Prediction of crop yield, water consumption and water use efficiency with a SWAT-crop growth model using remotely sensed data on the North China Plain

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Received 26 April 2002; received in revised form 25 June 2004; accepted 28 July 2004

Abstract

A process-based crop growth model is developed to predict regional crop yield, water consumption and water use efficiency (WUE) using remotely sensed data for a portion of Hebei province (88,779 km²), most of which is located on the North China Plain (NCP). Model inputs consist of Geographic Information System (GIS) maps of land use, Digital Elevation Model (DEM), soil texture, crop canopy leaf area index (LAI) which is retrieved from the 10-day maximum composite National Oceanic and Atmospheric Administration (NOAA)–Advanced Very High Resolution Radiometer (AVHRR) data, and daily interpolated meteorological variables. The model is run at 92.367 30′′ × 30′′ resolution grids at an hourly time-step for energy balance and daily time-step for crop growth simulation. Simulated winter wheat and summer maize yields in 1992 and 1993 are compared with both the point samples and the county-level census data. For the 108 counties, the root mean square error (relative deviation) is 1124 kg ha⁻¹ (23%) for winter wheat and 1359 kg ha⁻¹ (33%) for summer maize, respectively. Spatial patterns of simulated crop yield and water use efficiency are strongly influenced by irrigated/rainfed conditions. The modelled grain yield for irrigated winter wheat ranges from 3900 to 7200 kg ha⁻¹, which is significantly larger than when only rainfed, 100–2600 kg ha⁻¹. The modelled grain yield for irrigated maize ranges from 5800 to 8600 kg ha⁻¹, which is significantly larger than when only rainfed, 1400–4800 kg ha⁻¹. This suggests that the potential exists to increase yield in this region, if sufficient irrigation water is supplied. However, given the over allocation of limited surface water, an increase in irrigation is unlikely, and increasing importance will be placed on maximizing regional WUE over the NCP. The water consumption (defined here as modelled evapotranspiration (ET)) for winter wheat ranges from 330 to 500 and 70 to 280 mm for irrigated and rainfed conditions, respectively. The modelled ET for irrigated maize ranges from 350 to 520, and 140 to 350 mm for rainfed conditions. The simulated WUE...
ranges from 12.25 to 15.75 kg ha\(^{-1}\) mm\(^{-1}\) for irrigated winter wheat and from 0.5 to 8.25 kg ha\(^{-1}\) mm\(^{-1}\) in rainfed areas. The simulated WUE ranges from 11 to 19.25 kg ha\(^{-1}\) mm\(^{-1}\) for irrigated maize and from 5 to 11 kg ha\(^{-1}\) mm\(^{-1}\) in rainfed areas. These, together with the results of simulated crop yields, are comparable with previous studies in the NCP, other parts of China, and internationally, indicating the potential to apply this model to other agricultural regions. This study implicates a new view for regional agricultural and water resources management by assessing regional crop yield, water consumption and WUE consistently based on modelling biophysical processes with the aid of remote sensing.

Keywords: Simulation modelling; Spatial pattern; Regional scale; Evapotranspiration; Remote sensing; North China Plain

1. Introduction

For many important grain producing regions (defined here as >75,000 km\(^2\)) worldwide, including the North China Plain (NCP), there is increasing pressure to increase agricultural water use efficiency (WUE), i.e., the crop yield per unit of water consumed. Increasing WUE can be achieved by increasing the amount of food per unit of water consumed, or reducing the amount of water consumed to produce the same amount of food. That is, WUE combines two somewhat related processes in agricultural systems: crop yield and water consumption. A key question for managers of these large agricultural systems is how to monitor changes in WUE in a repeatable and reliable manner. Previously, only one study has monitored WUE for a large agricultural region, using an ‘input–output’ Geographic Information System (GIS) method (McVicar et al., 2002).

This method was data dependent, relying heavily on county yield statistics, and cannot be transferred to other key global agricultural regions. Hence there is a need to develop a process-based approach to capture the spatial and temporal variability of crop yield and water consumption, hence providing a means to calculate WUE regionally for the many important grain producing regions. This paper addresses that need.

Next we introduce two main types of crop growth models, many of which have been developed at points. Then we discuss, and provide examples, of how some of these point models have been extended spatially, using soil parameters and interpolated meteorological variables stored in GIS. Surfaces resulting from the interpolation of meteorological variables are often smooth, and combining these with the inherently high spatial density of remotely sensed data to perform the spatial extension of a point-based model provides greater spatial resolution; the benefits of this logical extension to the GIS approach are discussed. It should be noted that outputs from spatial–temporal modelling depend on both the model philosophy and the inherent data characteristics used to solve the model.

