} = \frac{SM_{i,j} - SM_{ave,j}}{SM_{ave,j}} \times 100 \qquad (4\text{-}3)$$

where i is year, j is dekad, SM is soil moisture and $SM_{ave,j}$ is the average soil moisture value for the same dekad j during 2000–2010. The average value was computed using all the records in the same dekad.

4.2.6 Data sources and collection

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).

Soil properties: Soil depth, sand content, silt content, bulk density, pH, organic carbon (C) content, and calcium carbonate fraction satisfies 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 and land use: 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. 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 understandings by different people. We selected only drought cases for which the records clearly show agricultural damage (Table 4-2).

4.2.8 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 (Zhang et al., 2009) 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).

4.3 Results and Discussion

4.3.1 Crop model performance

Both R^2 and RMSE confirmed that simulated yields fit actual yields well for the nine counties over 1996–2001 (Figure 4-3a and 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 (Figure 4-3c). 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. A recent study (Cooter et al., 2012) found that EPIC-simulated fertilizer rates agreed well with the spatial pattern of reported national-scale fertilizer application in the United States. 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 4-3b 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, 1999). 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 Northeast China and Inner Mongolia, wheat and maize are the two major grain crops, and both can be cultivated without

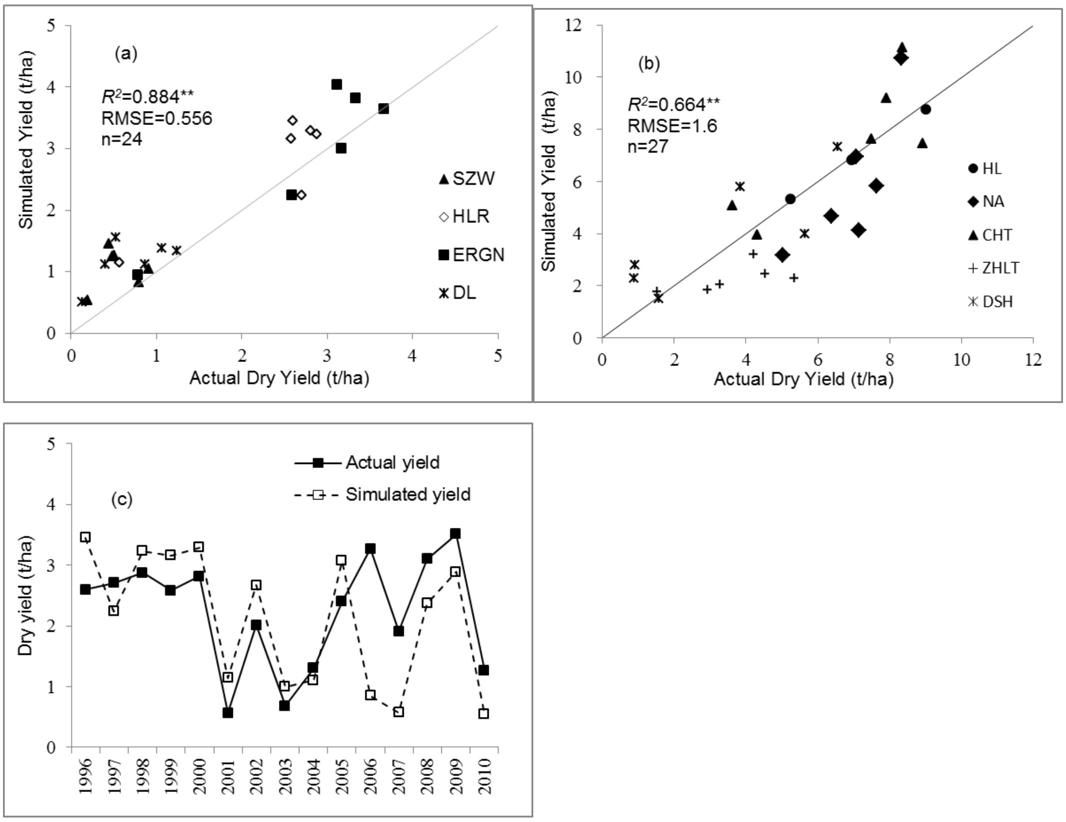


Figure 4-3 Validation of EPIC model for prediction of (a) spring wheat and (b) maize yield in rainfed cultivation, and (c) trend of spring wheat in Hailar county between 1996 and 2010.

Based on actual yield data from nine representative counties between 1996 and 2001, 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.

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, 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 (Figure 4-3c). Therefore, simulation bias could be reduced by considering additional information.

4.3.2 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%) (Figure 4-4a). 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%)

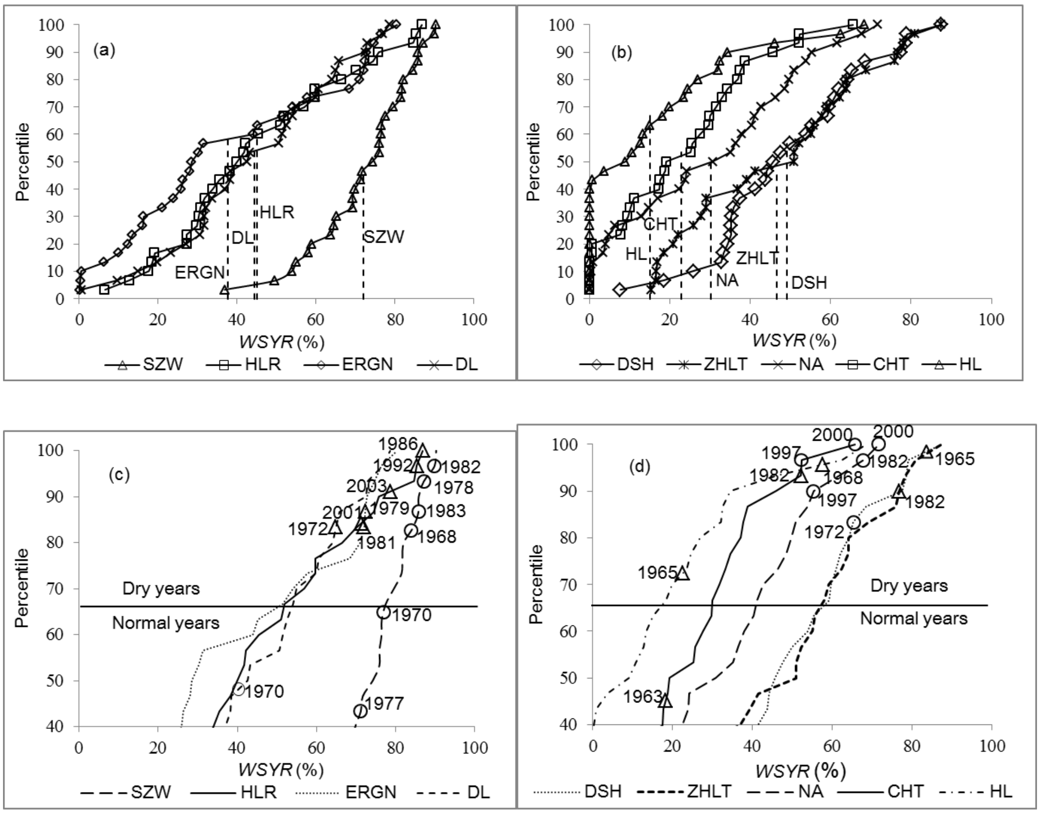


Figure 4-4 Percentiles of mean *WSYR* in (a) four counties that grew spring wheat and (b) five counties that grew maize from 1971 to 2000; percentiles of drought cases in (c) counties growing wheat and (d) counties growing maize.

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. The straight lines are classification threshold between dry and normal years.

(Figure 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 greater than in Hailun (Figure 4-4a and 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. The results indicate that crops suffered from frequent serious yield reductions in the west, 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 my study area.

A total of 26 drought cases were recorded in the chorographies and disaster compilation books (Table 4-2). 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% (Figure 4-4c and d). Exception were a few cases in both the wheat (1970 and1977 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 a spring wheat *WSYR*. 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% (Figure 4-4c and d), there was agreement for 22 of the 26 drought cases, or 85% (Table 4-2), with a high *WSYR*. Using the same threshold percentiles, agreements using *P* were 16 of the 26 cases (65%), and 17 of the 26 (68%) using *AI*. The agreement using *WSYR* is greater than with *P* or *AI*. For example, 1978, 1982 and 1983 in Siziwang, 1979 in Eerguna, and 1997 in Nong'an were identified by *WSYR*.

Table 4-2 Agricultural drought cases in nine counties of Northeast China and Inner Mongolia

County name	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 tons 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)

but not by *P* or *AI* (Figure 4-5). 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 4-3), 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,

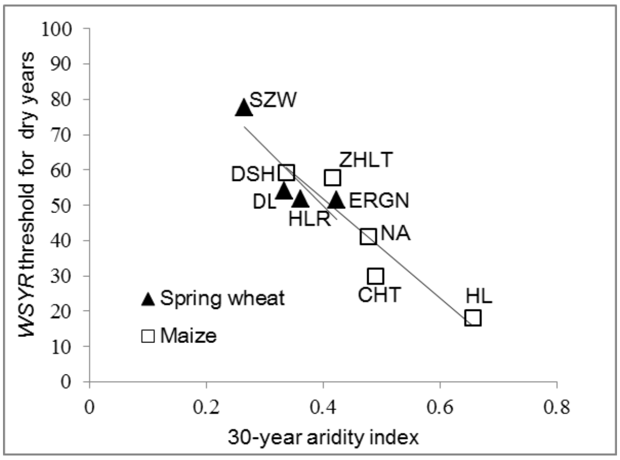


Figure 4-5 Relationship between aridity index (ratio of precipitation to potential evapotranspiration) from 1971 to 2000, and drought threshold based on WSYR.
County names: SZW, Siziwang; HLR, Hailar; ERGN, Eerguna; DL, Duolun; ZHLT, Zhalute; DSH, Dongsheng; NA, Nong'an; CHT, Changtu; HL, Hailun.