There are many crop growth models (Jørgensen, 1994), that can be broadly divided into two categories to estimate regional crop yield. The first category comprises empirical-statistical models; they relate regional crop yields to climatic variables using methods such as regression analysis (Doréa et al., 1997). While this type of models provides a means to estimate crop yield, water consumption cannot be estimated, and most of these models are locally calibrated, making extension to larger areas (or ‘porting’ to other regions) nearly impossible. For these reasons, this class of crop growth models will not be discussed further. The second category is comprised of process-based crop growth simulation models; they simulate the physiological development, growth and yield of a crop on the basis of the interaction between environmental variables and plant physiological processes such as photosynthesis and respiration. They are capable of providing mechanical description for prediction, both spatially and temporally. The mechanics is complex as crop growth is driven by both climatic variables (e.g., solar radiation, temperature and humidity) and soil variables (mainly moisture and nutrients). As leaf stomata are responsible for the intake of CO\(_2\) for photosynthesis and water loss through transpiration, its regulatory mechanisms are significant on the exchanges of mass and energy in soil–vegetation–atmosphere system (Lo Seen et al., 1997; Calvet et al., 1998; Cayrol et al., 2000; Ghaffari et al., 2001). It is thus acknowledged that an appropriate process-based model to predict regional agricultural crop yield should be moderately complex (Hansen and Jones, 2000; Lagacherie et al., 2000). The key is to model the main processes of both crop growth dynamics and soil–vegetation–atmosphere transfer (SVAT), and capture the essential mechanisms of crop responses.
to weather variability and its interaction with management.

Many process-based models have been developed at points that adequately take into account the interactions and feedbacks discussed previously. Given that regional land managers need methods to monitor and predict regionally, several models have been extended spatially, see the examples provided in Table 1. In all cases, the driving parameters and variables are determined for each input cell and the model is run repeatedly at the resolution covering the spatial extent of the study area. As meteorological variables are needed to run all process-based crop growth models, meteorological data are often interpolated to surfaces from the isolated stations where measurements are made. This modelling approach is described as ‘interpolate-then-calculate’, abbreviated as IC, see Stein et al. (1991) and McVicar and Jupp (2002) for further discussion.

A common feature of these examples is the need to access ground-truth databases over large regions. Gathering access to such databases with adequate resolution, both temporally and spatially, has remained difficult, as collecting field data is time-consuming, expensive and often not spatially explicit (Reynolds et al., 2000). This is the main reason that the models were validated at the entire country scale or the scale of the whole study area, usually with overestimates and underestimates of each of the individual grid cells primarily canceling each other out, hence providing a reasonable model result for these large regions. However, site-specific monitoring, which will enable site-specific management, is lost in this aggregation process. Furthermore, in all the above cases, the crop growth status is ‘simulated’ response; it is possible that this may diverge from reality. Given this, it is imperative to integrate other primary data that has high spatial and temporal resolution and provides another way to drive the model. Remote sensing offers a solution to these problems.

Remote sensing has recently been widely used for the simulation of regional crop yield and water consumption, given its inherent high spatial density and the measurements being repeatable, consistent and synoptic. Additionally, remotely sensed databases are able to immediately generate high priority global data sets and improve follow-on data sets and communication within the land science community (Sellers et al., 1995; Plummer, 2000). Operationally, yield can be predicted using remotely sensed data in three main ways. They are: (1) developing regression models; (2) using the light use efficiency (or Epsilon models) method; and (3) developing process-based models that capture the interactions between the SVAT and crop growth environment, as measured by remote sensing instruments. They are discussed in turn below.

Firstly, regressive relationships are developed between the within season cumulated crop spectral index and census crop yield data at the county level to operationally predict the regional or country crop yield (e.g., Hayes and Decker, 1996). Gaining relatively high accuracies with readily available input data has meant that these models are in wide use, particularly in operational environments. However, such models are not process-based, these relationships heavily rely on the determination of empirical coefficients, and model developers cannot easily extend such models to include a water consumption module.

Secondly, the light use efficiency method (Monteith, 1972) has been widely used for estimation of terrestrial net primary productivity (NPP) with remotely sensed data input (Kumar and Monteith, 1982; Fung et al., 1987; Maisongrande et al., 1995; Choudhury, 2001; Secaquist et al., 2003). It has also been used to predict crop yield (Clevers, 1997; Willocquet et al., 2002; Lobell et al., 2002, 2003; Bastiaanssen and Ali, 2003). Despite the popularity and simplicity of light use efficiency (or Epsilon models), this approach has several sources of uncertainty and inconsistencies. For example, light use efficiency has been found to vary with crop growth stages, and can be greatly influenced by other environmental factors (Gower et al., 1999).

Finally, the third approach involves using process-based models to trace processes of dry mass accumulation and final ecological production, which has shown a promising future in the use of remote sensing to predict regional crop yield (van der Keur et al., 2001); also see Maas (1988), Moulin et al. (1995) and Plummer (2000) for a detailed review. Of all the applications of remote sensing in process-based models, the simplest is to use remotely sensed images to classify the spatial patterns of crops to form a map layer in the GIS database (e.g., Thornton et al., 1997; Basso et al., 2001; Chiesi et al., 2002; Yun, 2003), thus remote sensing is an input to one data-layer, essentially this use of remote sensing is similar to the IC-based examples shown in Table 1. More complex applications assimilate remotely sensed reflectance and thermal radiance
<table>
<thead>
<tr>
<th>References</th>
<th>Crop(s)</th>
<th>Spatial extent and resolution</th>
<th>Time extent</th>
<th>Accuracy (where reported) and comments on accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tan and Shibasaki (2003)</td>
<td>Paddy rice, maize, wheat, soybean</td>
<td>Global 80°W–160°E and 84°N–56°S, 6° × 6°</td>
<td>1900–2003</td>
<td>Just test results in 2000 with FAO data, the deviations in most countries are small with a visual comparison</td>
</tr>
<tr>
<td>Priya and Shibasaki (2001)</td>
<td>Maize, wheat, rice</td>
<td>India, 8°4′–37°6′N and 68°7′–97°25′E, 50 km × 50 km</td>
<td>1974–1990</td>
<td>Simulated average yield in 1990 compares well with the reported via visual comparison; mean difference is 32% for rice, 15% for maize and 2% for wheat</td>
</tr>
<tr>
<td>Krysanova et al. (1998)</td>
<td>Winter, barley, silage, maize</td>
<td>Brandenburg, Germany sub-areas × sub-area</td>
<td>1981–1992</td>
<td>No comparison for specific locations; only for the total state statistically over the sub-areas</td>
</tr>
<tr>
<td>Saarikko (2000)</td>
<td>Spring wheat</td>
<td>Finland 10 km × 10 km</td>
<td>1961–1996</td>
<td>Making comparison at few sites in Finland with RMSD being 460 kg ha⁻¹; over the southern Finland, the mean was overestimated with RMSD being 1970 kg ha⁻¹</td>
</tr>
<tr>
<td>Smit and van der Goor (1999)</td>
<td>Wheat</td>
<td>France 50 km × 50 km</td>
<td>11 years</td>
<td>Better yield prediction results of total national yield was obtained than over regional or sub-regional level</td>
</tr>
<tr>
<td>Rosenthal et al. (1998)</td>
<td>Sorghum</td>
<td>QLD Shires, Australia, rainfall polygon × rainfall polygon</td>
<td>1975–1988</td>
<td>Three shires were examined in detail, showing a general tendency for the simulated yields to be greater and more variable than those reported</td>
</tr>
<tr>
<td>Harrison et al. (2000)</td>
<td>Wheat</td>
<td>11W–42E and 35–71.5N, 0.5° × 0.5°</td>
<td>1961–1990</td>
<td>Four issues were addressed, no yield result is available</td>
</tr>
<tr>
<td>Landau et al. (1998)</td>
<td>Wheat</td>
<td>UK</td>
<td>1976–1993</td>
<td>Substantial disagreement was found between the model predictions of both yield and yield loss due to water limitation</td>
</tr>
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data into the crop growth models for validation (e.g., 
Moulin et al., 1998; Olioso et al., 1999), adjusting some 
parameters and initial conditions to enhance model per-
formance (Guérif and Duke, 2000; Boegh et al., 2004), 
and retrieving vegetation biophysical variables, such as 
leaf area index (LAI) and fraction of absorbed photo-
synthetically active radiation (PAR) from remote sens-
ing data to force the growth model (Liu et al., 1997; 
Croops et al., 2001; Matsushita and Tamura, 2002). To 
date, this last approach has been primarily applied to 
natural vegetation (e.g., forests) and not to the more 
temporally varying agriculture systems. By forcing a 
plant growth model with remotely sensed data, this pro-
vides a means to conduct site-specific modelling. Pre-
viously, no regional research combining remote sens-
ing and a process-based model to predict crop yield 
and water consumption allowing WUE to be monitored 
has been reported; though Schuepp et al. (1987) pro-
vided remotely sensed, process-oriented estimates of 
WUE for a small area (about 100 km²). Given that the 
process-based model includes a SVAT, this allows crop 
water consumption, and hence WUE to be modelled, 
in addition to simulating crop yield. 