Hailun had the lowest threshold (18.3% *WSYR*), Zalute and Dongsheng high thresholds (57.9–59.3% *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 77.5% to 18.3% with increased 30-year *AI* from 0.26 to 0.66 (Figure 4-6). Thus, aridity has a strong influence on the classification of the drought intensity.

Table 4-3 Threshold of water stress yield reduction (*WSYR*) for classifying agricultural drought intensity in nine counties of Northeast China and Inner Mongolia for the period 1971–2000. Threshold values were determined by the same (one-third) percentile.

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

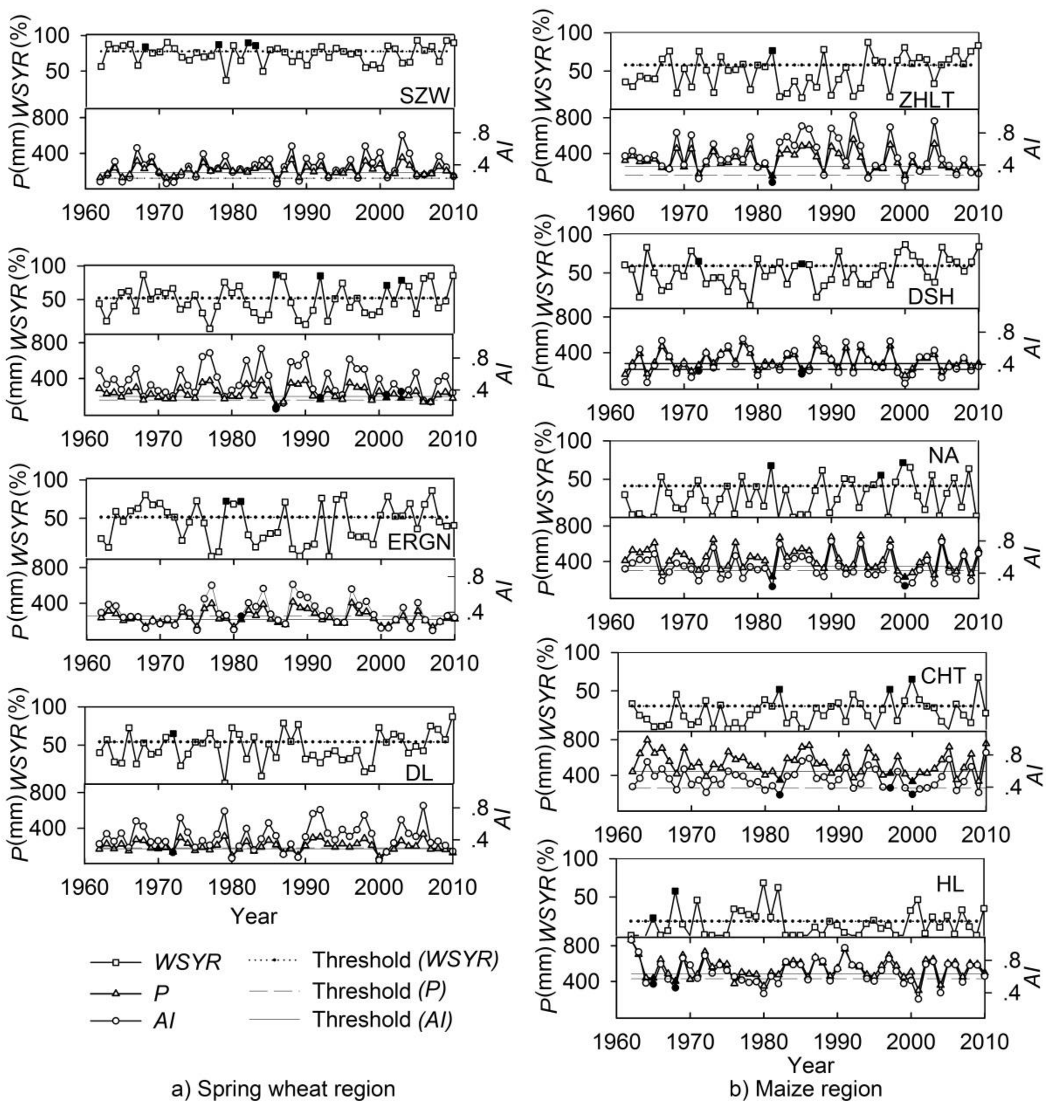


Figure 4-6 Dry years in time series of *WSYR*, precipitation (*P*) and aridity index (*AI*) from 1962 to 2010 in (a) four counties that grew spring wheat, and (b) five counties that grew maize.

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.

4.3.3 Validation of 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 4-4 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 yr^{-1} [a])	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

* 0.05 significance level; **0.01 significance level

[a]10 yr^{-1} – every 10 years

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

(Table 4-4). 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 frequency of decadal dry years classified by *WSYR* (Figure 4-7a) shows dry years in the 2000s were more frequent in the maize-growing counties (Zhalute and Dongsheng). Other maize-growing counties except Hailun had high frequencies of dry years in the 1990s and 2000s relative to the 1960s, 1970s and 1980s, but the

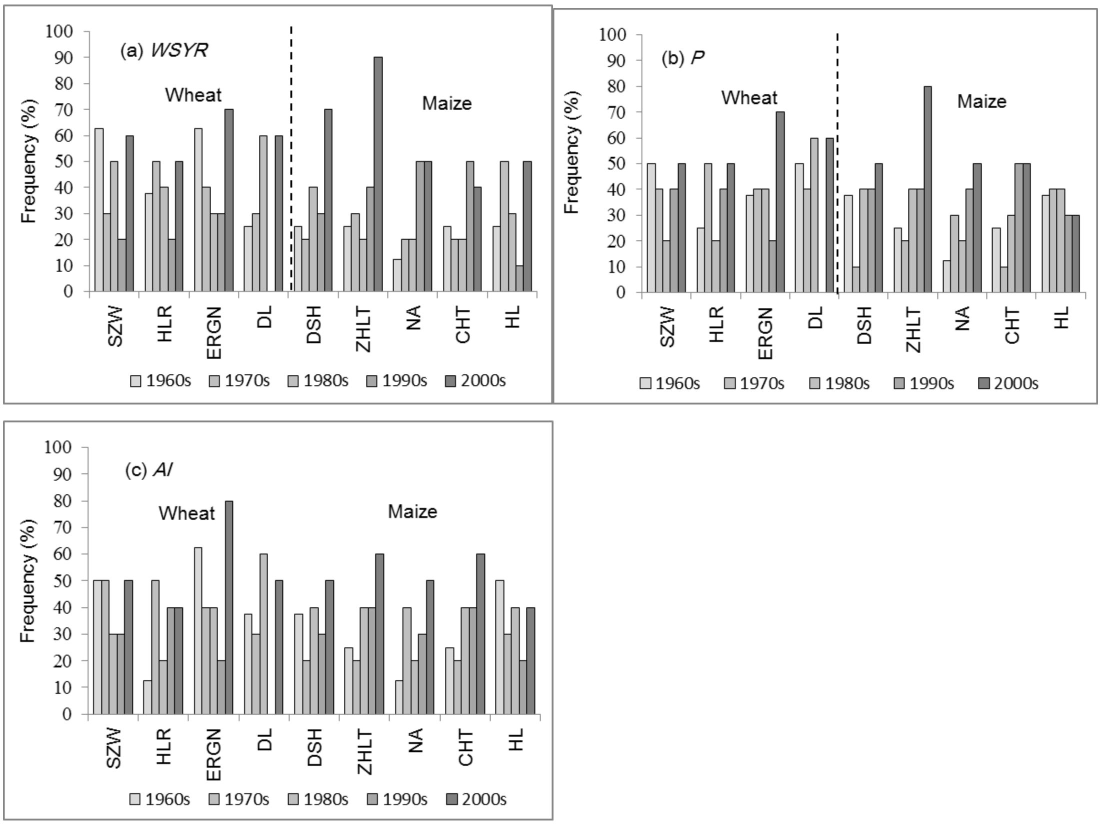


Figure 4-7 Frequency of decade dry year from 1960s to 2000s in nine counties, via (a) WSYR, (b) precipitation, (c) aridity index.

County names: SZW, Siziwang; HLR, Hailar; ERGN, Eerguna; DL, Duolun; ZHLT, Zhalute; DSH, Dongsheng; NA, Nong’an; CHT, Changtu; HL, Hailun.

frequencies were not as high as those for Zhalute and Dongsheng. All the wheat-growing counties had lower frequencies of dry years in the 1990s than other decades, and no increase in frequency was found in those counties. Using only maize *WSYR* to assess agricultural drought, the frequency of dry years increased in the five maize-growing counties, so 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% over mean yield during 2001–2008 was larger than that of 1980–2000 in Heilongjiang and Jilin provinces and Inner Mongolia, but not in Liaoning Province. The frequency identified by *P* in the 2000s was lower than that in the 1990s in Hailun County (Figure 4-7b). In all the counties, the frequency identified by the *AI* in the 2000s was greater than that in the 1990s (Figure 4-7c). The average frequency from *WSYR* for nine counties was 27.8% in the 1990s and 60% in the 2000s. The average frequency from P was 33.3% in the 1990s and 54.4% in the 2000s. Average frequency from the AI was 27.8% in the 1990s and 53.3% in the 2000s. The increase of frequency from the 1990s to 2000s via *WSYR* was greater than those via *P* and *AI*.