In this paper we implemented a biophysically 
process-based model by combining a moderately com-
plex crop growth model with a SVAT scheme to pre-
dict crop yield, water consumption and WUE conjunc-
tively under the support of remote sensing over the NCP 
region. The SVAT scheme used here has been vali-
dated previously at our study site, the NCP (Mo and 
Liu, 2001), and already has been scaled to a catchment 
(Mo et al., 2004). Remotely sensed 10-day maximum 
composite Normalized Difference of Vegetation Index 
(NDVI) data recorded by the Advanced Very High Res-
olution Radiometer (AVHRR) sensor with 1 km reso-
lution are used to retrieve LAI to drive the model. The 
paper is organized as follows: the development of a 
moderately complex process-based model by combining a moderately com-
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dict crop yield, water consumption and WUE conjunc-
tively under the support of remote sensing over the NCP 
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lution are used to retrieve LAI to drive the model. The 

2. Model description 

The energy partitioning of the SVAT model devel-
oped by Mo and Liu (2001) is coupled with a mod-
erately complex dynamic crop growth model. Carbon 
and water fluxes are coupled through the stomatal resis-
tance that directly links photosynthesis, LAI and root 
zone soil moisture. The model focuses on biochemical 
mechanism of photosynthesis, crop dry mass formation 
and water consumption, and scaling up method for re-
gional application. Due to widespread use of fertilizers 
on the NCP (e.g., McVicar et al., 2002), we do not con-
sider nutrient cycling. Many research documents show 
that this area is not short of nutrients and the demands 
are met by current agricultural practices. 

2.1. Photosynthesis and evapotranspiration 

The scheme to predict energy fluxes, photosynthe-
sis and water balance is designed for flat crop fields, 
in which the crop canopy is idealized as a plane 
parallel medium with random distributed leaves (Mo and 
Liu, 2001). Transfer of solar radiation within the 
crop canopy is simulated with a multi-layer approach 
that distinguishes the direct and diffuse components 
of both the visible (300–700 nm) and near infrared 
(700–1300 nm) fractions. Considering the highly non-
linear response of photosynthesis to incident light, pho-
tosynthetic rates for sunlit and shaded leaves are esti-
mated separately, then summed and up-scaled to the 

$$A_n = \min(A_v, A_e) - R_d$$

where $A_v$ and $A_e$ (both with the units $\mu$mol C m$^{-2}$ s$^{-1}$) are the gross rates of photosynthesis limited by ribo-
Close Biophosphate Carboxylase-Oxidase (Rubisco) activity and the rate of Ribulose Biophosphate (RuBP) regeneration through electron transport, respectively. \( R_d \) is the daytime respiration (\( \mu\text{mol m}^{-2} \text{s}^{-1} \)).

For C3 crops:

\[ A_v = V_{\text{max}} \frac{c_i}{c_i + K_c(1 + c_2/K_o)} \]

\[ A_o = J \frac{c_i}{4c_o + 2c_i} \]

and for C4 crops:

\[ A_v = 2 \times 10^{4} \frac{Q_{\text{PAR}}}{V_{\text{max}}} \]

\[ A_o = a Q_{\text{PAR}} \]

where \( V_{\text{max}} \) is the maximum catalytic activity (\( \mu\text{mol C m}^{-2} \text{s}^{-1} \)) of Rubisco in the presence of saturating levels of RuBP and CO2; \( c_i \) and \( c_2 \) represent the intercellular CO2 and O2 concentrations (Pa) in the chloroplasts; \( J \) is the CO2 compensation point (Pa, equal to 0.5 \( c_o \) for C3 crops or 0.5 \( c_o/S \) for C4 crops); \( S \) is the Rubisco specificity for CO2 relative to O2 (dimensionless); \( c_o \) is the air density (kg m\(^{-3}\)); \( C_p \) is the specific heat of air at constant pressure (J kg\(^{-1}\) K\(^{-1}\)), \( D_0 \) is the water vapor deficit (hPa) at the source height, \( \lambda \) is the latent heat of vaporization of water (J kg\(^{-1}\)), \( \Delta \) is the slope of saturated vapor pressure-temperature curve (Pa K\(^{-1}\)), \( \gamma \) is the psychrometric constant (hPa K\(^{-1}\)), \( r_s \) is the leaf boundary aerodynamic resistance (s m\(^{-1}\)), \( r_w \) is the aerodynamic resistance (s m\(^{-1}\)) from soil surface to source height, \( r_c \) is the canopy resistance (s m\(^{-1}\)) and \( r_o \) is the soil resistance (s m\(^{-1}\)). The parameterization of resistances and the working variable \( D_0 \) is described in detail in Mo et al. (2004). \( G \) is the soil heat flux (W m\(^{-2}\)) and can be estimated as a fraction of net radiation above canopy, expressed as (Mo et al., 2004):

\[ \frac{G}{R_w} = 0.183 \exp(-0.209 L_{c}) \]

where \( R_w \) is the net radiation (W m\(^{-2}\)) above canopy, \( L_{c} \) is the total green LAI.