4.3.4 The relationship between soil moisture simulation and *CMI*

All of the counties are significantly correlated with moisture variation in 20cm root layer (Table 4-5). The R^2 ranges from 0.3 to 0.57. There is smallest R^2 (R^2=0.306) in Siziwang county. There are also smaller R^2 in Duolun and Dongsheng counties. There are similar R^2 in Hailar county (R^2=0.542), Zhalute county (R^2=0.51), ERGN

Table 4-5 The correlation of determination (R^2) of soil moisture based drought indices (*CMI*) to predict 20cm dekad soil moisture anomaly by model in 9 counties from April to September (n=918)

County	Correlation of determination (R^2)	County	Correlation of determination (R^2)
Siziwang	0.306**	Dongsheng	0.357**
Hailar	0.542**	Zhalute	0.51**
Eerguna	0.538**	Nong’an	0.504**
Duolun	0.393**	Changtu	0.542**
		Hailun	0.573**

** Statistically significant at the 0.01 level

county (R^2=0.538), Changtu county (R^2=0.542) and Nong’an county (R^2=0.504). The largest R^2 is in Hailun (R^2=0.573). It shows that *CMI* can depict the root layer soil moisture variation very well. Considering 30-year aridity index (Figure 4-5) of 9 counties, the counties with higher aridity index values have higher R^2.

4.4 Conclusions

Following the newly proposed drought assessment framework, the performance of agricultural drought indices were quantified and compared in a rainfed region of the Northeast China and Inner Mongolia. The EPIC model simulated long-term crop yields under rainfed conditions and performed reasonably well in estimating both wheat and maize yields at county level. The percentage of yield reduction caused by drought (*WSYR*) was used to classify the intensity of agricultural drought for the nine counties in the study area. The one-third probability of *WSYR* was identified to differentiate drought years from other years. *WSYR,* which is a crop-specific index, was more accurate in representing agricultural drought than meteorological drought indicators such as *AI* and *P*. The 49-year trend of agricultural drought from *WSYR* was more significant than those from the meteorological indices. The average increase in decadal frequency of drought years from the 1990s to 2000s via *WSYR* was greater than those via *AI* and *P*. This shows that my framework can be validated by long-period analyses. The soil moisture index (*CMI*) can be validated with surface soil moisture anomaly by crop model. It suggests that possibility to improve drought indicator by crop model. As demonstrated here, a crop model such as EPIC can be useful for simulating the impact of drought on yield, classifying the intensity of agricultural drought, and thereby assessing the trend of regional drought.

Chapter 5

The comparison of agricultural practices to mitigate drought by the crop model

5.1 Introduction

The Northeast China and Inner Mongolia, plays a vital role in securing food production in China, where grain accounts for 20.9% of China's total grain production (China Statistical Yearbook, 2009). However, large areas of crops are rainfed and supplemental irrigation (SI) is used effectively in only 32% of this agricultural area (China Statistical Yearbook, 2009). Chapter 2 shows that the agricultural productions were heavily influenced by precipitation fluctuation.

Drought directly affects household and national food security, as it represents a period in which insufficient rain falls or when soil moisture decreases enough to cause water stress to crops, leading to some degree of yield reduction and possibly to crop failure (Agnew and Anderson, 1992). Human factors, such as farming methods, have an effect on the vulnerability of farms to drought, but have received little research or policy attention (Knutson et al., 2011). Agricultural practices vary widely from place to place. The United Nations Food and Agriculture Organization (FAO's) provides specific recommendations related to agricultural practices; these are related to several aspects of agricultural production including water, soil, crop and fodder production, harvest and on-farm processing and storage (FAO, 2003). I selected three low cost and widely used agricultural practices that I believe are designed to mitigate agricultural drought: 1) Supplementary irrigation (SI), 2) changes in sowing date and 3) changes in crop variety.

The FAO has identified irrigation as an important aspect of agricultural production, and changes in variety and sowing date are two practices that are representative of crop and fodder production. SI is one of the most effective strategies used to increase crop yield in rainfed regions. The meaning of SI has been defined as providing “additional moisture [to supplement the] limited amounts of water [initially available] to [what are] essentially rainfed crops, [with the goal of improving and stabilizing] yields during times when rainfall fails to provide sufficient moisture [required for] normal plant growth” (Oweis and Hachum, 2012). Droughts occur in irregular patterns. In regions lacking the water resources needed to provide adequate moisture for crops, using limited irrigation water efficiently is important to the goal of reducing the effects of drought on yield. Previous study on determination of the optimal sowing date always requires field experiments to be conducted across a large region (Jin, 1991). However, these regional experiments consume a considerable amount of time and money. The present study employed some new technology, such as using RZWQM and CERES-Maize models; for example, Anapalli et al. (2005) simulated the effects of sowing date on corn production using these models. Liu et al. (2013) used the APSIM-Maize crop model in northeastern China to simulate the effects of earlier sowing dates and the introduction of different varieties with higher thermal time requirements and successfully showed how these methods can compensate for the negative effects of climate change. Lv et al. (2013) showed that a change in variety can potentially increase yield. These research studies did not model variations in climate in different years. I wanted to study the effects of changes in sowing date and crop variety on yield and model the effects of drought under dry, normal and wet years in the Northeast China and Inner Mongolia.

The use of SI as well as changes in sowing date and variety may play different roles in drought mitigation. However, common experimental methods make it difficult to make a quantitative comparison of the effects of these measures on crop yield. Crop models provide a good choice for investigating the measurement of crop yield. This is because these models can simulate the underlying physiological processes of crop growth and show how these processes change in response to changes in the ambient environment. Using a crop model that measures the influence of various factors on yield, makes it is possible to quantifiably assess the effects of different factors. Commonly used physical crop growth models include The Environmental Policy Integrated Climate (EPIC) model (Williams et al. , 1989), the Decision Support System for Agrotechnology Transfer (DSSAT) model (IBSNAT 1989), World Food Studies (WOFOST) model (de Wit 1965), and the Agricultural Production Systems sIMulator (APSIM) (McCown et al. , 1996). EPIC was developed to estimate soil productivity as affected by erosion; this model simulates crop growth using unique parameter values for each crop (Williams et al., 1989). A number of studies have demonstrated the performance of the EPIC model at both plot (Li et al. 2004;Wang et al. 2011) and regional scales. Liu et al. (2007) and Liu (2009), for example, showed that a good agreement exists between the country-level simulated yields of wheat, maize, and rice worldwide. Previous research (Bryant et al., 1992; Rinaldi, 2001; Ko et al., 2009) has also shown that the EPIC model can be used to model crops grown under different irrigation conditions. The study in Chapter 4 has confirmed that EPIC can accurately simulate the annual time series of county-level yield in typical counties having rainfed cultivation of spring wheat and maize in Northeast China and Inner Mongolia China. Using county level yield as a reference, I will use an EPIC crop model to simulate our measurement effects on the increase in yield.

The main objective of this chapter is to assess the effects of different drought management techniques currently used in Northeast China and Inner Mongolia. Using the crop model, I will study (1) the effects of a single 50 mm of SI, as well as changes in (2) sowing date and (3) crop variety on yield.

5.2 Date and Methods

5.2.1 Study area

The geographic environment of 9 counties in the Northeast China and Inner Mongolia is same as the Chapter 4 (Figure 4-1). Considering the base temperature, 30-year average total heat units for spring wheat counties ranges from

2,339-2,859 ℃ and for maize ranges from 1,494-2,019 ℃ (Table 5-1).

Table 5-1 Crop and heat resources conditions in the nine counties.

County	Main crop type	30-year average total heat units (℃) [c]
Siziwang	spring wheat	2859.10
Hailar	spring wheat	2540.04
Eerguna	spring wheat	2339.07
Duolun	spring wheat	2665.65
Zhalute	maize	1974.00
Dongsheng	maize	1594.25
Nong'an	maize	1824.13
Changtu	maize	2019.37
Hailun	maize	1494.37

[a]The 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]The main soil texture was determined from the FAO soil map (http://www.iiasa.ac.at/Research/LUC/External-World-soil-database/).
[c] Base temperature for spring wheat is 0℃ and for maize is 8℃. Five-day smooth method (Tian et al., 2007) was used to identify the start and end days for temperature accumulation.

5.2.2 Materials

1) Meteorological data

I downloaded daily meteorological datasets, including precipitation, maximum and minimum temperatures, relative humidity, wind speed, and hours of sunshine, from 1960 to 2010 for the nine counties from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/). The data were undertaken restrict quality control. From the remaining data, I estimated solar radiation by using the number of sunshine hours following Angström (Angström, 1956). Next, I transformed the weather data file for input by EPIC using the Weather Import utility provided by Texas A&M University AgriLife Research (http://epicapex. tamu. edu /downloads/model-executables/weather-import/).

2) Soil properties

I calculated the soil depth, sand content, silt content, bulk density, pH, organic carbon content, and calcium carbonate fraction for farmland in the nine counties using an area-weighted method based on a 1:1,000,000 scale soil map of China created by the Chinese Academy of Sciences and downloaded from the FAO Harmonized World Soil Database v 1.2 Web site (http://www.iiasa.ac.at /Research/LUC/External-World-soil-database/).These seven soil parameters can satisfy the minimum soil input requirements of EPIC (Liu et al. 2007).

3) Farmland and land use

Farmland locations were obtained from a 1-km-scale land-use map of China in 2000. 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 Web site (http://westdc.westgis.ac.cn). The original dataset was a county-level land-use and cover type dataset (vector format, 1:100,000 scale) created by the Chinese Academy of Sciences. Using the maximum-area method, the datasets were combined and transferred to the final 1-km raster product by Liu (Liu et al. 2001).