The soil moisture budget is estimated with a three-layer scheme in which crop roots only uptake water from the second layer (Sellers et al., 1986). The depth of soil layer is set as 3 m with 0.05, 1.95 and 1.00 m used for each layer, respectively, soil hydraulic parameters are estimated with the Clapp and Hornberger (1978) empirical formula for sandy loam and loam, the dominant soil textures of the NCP.

The summation of \( E_c \) and \( E_o \), denoted as ET, is for the estimation of water consumption, which is related with canopy height. The canopy height (\( H_{c, m} \)) is esti-
mated by a logistic function as follows:

\[ H_1 = \frac{H_{\text{max}} \times 1.11}{1 + \exp\left(3.51D_1 - 12.59D_1 + 5.34D_1\right)} \quad D_1 \leq 1 \]

\[ H_1 = \frac{H_{\text{max}} \times 1.11}{1 + \exp\left(2.47D_1 + 5.24D_1\right)} \quad D_1 > 1 \quad (9) \]

where \( H_{\text{max}} \) is the maximum of canopy height (m), \( D_1 \) is the thermal growing variable related to phenological development stage (dimensionless), varying from 0 at emergence to 1 at flowering, and finally reaching 2 at maturity. The quantity \( D_1 \) is calculated as follows:

\[ D_1 = \begin{cases} \sum t_1 \cdot B_t / A_1 & 0 < D_1 \leq 1 \\ \sum t_2 \cdot B_t / A_2 & 1 < D_1 \leq 2 \end{cases} \quad (10) \]

where \( t_1 \) and \( t_2 \) are the cumulative days (d) from emergence to flowering and from flowering to maturity, \( A_1 \) and \( A_2 \) are the active cumulative temperatures (°C) of the above two periods, respectively, \( B \) is the minimum effective temperature (°C) for crop growth, \( T_a \) is the daily average air temperature (°C). To calculate \( D_1 \), a cumulative temperature from planting to emergence, denoted as \( A_1 \) (°C), which is assigned a value initially, is needed. Values of \( A_1, A_2, B \) and \( A_0 \) used in this paper are listed in Table 2.

### 2.2. Dynamic crop growth

The daily growth of crop dry mass (DM, mol C m\(^{-2}\)) denoted as \( W \), is expressed as the balance of gross photosynthesis, respiration and senescence, namely

\[ \frac{dW}{dt} = A_0 - R - S \quad (11) \]

where \( A_0 \) is the daily net photosynthesis (mol C m\(^{-2}\)·s\(^{-1}\)) at canopy level derived by integrating the instantaneous \( A_0 \) values over daytime and the canopy profile, \( R \) is the total respiration composed of construction respiration \( R_c \) (mol C m\(^{-2}\)·d\(^{-1}\)) and maintenance respiration \( R_m \) (mol C m\(^{-2}\)·d\(^{-1}\)). \( S \) is the senescent rate (mol C m\(^{-2}\)·d\(^{-1}\)) taken as a fraction of the green biomass until seed maturation, affected by soil moisture (Cayrol et al., 2000). At seed maturation stage, \( S \) increases rapidly due to leaf senescing. The \( R_c \) and \( R_m \) are calculated by (Amthor, 1989)

\[ R_c = (1 - V_c)(A_1 - R_m) \quad (12) \]

\[ R_m = mW \quad (13) \]

where \( V_c \) is the growth conversion efficiency (dimensionless), \( m \) is the maintenance coefficient (d\(^{-1}\)). According to Johnson and Thornley (1983), \( V_c \) is typically about 0.75 and \( m \) is set as 0.01 d\(^{-1}\) under 20°C condition and corrected with a Q\(_{10}\)-type function with temperature.

In this paper crop yield is calculated as the total DM (including the root system) multiplied by the harvest index, HI, which is slightly different from what Bastiaanssen and Ali (2003) used where only aboveground DM was considered. For winter wheat, the HI is taken as 0.48 and for summer maize 0.38.

Crop WUE can be defined as the ratio of crop growth amount to ET on physiological aspect (Viets, 1962; Stanhill, 1986). The crop growth amount can be either the net DM or crop yield. There are several concepts for crop WUE which correspond to a range of spatial scales such as leaf – canopy – field – regional scales (McVicar et al., 2002), and time scales, as second – day – growth stage – season – year scales (Sinclair et al., 1984). Our working definition of WUE is the ratio of crop yield to seasonal ET, and has the unit of kg crop per mm of growing season ET per hectare, that is, kg ha\(^{-1}\) mm\(^{-1}\).