4) Crop variety information

The experiment information of spring wheat and maize can be obtained from regional variety experiments in Inner Mongolia downloaded from 2008 to 2010 from Seed Association of Inner Mongolia Automous region http://www.nmseed.com/NewsList.aspx?oid=1401. The field experiments were organized and strictly operated annually in order to identify the productivity, growth period and genetics stability and environment adaptation of the new varieties. The experiments were designed by using the randomized block arrangement. Not less than 4 protect lines surrenders the experiments region. The topography of plot is flat. The sowing dates water and fertilizer condition were in accordance with local agricultural production condition. But the management is a little higher than local level. Any types of management and measures need to be finished within the same day. The control check (CK) varieties which can be adaptive to the changing environment were chosen as the widely spread

Table 5-2 The experiment sites and crop varieties

Variety	County	Year	Soil texture	Planting density (thousand/ha)	Sowing date	Seeding date	Earing (wheat) or Silking (corn) date	Maturation date	Condition
'Longmai 26'(Spring wheat)	Hailar (SAIMAR, 2008a, 2009a, 2010a)	2008	Loam	576	5/5	5/24	6/28	8/10	Irrigated
		2009	Loam	486	5/6	5/23	7/12	8/18	Irrigated
		2010	Loam	612	5/4	5/15	6/27	8/20	Irrigated
	Eerguna (SAIMAR, 2008b, 2009b, 2010b)	2008	Loam	597	5/17	6/1	7/10	8/12	Rainfed
		2009	Loam	562.5	5/5	5/26	7/16	9/3	Rainfed
		2010	Loam	612	5/16	5/24	7/1	8/22	Rainfed
'Dadi' (Maize)	Zhalute (SAIMAR, 2009c, 2010c)	2009	Loam	5.95	5/8	5/25	7/21–7/22	9/12	Irrigated
		2010	Loam	5.95	5/13	5/28	7/15–16	9/6	Irrigated
'Zhedan 37' (Maize)	Zhalute (SAIMAR, 2009d, 2010d)	2009	Clay	5.95	5/8	5/25	7/27–7/30	9/24–25	Irrigated
		2010	Clay	5.95	5/13	5/28	7/20	9/15	Irrigated

representative variety (Table 5-2). The experiment was done without irrigation in Eerguna County during 2008 to 2010. I would like to use such data to validate the simulated crop yield (Table 5-3).

5.2.3 Agricultural practices

For maize, I changed the origin *WA* parameter (i.e., the biomass energy ratio) value from 43 to 40 based on calibration of the model in northern China by Wang et al. (2011). I selected the Penman-Monteith equation to estimate potential evapotranspiration. With the assumption of no soil nutrient deficiencies, the county level sowing date and harvest date (Table 5-1) were first fixed to determine the county level potential heat units and then I simulated the county level maize rainfed dry yield and wheat dry yield by EPIC model.

Table 5-3 The management of seed experiments in Eerguna county during 2008-2010 (SAIMAR, 2008b, 2009b, 2010b)

Year	Preceding crop	Area (m^2)	Fertilizer during sowing	Weeding date	Yield (t/ha)
2008	Oil rape	200	$(NH_4)_2HPO_4$ 8kg, Urea 4kg, Compound fertilizer of potassium sulfate 8kg	Weeding during seedling stage	3.54
2009	Oil rape	200	$(NH_4)_2HPO_4$ 8kg, Urea 4kg, Compound fertilizer of potassium sulfate 8kg	Weeding on June 2rd，June 23th	5.28
2010	Oil rape	200	$(NH_4)_2HPO_4$ 8kg, Urea 4kg, Compound fertilizer of potassium sulfate 8kg	Weeding on June 8th	3.31

(1) Irrigation

A single irrigation serves as the basic unit of an irrigation schedule, the results for this treatment can also provide insights into the potential of multiple irrigations. For maize and wheat in Northeast and Inner Mongolia, single irrigations usually use 30 to 50 mm and 40 to 60 mm of water, respectively (Cui 1990). In dry years, surface irrigation quota in Inner Mongolia for spring wheat ranges 270-490mm and for maize is 200-430mm (IMWCQ, 2010). I therefore ran the model using a specific irrigation amount of 50 mm (an intermediate value suitable for both crops) and examined the response to that irrigation which were supplied on each day of growth period from the sowing date in 1962 to the harvest date in 2010, and looked for the day in each year that gave the highest yield increase.

(2) Sowing date

These is a switch for heat unit schedule: one is the normal operation and EPIC model can calculate the potential heat unit (*PHU*), and the other is automatic heat unit schedule which potential heat unit must be input at sowing. I firstly used normal operation and made the model calculate the *PHU* and then took it as the input and changed the sowing date and used automatic heat unit schedule to determine the maturity date. By using EPIC model based simulation experiments, compared with county level normal sowing date(Table 5-1), I designed 7 sowing date scenario series for maize ranging from 30 days earlier to 40 days late and 12 scenarios series for spring wheat ranging from 30 days earlier to 80 days late. After calibration of the model with county level yield, by using same county level potential heat units, I simulated the multiple sowing dates and the maturity dates were automatically determined by the model.

(3) Crop variety changes

From the reports from 2008 to 2010 (Table 5-2), I used the modified height of crop types by using the actual values. The normal height of 'Longmai 26' is 112cm. The average height for 'Yongliang 4' is 82cm, 'Dadi' is 180cm, 'Zhedan37' is 231cm. I took the average values of same variety in several plots (Table 5-2) as suitable potential heat units. Based on the sowing date and maturity date, I calculated the potential heat units according to the EPIC model document (Sharpley, A.N., and J.R. Villiams, 1990). In 2001, the total sowing area of 'Longmai 26' is 13×10^4 ha which is top among all wheat varieties in China (Sun et al., 2002). The potential heat unit of wheat variety 'Longmai 26' is 1853.3℃. For maize, "Dadi" is 1829.9℃ and 'Zhedan37' is 1941.4℃. The crop growth experiment of 'Yongliang 4' is from Hohhot County. I calculated the potential heat unit (1989.8℃) and used the planting density is determined as 450 thousand/ha. I assumed that all the farmland in one county was planted with specific variety and there is no change of the sowing date in the county. When validating the simulation results with seeding date and actual yield, it can be seen that the simulated result fits well with actual seeding date (Figure 5-1a), the *RMSE* is 3-4 days. The yield variation fits well with measured dry yield in Eerguna County (Figure 5-1b). The earlier stage of 'Longmai 26' is resistant to water shortage and later stage is resistant to waterlog (Song, 1999). The fitness of seeding and yield show that EPIC model can reflect the water sensitivity of 'Longmai 26' variety.

Therefore, EPIC model is suitable model in this chapter to simulate the growth of crop variety.

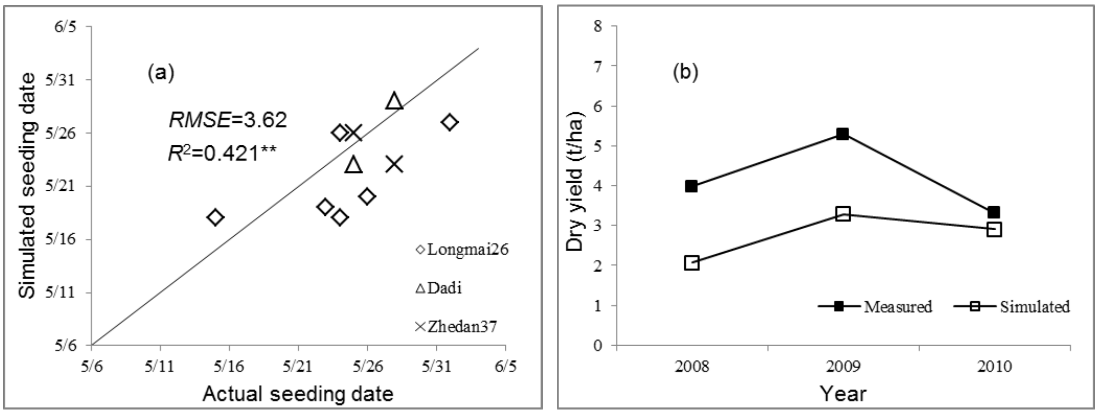


Figure 5-1 The comparison between (a) actual and EPIC model simulated seeding date and (b) between simulated and actual experimental yields of 'Longmai 26' in Eerguna county

double asterisks (**) denote significant trend at 1% probability level

(4) Statistical analysis

In order to validate the crop model for new varieties, I compared the measured and predicted seeding date and yields. The coefficient of determination (R^2) and root-mean-square error (*RMSE*) were used to evaluate goodness of fit of the EPIC model.

I have totally 9 sample counties and two crop types. A paired sample t-test is used to determine whether there is a significant difference between the average values under two different conditions. Analysis of Variance (ANOVA) was used to compare means of three or more samples (using the F distribution) (David C.H., 2002). Post Hoc Multiple Comparison option was selected with the equal variances assumption of Scheffe because it refers to different sample size comparison. In this chapter, I divided the 49 years into three types of climate years (defined here as dry, normal and wet) based on growth period precipitation using the 1/3 percentile method. The number of normal years is 17 years. Dry years and wet years are 16 years, respectively.

For the irrigation scenario, t-test was firstly used to compare yields under reference non-irrigation and 50 mm irrigation. The yield increments (yield difference between non- and 50mm irrigation) under 3 types of climate years was compared by using ANOVA and Post Hoc test.

For the sowing date change, in order to find suitable date, I firstly used ANOVA to test the difference among all sowing date scenarios. The Post Hoc (Scheffe) were used to test the difference between reference yield and yield under sowing date scenarios (e.g. 10 days later than the reference date) under dry, normal and wet climate years.