### 2.3. Model parameters

The parameters used in the model were derived from the field experiments and obtained from published references (see Table 1 of Mo and Liu, 2001). It is recognized that the two parameters, \( V_{\text{max}} \) and \( \alpha \), are much more sensitive to the canopy photosynthesis rate than other parameters. In this study \( V_{\text{max}} \) and \( \alpha \) were set as 150 μmol C m\(^{-2}\)·s\(^{-1}\) and 0.385 μmol C μmol\(^{-1}\) photon for winter wheat (Wang and Leuning, 1998) and 41.5 μmol C m\(^{-2}\)·s\(^{-1}\) and 0.062 μmol C μmol\(^{-1}\) photon for maize (Choudhury, 2001), respectively.

<table>
<thead>
<tr>
<th>Parameters (°C) for calculating thermal growing variable</th>
<th>( A_0 )</th>
<th>( A_1 )</th>
<th>( A_2 )</th>
<th>( B )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter wheat</td>
<td>110</td>
<td>1110</td>
<td>860</td>
<td>0</td>
</tr>
<tr>
<td>Summer maize</td>
<td>130</td>
<td>1400</td>
<td>1400</td>
<td>0</td>
</tr>
</tbody>
</table>
3. Study area and key datasets

3.1. Hebei province portion of the NCP

The study area is located in Hebei province and covers 88,779 km$^2$ (or 29% of the NCP) consisting of 108 counties (Fig. 1). To the west are the foothills of the Taihang Shan mountain range, with the NCP gently sloping to the Bohai Sea in the east. Physiographically, the study area is divided into three parts from west to east: the piedmont, lowland and seashore plains (Fig. 2). Traditionally high crop yields are reported from the piedmont plain where soil and climatic conditions and irrigation from groundwater recharged by Taihang Shan mountain range are favorable for agriculture. In the lowland plain, deep groundwater is insufficient and the shallow groundwater is contaminated by secondary salinity, which is not so suitable for irrigation. The seashore plain is affected by the seawater intrusion, and hence low crop yields are reported from this area.

The land use in the area is dominated by the intensive dual-cropping system based on winter wheat and summer crops, including maize, millet, soybean, cotton and sorghum. Despite a variety of crops in summer, maize is the dominant summer crop in most counties (e.g., McVicar et al., 2002). According to the traditional tillage practice, winter wheat is sown in early October, harvested in early or mid June next year, and summer maize is planted in early to mid June and harvested at the end of September, from where the cycle is repeated.

Annual precipitation is about 600 mm, more than 50% of which arrives during the summer monsoon between July and September. Due to the limited and variable precipitation, in spring the winter wheat productivity is only guaranteed by irrigation; otherwise the pro-
ductivity will be low, with no grain being yielded in extreme drought conditions. The intensive cropping systems have increased the irrigation water requirement from 100 mm year\(^{-1}\) in the 1950s to 300 mm year\(^{-1}\) in the 1980s for winter wheat (Wang et al., 2001). Because of the low annual precipitation and shortage of surface water, the intensive agricultural systems mainly rely on irrigation water extracted from ground aquifers. Continuous over-extraction of regional groundwater has resulted in the aquifer levels decreasing by as much as 1 m year\(^{-1}\) over a prolonged 40-year period in some areas (Liu et al., 2001).

3.2. GIS data

The GIS datasets include: (1) land use/cover digital data and land use map; (2) an irrigated/rainfed distribution map; (3) Digital Elevation Model (DEM); and (4) soil texture map. All were resampled to 30\(^{′′}\) × 30\(^{′′}\) grid cell (each cell being approximately 926 m × 725 m at 38.5° N) and the data source for each is as follows. The land use/cover digital data was derived from Landsat Thematic Mapper (TM) images and was used to identify arable fields. In our simulation, only winter wheat and summer maize were considered. The 1:1 000 000 land use map (Wu, 1990) was digitized to identify irrigated and rainfed fields; this is illustrated in Fig. 2. The topographical elevation above sea level is described with a 30\(^{′′}\) × 30\(^{′′}\) resolution DEM (from USGS, 1998), most of which is below 300 m. Soil texture was digitized from a 1:14 000 000 scale map (Institute of Soil Science, 1986).