For the variety change, due to it refers to three variety types, I firstly used ANOVA to test the difference among three varieties (including the reference). The Post Hoc (Scheffe) was used to test the difference between reference yield and yield under each variety.

Different sowing date and variety may have different yield, in order to make the comparison among the different strategies, I took the maximum effects of sowing date, variety and irrigation to be the representative. I can make the comparison by using the ANOVA and Post Hoc.

Using SPSS ver. 13.0 software (SPSS, Inc., Chicago, IL, USA), I tested the factors influenced the variances due to irrigation, sowing date and variety change respectively and attempted to make the comparison of the three strategies on yield.

5.3 Results

5.3.1 The effects of irrigation on yield

Yield under a single SI was significantly different from county level yield without SI for all counties based on the t test (Figure 5-2). However, the effectiveness of SI on improving yield seemed to vary with diverse types of climate years.

For spring wheat counties, the ANOVA test revealed a single SI resulted in significantly increased yield in all the counties except Siziwang (Table 5-4). The increase in yield with SI during dry years was significant larger than that in wet years in Eerguna, Hailar and Duolun counties. The increase in yield during normal precipitation years was significantly larger than that in wet years only in Hailar County (Table 5-4). The increase in yield during dry years was significantly larger than that in normal years only in Duolun County.

For maize-growing counties, the ANOVA test revealed a single SI resulted in significantly increased yield in all the counties (Table 5-4). The increase in yield with SI during dry years was significant larger than those in wet years in all four maize-growing counties (Table 5-4). The increase in yield during normal years was significantly larger than that in wet years in all counties except Hailun County.

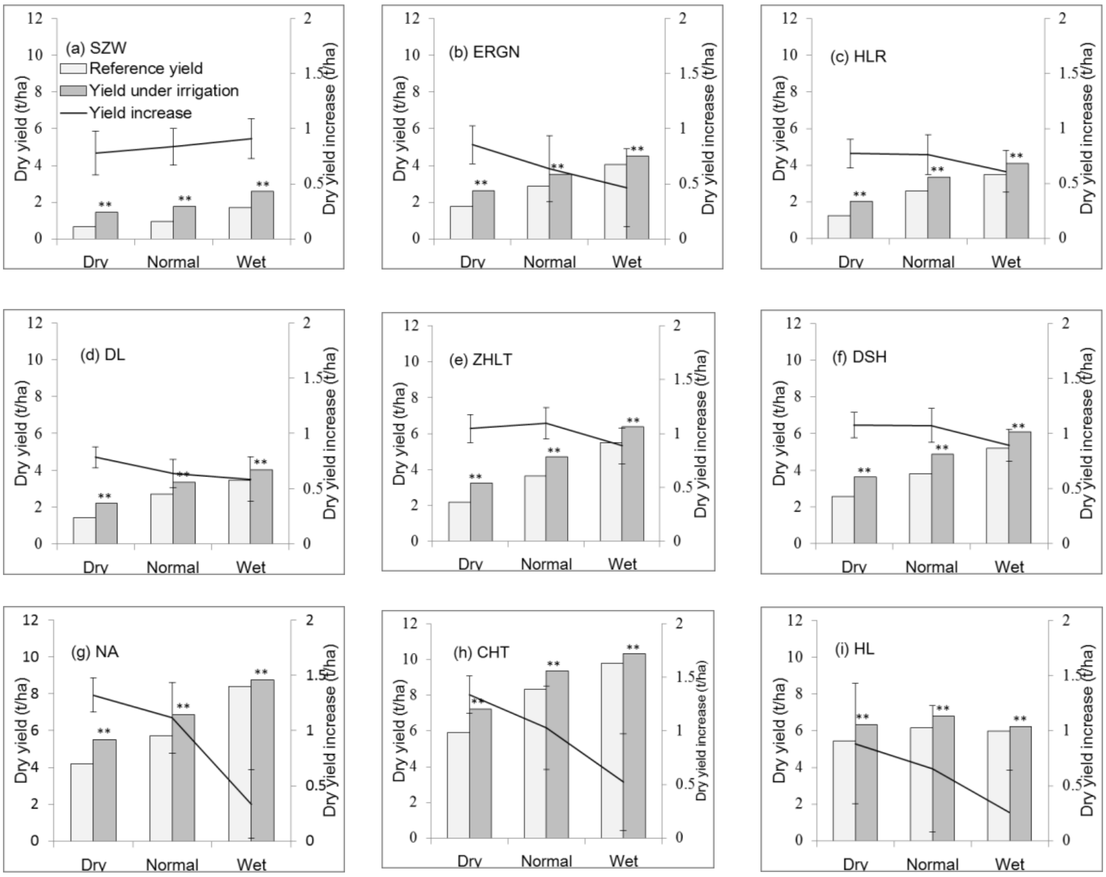


Figure 5-2 The comparison of irrigated yield and county level yield and yield increase under one time irrigation in (a-d) 4 counties dominated by wheat and (e-i) 5 counties dominated by maize

County names: CHT, Changtu; DL, Duolun; DSH, Dongsheng; ERGN, Eerguna; HLR, Hailar; HL, Hailun; NA, Nong'an; SZW, Siziwang; ZHLT, Zhalute.

Generally, for most counties where spring wheat and maize were grown, a single 50 mm SI was more effective in dry years than in wet years in providing increased yield.

Table 5-4 The ANOVA test and Post Hoc test (Scheffe) of yield increments among 3 climate year types

County	ANOVA			Significance of Post Hoc test (Scheffe)		
	Sum of Squares	Mean Square	Significance	Dry–Normal	Normal–Wet	Dry–Wet
SZW	0.767	0.384	0.130	0.646	0.518	0.131
ERGN	0.143	0.071	0.001*	0.103	0.229	0.002*
HLR	1.234	0.617	0.014*	0.991	0.042*	0.034*
DL	0.269	0.134	0.001*	0.028*	0.571	0.002*
All spring wheat counties	0.338	0.169	0.001*	0.149	0.150	0.001*
ZHLT	13.375	6.687	0.001*	0.641	0.001*	0.015*
DSH	0.396	0.198	0.000*	0.996	0.002*	0.002*
NA	0.359	0.179	0.000*	0.105	0.000*	0.000*
CHT	8.705	4.352	0.000*	0.057	0.001*	0.000*
HL	5.415	2.708	0.004*	0.442	0.092	0.005*
Maize counties	3.233	1.616	0.000*	0.059	0.000*	0.000*

* 0.05 significant level

5.3.2 The effects of sowing date on yield

For spring wheat-growing counties, a change in sowing date resulted in significantly different yield all the counties with all three types of climate years (dry, normal, and wet) with all three types of climate years (dry, normal, and wet) except for Hailar County during dry years. The *p* values in wet and normal years were smaller than that in dry years (Table 5-5). Postponing of the sowing date for spring wheat caused yield to increase for short postponements and then decrease for longer postponements in Siziwang and Duolun. For the other counties, postponing of the sowing date for spring wheat caused yield to initially remain stable and then to gradually decrease when sowing was postponed for a longer time (Figure 5-3).In dry years, the yield increase is not significant in all counties. In normal years, the yield increase significantly in Siziwang county when sowing date was postponed to 60 days. In wet years, the yield increase significantly in Siziwang County when sowing date was postponing from 50 to 70 days.

For maize-growing counties, a change in sowing date caused significant differences in yield in all counties but varied with climate (defined here as dry,

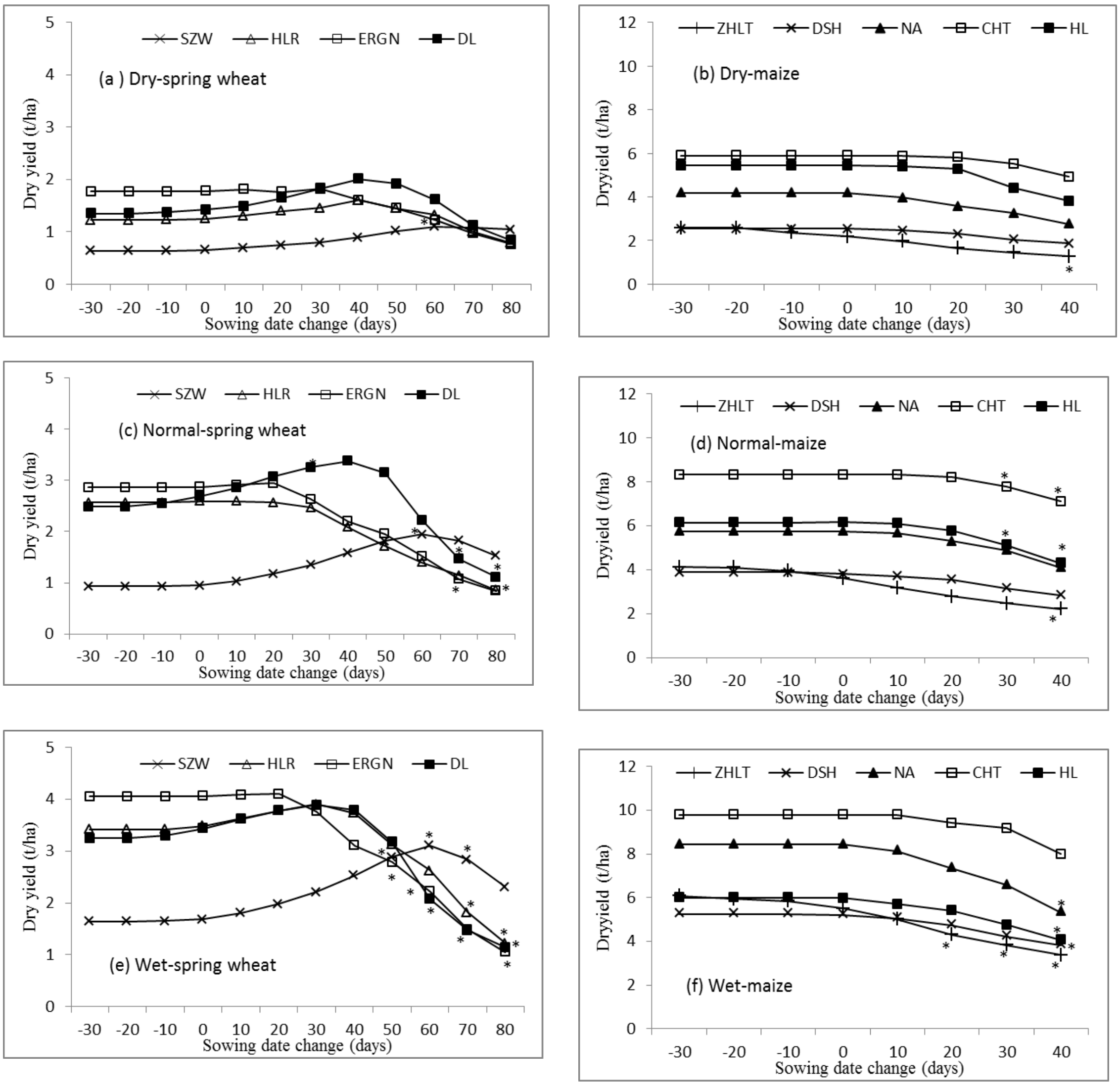


Figure 5-3 The impact of average yield under different sowing date in 4 counties dominated by spring wheat and 5 counties dominated by maize under dry (a-b), normal (c-d) and wet conditions (e-f)
(0 means current sowing date, positive sign (+) means postpone and negative sign (-) means advance)
County names: CHT, Changtu; DL, Duolun; DSH, Dongsheng; ERGN, Eerguna; HLR, Hailar; HL, Hailun; NA, Nong'an; SZW, Siziwang; ZHLT, Zhalute.
* 0.05 significant level (the comparison between yield under changed sowing date and county level yield based on Post Hoc test (Scheffe))

normal, and wet years) except in Dongsheng and Hailun counties during dry years, and in Changtu County during dry and normal years. The *p* values in wet and normal years were smaller in all counties than that in dry years (Table 5-5). Significant decrease were observed in county level maize yield by postponing sowing 20 days in Zhalute County, or 30 days in Nong'an County, or 40 days in Hailun County.

However, the *p* values show that an decrease in yield caused by a change in sowing date was higher in a normal or wet year than that in dry year.

In summary, for most counties analyzed here, a change in the sowing date in dry years was less effective in improving yield than during normal and wet years.

Table 5-5 The ANOVA test of yields in multiple sowing date

Wheat county and climate	Significance	Maize counties and climate	Significance
SZW-dry	0.000*	ZHLT-dry	0.000*
SZW -normal	0.000*	ZHLT-normal	0.000*
SZW -wet	0.000*	ZHLT-wet	0.000*
ERGN-dry	0.000*	DSH-dry	0.102
ERGN-normal	0.000*	DSH-normal	0.005*
ERGN-wet	0.000*	DSH-wet	0.000*
HLR-dry	0.145	NA-dry	0.011*
HLR -normal	0.000*	NA-normal	0.000
HLR -wet	0.000*	NA-wet	0.000*
DL-dry	0.001*	CHT-dry	0.389
DL-normal	0.000*	CHT-normal	0.285
DL-wet	0.000*	CHT-wet	0.040*
		HL-dry	0.115
		HL-normal	0.000*
		HL-wet	0.000*

* 0.05 significant level

5.3.3 The effects of varieties on yield

ANOVA was used to test the effects of three varieties of spring wheat on yield (including the reference variety). Due to changes of varieties, yield increased significantly in Siziwang and Duolun Counties in normal and wet years (Table 5-6). ‘Yongliang 4’ in Duolun County in normal and wet years had significantly higher yield than the reference variety. ‘Yongliang 4’ in Siziwang County in normal years had significantly higher yield than the ‘Longmai 26’ variety (Figure 5-4).

ANOVA was also used to test the effects of three varieties of maize on yield (including the reference variety). For maize, the three varieties had significantly higher yield in Zhalute and Changtu counties in wet years and in Hailun in normal years and wet years. By Post Hoc test (Scheffe), the yield in ‘Dadi’ of Zhalute and Changtu in wet years was significant larger than reference (Table 5-6).

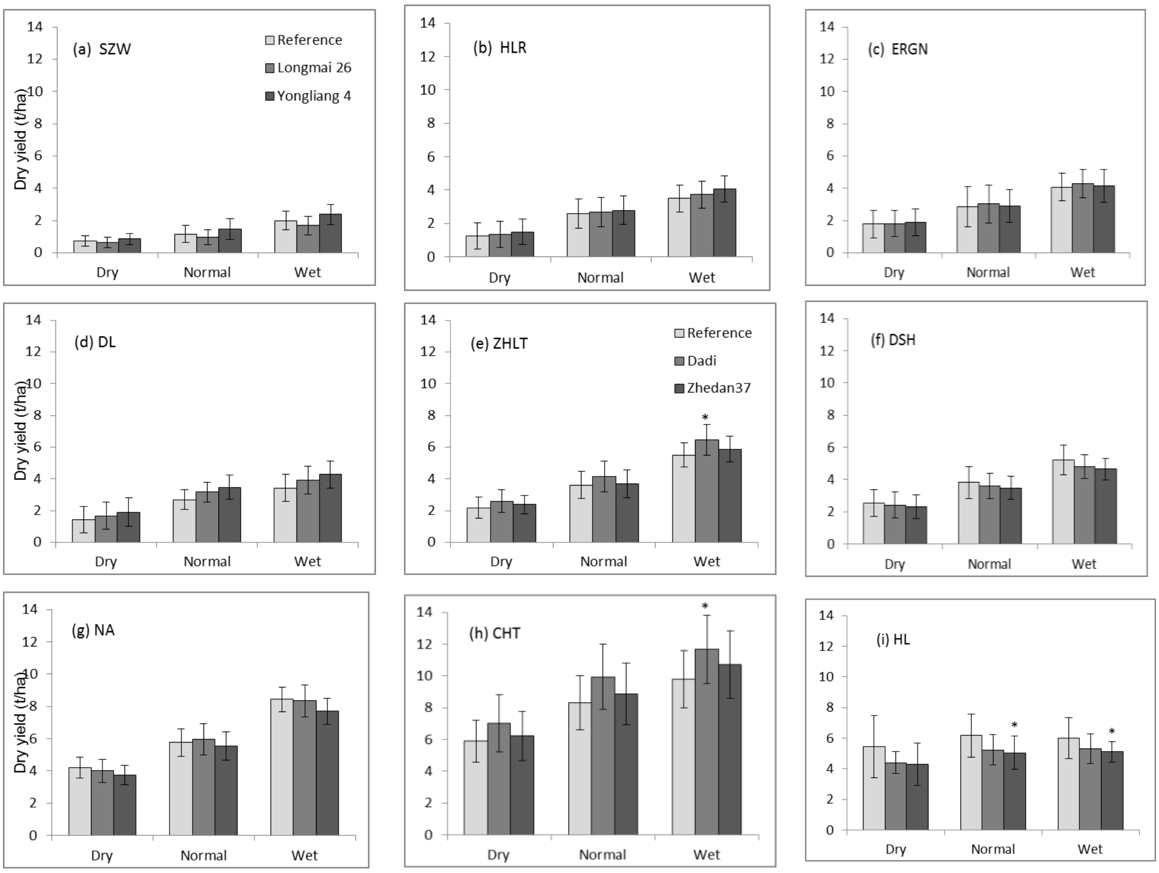


Figure 5-4 The average yield under different varieties in dry, normal and wet years in (a-d) 4 counties dominated by wheat and (e-i) 5 counties dominated by maize

County names: CHT, Changtu; DL, Duolun; DSH, Dongsheng; ERGN, Eerguna; HLR, Hailar; HL, Hailun; NA, Nong'an; SZW, Siziwang; ZHLT, Zhalute.

** 0.05 significant level (the comparison between yield under variety change and county level yield based on Post Hoc test (Scheffe))

In summary, the long growing season variety of wheat tended to have greater yield than the reference variety and more than the short growing season variety. The short growing season maize variety tended to have increased yield more than the long growing season variety especially in wet and normal years.

5.3.4 The comparison among three practices

For spring wheat (Figure 5-5a, Table 5-7), significant differences were observed in maize yield in dry years among the three practices tested here (SI, variety and sowing date). SI improved average yield significantly more than a change in variety. For maize (Figure 5-5b, Table 5-7), significant differences in yield were observed among SI and among changes in variety and sowing date in both dry and normal years.

The increase of yield caused by a change in sowing date was smallest in the maize-growing counties (Figure 5-5b). This test shows that the average increase in yield caused by SI was significantly larger than that by change in sowing data in dry years.