3.3. Remotely sensed data

Data recorded by the National Oceanic and Atmospheric Administration (NOAA) series of satellites with the AVHRR sensor have a 1.1 km resolution at nadir and daily coverage. The two reflective bands (Red (580–680 nm) and near infrared (NIR 725–1100 nm))) are useful for monitoring vegetation development. The Normalized Difference Vegetation Index (NDVI, defined as (NIR − Red)/(NIR + Red)), and the Simple Ratio (SR, defined as NIR/Red) are two common transformations of AVHRR data that allow the prolonged effects of water stresses that reduce LAI to be detected (Mansongrande et al., 1995). We obtained ‘10-day’ composites from http://edcdaac.usgs.gov/1km/ for 1992 and 1993, and then interpolated linearly to the daily time-step. The relationship between LAI and the fraction of Absorbed PAR, denoted as \(F_{\text{PAR}}\), by the vegetation at nearly noon for crop is expressed as (Monteith and Unsworth, 1990)

\[
L_t = L_{t \text{max}} \ln \left(1 - \frac{F_{\text{PAR}}}{F_{\text{PAR} \text{max}}} \right) \ln \left(1 - \frac{F_{\text{PAR} \text{max}}}{F_{\text{PAR} \text{min}}} \right) \quad (14)
\]

where \(F_{\text{PAR}}\) is calculated as a linear relation of vegetation index (dimensionless, Sellers et al., 1996):

\[
F_{\text{PAR}} = \frac{(\text{SVI} \text{max} - \text{SVI} \text{min} \times F_{\text{PAR} \text{max}} - F_{\text{PAR} \text{min}})}{\text{SVI} \text{max} - \text{SVI} \text{min}} \quad (15)
\]

where SVI is the spectral vegetation index. \(\text{SVI}_{\text{max}}\) and \(\text{SVI}_{\text{min}}\) are the maximum and minimum SVI, respectively. \(F_{\text{PAR} \text{max}}\) and \(F_{\text{PAR} \text{min}}\) are the maximum and minimum \(F_{\text{PAR}}\) corresponding to \(\text{SVI}_{\text{max}}\) and \(\text{SVI}_{\text{min}}\), set as 0.95 and 0.001. Both the SR and NDVI were substituted into Eq. (15) as the SVI in this study; differences were examined and are discussed in Section 6. The above empirical relationship is sensitive to soil reflectance and differences in sun/sensor geometry (e.g., Hatfield et al., 1984; Myneni and Williams, 1994; Sellers et al., 1996). A generalized relationship between \(F_{\text{PAR}}\) and NDVI must be seen as an average model for a variety of canopy conditions.

3.4. Climatic data

Daily meteorological data were recorded at 52 climatological stations in and around the focus area, including mean, minimum and maximum air temperature, mean vapor pressure, atmospheric pressure, daily sunshine duration and rainfall. Except sunshine duration, all variables above were corrected with elevation above sea level. The daily variation of air temperature was approximately expressed as Fourier harmonics (Kondo and Xu, 1997) and solar radiation was estimated with clear sky radiation and relative sunshine duration. All variables above were interpolated into hourly data according to temperature. As spatial interpolation of climatic data was required to obtain the driving variables over the grid cells, the thin plate spline method was employed for rainfall interpolation, whereas the inverse distance squared method was used for other variables.
3.5. Crop yield data

To validate the processes incorporated in the model for both winter wheat and summer maize, field experiments were conducted at the Yucheng Agro-Ecosystem Experimental Station (37°53′N, 115°41′E) from October 1991 to September 1992 for the measurements of total DM. The wheat and maize were fertilized with 300 and 480 kg N ha\(^{-1}\), respectively. Each irrigation event was 60 mm; applied six times in a year, four for wheat and two for maize; typical of irrigation management on the NCP.

County-level crop yield data were available from the Agricultural Bureau of Hebei Province, which records the total grain yield and its planting area of a crop. County-level crop yield relies on the aggregating yield estimates from village to township, then to the county, using a Chinese National standard (e.g., McVicar et al., 2002). The county-level fraction of maize area of the total summer planted crops in 1993 is 0.666 with standard deviation around the mean reported for the 108 counties being 0.145, and the fraction of winter wheat of autumn planted crops is 0.990 with standard deviation being 0.041.

4. Model running

We simulated the winter wheat–summer maize rotation from 1 October 1991 to 30 September 1993 hourly at 30′ × 30′ grid resolution. The sowing dates of winter wheat and summer maize were artificially set as 1 October and 15 June, respectively, and harvest dates were determined, as \(D_v\) was equal to 2. Model initialization period was performed from 1 October 1991 to 14 June 1992, with simulation results from the 1992 summer maize, and 1993 winter wheat and summer maize being used for analysis. During each dual-crop (one winter wheat followed by one summer maize) rotation (from 1 October to 30 September the following year), the dates of irrigation were determined according to the agronomical conditions. Since the exact irrigation dates were unavailable over the study areas, the uniform irrigate dates were set as 11 October, 30 March, 24 April, 14 May, 18 July and 17 August according to the most popular and traditional irrigation systems from the local averaged information collected. We assume that fertilizers were applied in time so that the water stress is the only factor limiting crop growth and grain formation. Often on the NCP fertilizers are applied simultaneously with irrigation water, termed ‘fertigate’, this assists in dissolving the fertilizer so plant can effectively access to the nutrients.