Table 5-6 The ANOVA test and Post Hoc test (Scheffe) of yields in three varieties and relationships between varieties

Wheat County and climate	Significance	Post Hoc test (Scheffe)			Maize County and climate	Significance	Post Hoc test (Scheffe)		
		R-L	R-Y	L-Y			R-D	R-Z	D-Z
SZW-dry	0.256	0.789	0.623	0.260	Zhalute-dry	0.222	0.222	0.711	0.649
SZW -normal	0.033*	0.523	0.312	0.034*	Zhalute-normal	0.191	0.244	0.974	0.345
SZW -wet	0.007	0.342	0.197	0.007*	Zhalute-wet	0.010	0.010*	0.465	0.167
ERGN-dry	0.905	0.991	0.909	0.956	Dongsheng-dry	0.674	0.894	0.674	0.916
ERGN-normal	0.919	0.930	0.998	0.949	Dongsheng-normal	0.490	0.759	0.497	0.905
ERGN-wet	0.810	0.812	0.964	0.931	Dongsheng-wet	0.128	0.347	0.146	0.869
HLR-dry	0.686	0.955	0.693	0.857	NA-dry	0.539	0.899	0.543	0.809
HLR -normal	0.823	0.963	0.824	0.941	NA-normal	0.370	0.779	0.775	0.370
HLR -wet	0.134	0.719	0.137	0.479	NA-wet	0.239	0.980	0.297	0.395
DL-dry	0.276	0.694	0.276	0.746	CHT-dry	0.123	0.138	0.843	0.358
DL-normal	0.003*	0.107	0.003*	0.365	CHT-normal	0.052	0.058	0.730	0.261
DL-wet	0.028*	0.272	0.029*	0.528	CHT-wet	0.042*	0.042*	0.449	0.416
					Hailun-dry	0.222	0.222	0.711	0.649
					Hailun-normal	0.022	0.093	0.035*	0.903
					Hailun-wet	0.030	0.131	0.041*	0.858

R: reference; L: ‘Longmai 26’ ; Y: ‘Yongliang 4’; D: ‘Dadi’; Z: ‘Zhendan37’

* 0.05 significant level

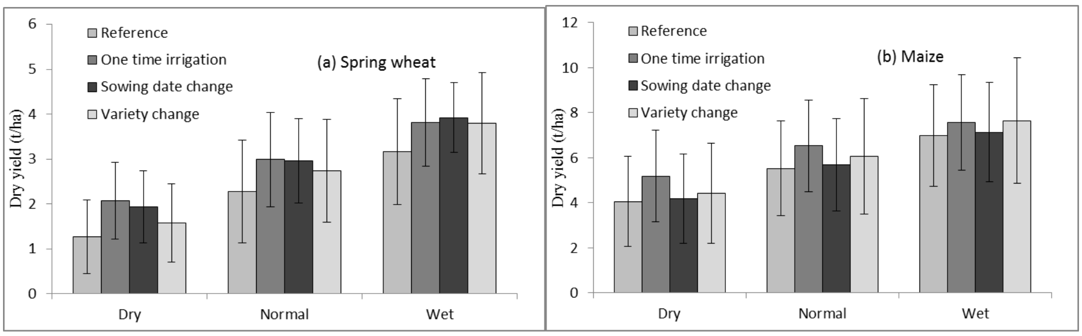


Figure 5-5 The average dry yield due to best date of sowing date, best variety and one time irrigation under dry, normal and wet conditions for (a) spring wheat and (b) maize.

Table 5-7 The One-way ANOVA test and Post Hoc test (Scheffe) of maximum yield among irrigation, sowing date and variety

Significance	Spring wheat			Maize		
	Dry years	Normal years	Wet years	Dry years	Normal years	Wet years
Irrigation- Variety - Sowing	0.003*	0.298	0.705	0.008*	0.050*	0.344
Irrigation- Sowing	0.659	0.986	0.793	0.012*	0.051	0.524
Irrigation- Variety	0.005*	0.362	0.997	0.073	0.404	0.974
Variety- Sowing	0.056	0.454	0.749	0.776	0.544	0.394

* 0.05 significant level

In summary, the use of SI was more effective in increasing yield than was changing the sowing date and variety in dry years.

5.4 Discussion

5.4.1 Use of irrigation

SI is normally scheduled to fill the gap between precipitation and crop evapotranspiration (FAO, 1989). My simulation results reveal the difference in the effectiveness of SI in dry, normal and wet years. Dry years always include long periods without rain. A single SI will easily result in increased yield because the danger of water shortage is interrupted resulting in increased yield. Conversely, in wet years, the intervals between rainfall days are small, so that a single SI event may be less effective in increasing yield.

5.4.2 Sowing date change

The staff of Agricultural and Husbandry Bureau in Hailar County shared their experiences (personal communication) and stated that early sowing and spring drought always cause a large reduction in crop yield. Therefore, they postponed the sowing date of spring wheat by 10–15 days to May 10–28 in 2011 in their agriculture demonstration area in Hailar County while waiting for natural rainfall to prevent spring drought. My simulation results confirmed that better than average yield can be obtained in Hailar County if the sowing date is postponed by three dekads. Based on maize sowing experiments conducted from 1977–1982 in Tieling County (adjacent to

Changtu County), Ma et al. (2008) found that dry weight, leaf weight, leaf area index and yield of the same variety was larger with an earlier sowing (April 10) than that with a late sowing date (May 30). The simulation in Changtu County can be compared with that experiment (Ma et al., 2008). Greater yield will be obtained by postponing the sowing date by more than 2 months in Siziwang County and a similar situation was found in Duolun County. In some unirrigated regions of Chifeng (a city adjacent to Duolun County), spring wheat was planted every year in summer; this was effective in preventing drought (Fan, 2006; Si and Liu, 1987). These facts can be compared with my simulation results.

5.4.3 Variety selection

Use of a long growing season variety is expected to result in a large increase in yield in Siziwang and Duolun counties because the earlier planting of this wheat variety did not make good use of heat resources. Eerguna County has poor heat resources; therefore, changing variety resulted in little increase in yield. The autumn drought is more frequently than summer drought in Inner Mongolia (Shen 2008); autumn drought has a 4 year return period in Liaoning Province (Li and Meng, 2005). Use of the variety of maize with a short growing season will increase yield largely because this reduces the effects of serious drought in August and September on the flowering stage of maize. For example, in Zhalute County the flower stage for shorter growing season variety ‘Dadi’ starts from middle July and the flowering stage for the longer growing season variety ‘Zhedan 37’ starts in about late July (Table 5-2). Precipitation from June to August includes 75.8% of annual precipitation (1962–2010). The top three dekads with maximum precipitation of the year are in the middle of July (43.4 mm), early July (42.0 mm) and late July (35.4 mm). ‘Dadi’ makes better use of precipitation than ‘Zhedan 37’ especially in wet and normal years.

5.4.4 Three practices comparison

A subjective, quantitative and empirical method was always used in a previous study to compare different measures to provide social economic options for disaster management (such as Mizina, et al., 1999; Yohe and Tol, 2002). The chapter attempted to accurately compare three drought management practices based on model simulation. All nine counties analyzed here are located in middle and high latitudes and have a short growing season (Table 5-1). The time available for seeding is limited if crops are to reach fully maturity in autumn (Table 5-2). The base temperature of maize is higher than wheat. Therefore, the growing season of maize is short, making it difficult to effectively increase yield increase by changing the sowing date.

5.5. Conclusion

Using the EPIC crop model, I successfully evaluated three agricultural practices quantitatively that are typically used to mitigate drought in Northeast China and Inner Mongolia, and found these practices have different effects on drought mitigation in dry, normal and wet years. For example, a single SI event was more effective in increasing yield in dry years than in normal or wet years. Compared with normal and wet years, delaying the sowing date was less effective in dry years. For wheat-growing counties, the long growing season variety ‘Yongliang 4’ can increase the yield, and the short growing season variety ‘Dadi’ performed better in increasing yield than ‘Zhedan37’ for maize-growing counties. However, none of the varieties provided a significant increase in yield during dry years. The results suggest that caution should be used in the implementation of drought mitigation measures. The results of this study reveal that changes in crop variety and sowing date were less effective in improving yield than was SI; the development of SI may be the most stable measurement used to mitigate drought in Northeast China and Inner Mongolia. Changes in sowing date and variety are also important to the mitigation of drought in an effort to improve food security especially in normal and wet years. Future research of the process of drought should consider the calibration of the EPIC model based on the addition of more details related to each variety’s biological characteristics and to the actual schedule of SI used for drought mitigation. The methods using this type of model simulation are expected to be introduced for drought response and management in other drought prone regions.

Chapter 6

General conclusions

6.1 Organization of the research

The agricultural drought management system I built composes three main parts: agricultural drought occurrence, agricultural drought impact and agricultural drought mitigation. The study area is chosen in the Northeast China and Inner Mongolia where agricultural production is heavily relied on rainfall. In order to explain this point, in Chapter 2, I first examined the temporal and spatial pattern of precipitation variation in farmland of the Northeast China and Inner Mongolia which provides background of agricultural drought. Before yield reduction, it is not easy to judge the occurrence of agricultural drought. In Chapter 3, I built and validated new drought monitor assessment framework. Based on indices, I make the drought assessment in Hailar County, one typical rainfed county in Inner Mongolia for instance; Yield is final result of agricultural drought. Therefore, the Chapter 4 is to assess agricultural drought severity based on yield damage. I made the drought severity division by using EPIC model in 9 counties following steps: standard period setting, mean value and agreement assessments with agricultural drought records; after drought severity was assessed, how it influenced the drought mitigation? In order to answer this question, the Chapter 5 is to assess the effectiveness of irrigation, sowing date change and variety change agricultural practices under different drought severity in the 9 typical counties.

The results of the study revealed that there are some internal relationships among different chapters. All the counties in Chapter 3, 4 and 5 are located in the regions where precipitation show decrease tendency from 1961-2010 in the Chapter 2. The wheat yield used in Chapter 3 for prediction in Hailar County can be simulated by EPIC model in the Chapter 4. There is good relationship between soil moisture based index CMI and soil moisture anomaly simulated by EPIC model in 9 counties in the Chapter 4. Drought classification can be validated by drought cases of 9 counties in

Chapter 4. It also influences the effectiveness of three practices in Chapter 5. It suggests that in order to manage agricultural drought, drought occurrence monitor, drought severity assessment and drought mitigation practices assessment should be regarded as a whole for consideration.

6.2 Main findings and discussions

6.2.1 Temporal-spatial pattern of precipitation

Based on monthly 0.5 degree precipitation dataset from 1961-2010, I analyzed inter-annual trend by using linear trend method and the seasonal precipitation variation by using coefficient of variation (*CV*) in Northeast China and Inner Mongolia. I found that meteorological drought in farmland of Northeast China and Inner Mongolia became serious after 2000s. The linear trend method further show that there is decrease but not significant trend of annual precipitation for whole Northeast China and Inner Mongolia from 1961-2010. Based on *CV*, I identified the spatial pattern of variation; it shows that annual precipitation varied seriously in east part, west end of Inner Mongolia, west part of Jilin and Liaoning province. There is decrease tendency after 2000s in most of the study areas for case study in Chapter 3 and Chapter 4.

6.2.2 Index-based agricultural drought monitoring assessment

The comparison between selected drought indices and assessment show that my built agricultural drought assessment model is suitable for regions like Hailar county where crop yield is closely related to conditions during the reproductive growth stage.

Because the water deficit occurs during the key reproductive growth period (flowering time) of crops, the energy yield has suffered greatly from the water deficit. The results suggest that in semi-arid regions such as Hailar County, the dry and warm climate trends that have occurred during the growing season over the past decade mean that meteorological drought has easily transformed into agricultural drought.

The result reveals that soil moisture–based and vegetation indices during the late vegetative to early reproductive growth stages (*CMI* in June and *NDVIA* in July, respectively) could be used to detect agricultural drought in regions where majority of the crops is closely related with reproductive growth.

In this study, the cumulative period from *SPI* to *CMI* was about 4 dekads. Monthy SPI is always used for short-term soil moisture. The research seems to show more accurate result. The findings show that dekad-scale *CMI* can bridge the gap between short-term vegetation change and water deficit as depicted by an in situ meteorological dataset. In May, June, and September, the time lag between CMI and *NDVI* was longer than that in July and August, during the growing period.

The most frequent average time lag between *CMI* and *NDVI* was 1 dekad, especially in July. Previous studies by using remote sensing reversal soil moisture and actual soil moisture show similar time lag with *NDVI* in US and Africa. The finding that the response time of crop vegetation to soil moisture is 1 dekad is comparable with the results of previous studies.

The result can be compared with previous water stress or *NDVI* prediction studies in regions with a similar crop planting structure. The reason is that there are some relationships between leaves detected by remote sensing and yield.

The results of this 11-year assessment at the dekad time scale in Hailar County fit the conceptual model of the agricultural drought process well. *SPI*, *CMI*, and *NDVI* can depict the processes underlying a serious drought at the dekad time scale during the growing season. Based on these three indices, it is possible to judge the likelihood of drought developing and to assess the possible yield damage. Dekad-scale *SPI* can be regarded as the earliest indicator of the drought’s impact on crops. The relationship between *CMI* and *NDVIA* displays a significant time lag. It suggests that dekad-scale *NDVI* provides sufficient information to reflect the response of crops to drought at the dekad time scale.

6.2.3 Agricultural drought severity assessment

Following the newly proposed drought assessment framework, the performance of agricultural drought indices were quantified and compared in typical rainfed regions of Northeast China and Inner Mongolia.

The study found that EPIC can accurately simulate the annual time series of county-level yield in typical counties with rainfed spring wheat and maize cultivation in the Northeast China and Inner Mongolia.

The one-third probability of *WSYR* was identified to differentiate drought years from other years. *WSYR*, which is a crop-specific index, was more accurate in representing agricultural drought than meteorological drought indicators such as *AI* and *P*. The 49-year trend of agricultural drought from *WSYR* was more significant than those from the meteorological indices. The average increase in decadal frequency of drought years from the 1990s to 2000s via *WSYR* was greater than those via *AI* and *P*. This shows that the framework can be validated by long-period analyses. I also found that the soil moisture index (*CMI*) can be validated with surface soil moisture anomaly by crop model. It suggests that possibility to improve drought indicator by crop model.

6.2.4 Agricultural drought practices comparison

Compared with one time irrigation and variety change, there is less effect of sowing date change on yield recovery. All the nine counties are located in middle and high latitude and the growth period is short (Table 5-1). Therefore, even the sowing date is different; seeding date will be limited to the few days for fully maturity in autumn. The comparison result reveals that crop variety and sowing date change are less effective than supplementary irrigation; the development of supplementary irrigation in Northeast China and Inner Mongolia may be the most stable measurement for mitigation.

6.2.5 Practical application of the drought management framework

Droughts are particularly well suited to early warning systems because the disasters have a slow onset (Wilhite et al., 2000). In order to alert the agricultural drought for a region, the meteorology department would like to know timely weather information. The agricultural department would like to know the soil moisture and crop growth condition. Water resource department would like to know the best mitigation time for low cost and high effectiveness. The thesis provides new drought monitoring system in Chapter 3 with the consideration from precipitation to yield reduction. The assessment suggested that the precipitation, soil moisture and vegetation play the different roles for drought monitoring and yield damage prediction. For the government, the similar assessment is useful to estimate the possible damage ahead of time and for forward market, it is helpful to assess future grain price. The conventional work for agricultural department needs to take many samples of the local soils and determine the soil moisture. The indicators methods have advantage of information integration and low cost for timely early warning.

The contradiction between crop water requirement and water supply occur nearly every year. Under limited assistance resources, the civil departments would like to know which year is drought year. The Chapter 4 of the thesis provides more objective method for drought severity classification. Based on such information, the government can determine the high risk drought region for subsidy and long term financial support. The research also is helpful insurance company to determinate agricultural disaster insurance rate and compensates the economic loss of farmers.

Agricultural drought mitigation practices include mitigation activities at national government level, agricultural technology extension station level and household level. The practices selections by farmers and government are always based on experiences and field experiments. The Chapter 5 of the thesis introduces crop model new technology for practices selection which has advantages of low cost and high efficiency. The method is helpful for agricultural department and agricultural technology extension station level to guide farmers to effectively mitigate drought. It is also helpful for local farmers to arrange the agricultural affairs for drought mitigation.

In all, the agricultural drought management framework in this thesis which include drought monitoring, drought severity assessment and practices comparison considers the practical demands of drought management from different departments and levels. They constitute a complete framework for agricultural drought management.

6.3 Significance of the study

Combined with the new technologies of remote sensing and crop model, I built the new operational agricultural drought management framework to objectively monitor drought, assess drought intensity and compare drought mitigation practices. The studies in the Northeast China and Inner Mongolia successfully validated the reasonability of framework.

A new testable multi-index agricultural drought monitoring model was built. The multi-index drought assessment has been challenging because there has been a lack of systematic methods for their combination, use, and evaluation (Steinemann and Cavalcanti, 2006). I built new drought process conceptual model. The typical rainfed county-Hailar county was taken as study area and the evaluation results fit well with my built conceptual model. The results reveal the internal logic among short time indices and filled the gap of indices combination.

The regional agricultural drought intensity was validated by historical drought cases. The intensity of agricultural drought is difficult to be classified objectively. EPIC model can be well simulated county-level rainfed wheat and maize yield in northeast China and Inner Mongolia. I found that simulated yield damage and historical drought cases can be compared with each other and validated the intensity. China has drought records which back to thousands years ago. By the way of comparison between drought intensity based on crop model and drought cases, it is expected to assimilate information for long term agricultural drought reconstruction.

The quantitative comparison among different agricultural practices to mitigate drought were done. The simulation results show the difference in their effects on yield in different dry, normal and wet climate years. It reveals the necessary of drought intensity classification for mitigation.

There is internal relationship between drought index and crop model two different quantification methods. There are good correlation (R^2) between soil moisture anomaly and *CMI*. I filled the gap between two different methods. It is possible to improve the drought index based on the crop model in future.

The simplest water-agricultural system was chosen as study area in this thesis. The crop production system in Northeast China and Inner Mongolia is typically characterized as rainfed and one harvest per year. It may be the one of the simplest among diverse crop production systems all over the world. Although my systems are built based on farmland, due to many water use similarities among crop, grass and forest, the methods and results of agricultural drought management in the thesis are expected to provide suggestions for other vegetation types and for other cropping systems such as with crop rotation and irrigation in future.

6.4 Limitations of the work and suggestions for future research.

Future research of the drought process should consider the calibration of fixed parameters for *CMI* using cases of drought lasting for longer time periods, the effects of snow melt and strong wind on soil moisture in spring, and crop types in the drought process.

The research show that crop models such as EPIC can be useful tools to support drought mitigation planning, although county-specific factors such as crop rotation and the technology level should be considered in future research to improve the simulation. In addition, there are only 0-30cm and 30-100cm two layer soil properties in FAO soil dataset. More information is needed in future research. The bias of the model could be decreased by accounting for these factors.

The research considered 50mm single irrigation. Future research of the drought mitigation should consider details of irrigation regulation when drought occurs; The yield-based index *WSYR* has great potential because it both describes the drought intensity and provides a better explanation of the effects of improving the water environment on the yield recovery after irrigation.

Future research of the drought assessment should consider the role of human activity (Economy and society factors) during agricultural drought. Crop models have limitations in regional application and remote sensing in describing the growth process. Future drought research can focus on their combination. It has been several combination works for winter wheat (Ma et al., 2005). For autumn harvest regions, due to complex crop planting structure, with the improvement of resolution for remote sensing, annual crop type classification may be required to improve the combination. Based on my assessment framework, more details are expected to be considered to improve assessment accuracy of agricultural drought in future.

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