5. Results

5.1. Validation with the field data

The simulated DM of winter wheat and maize were validated with Yucheng field data. The growing processes of the live bio-DM for winter wheat and maize are shown in Fig. 3a and b, respectively. It is shown that the simulated and the observed DM agree quite well over the whole growing period, with Pearson correlation coefficient approaching 1. Data collected at the Yucheng field treatments had an above ground bio-DM at harvest in the range of 14 500–17 500 kg ha\(^{-1}\) for winter wheat with 300 mm of irrigation, similar results have been presented by Kang et al. (2002) and Zhang et al. (1998). The above ground bio-DM for summer maize at harvest ranged from 17 000 to 21 000 kg ha\(^{-1}\).

![Fig. 3. Simulated and observed dry mass (DM) for (a) 1993 winter wheat and (b) 1992 maize over their respective growing seasons with Pearson correlation coefficient (\(R^2\)) and the number of the observations.](image-url)
The root system DM is usually estimated by its ratio to the above ground part; values from 0.15 to 0.20 for winter wheat and 0.10 to 0.15 for summer maize are common in this region.

5.2. Validation with the county census yield data

While we recognize that the county yield statistics are derived by estimating yields under different productivity levels and their relevant planting sizes, and hence are potentially prone to errors (McVicar et al., 2002), these data, to some extent, represent a regional ‘ground truth’, and offer a validation of the prediction. Fig. 4 shows the county records and simulated yields for wheat and maize. For winter wheat, the absolute deviation is 908 kg ha\(^{-1}\), relative deviation is 23% and root mean square error is 1124 kg ha\(^{-1}\). The model performance for the 2 years of maize is a bit lower, the absolute deviation is 1282 kg ha\(^{-1}\), relative deviation is 33% and root mean square error is 1359 kg ha\(^{-1}\), in spite that the Pearson correlation coefficient of maize 1992 is higher than that for wheat 1993. These relative deviations are quite similar to those reported by Bastiaanssen and Ali (2003) for the Indus Basin in Pakistan. The variability of county-level crop yields shows a wide range, coinciding with heterogeneity of soil, water resources and climatic conditions over the study site. In the NCP there are a variety of summer

![Cross plots of county-level and simulated yields for (a) wheat in 1993; (b) maize in 1992 and (c) maize in 1993 with Pearson correlation coefficient \(R^2\) and the number of samples; and (d) the relation between the ratio of the area of maize in 1992 to the total county cropping area with the difference between the simulated and observed. The empty circles in (b) show the counties with the ratio over 0.6 and the stars show the counties with the ratio less than 0.4.](image-url)
crops, such as soybean and cotton that are cultivated broadly in the southeast of the study site, however, as the summer crops have a similar NDVI time series it is not possible to identify these crops directly from AVHRR NDVI images. The differences between the field size (some 10,000 m$^2$) and the 1.1 km resolution of the AVHRR data exacerbate this problem. As a consequence, mixed crop types within an AVHRR pixel may significantly interfere with the inversion of crop characteristics, and in some cases will enhance model uncertainty. On the other hand, the bias of planting area estimates may also result in uncertainty of yield.

It is found that the maize yields are better modelled in counties where maize dominants the summer planting (Fig. 4d). As shown in Fig. 4b, the maize area at those counties with small difference between the simulation and observation is over 60% of the total county cropping area (empty circles) and that with large difference is less than 40% (stars), approximately.

5.3. Spatial patterns of crop yield

The potential crop yield (defined as crop yield without water or nutrition stress) was calculated as 7500 kg ha$^{-1}$ for winter wheat and 8800 kg ha$^{-1}$ for summer maize, with LAI estimated by logarithmic functions shown in Appendix A. There is considerable spatial structure presented in both winter wheat and maize yields, see Fig. 5. The wheat yields (Fig. 5a) are over 4800 kg ha$^{-1}$ in the northern, western and southern areas where irrigation water quality is high, and irrigation demand is guaranteed. With more than 200 mm of irrigation over the growing period, winter wheat

plot-level yields range from 5000 to 7000 kg ha$^{-1}$ in the NCP (Zhang et al., 1999; Jin et al., 1999). As expected, due to no irrigation infrastructure and poorer soils, lower winter wheat yields were modelled for the mid and eastern portions of the study area. During the wheat-growing season, total precipitation is usually scant and erratic (less than 150 mm), resulting in severe water stress, consequently low harvest grains in these areas.

Prior to the 1980s soil salinity was the main factor limiting crop yield in the lowland plains, the southwest to northeast belt in the mid of the study area. These soil conditions were greatly improved after a 10-year effort in the 1980s by: (1) increasing soil organic matter; (2) lowering groundwater table by using many motor-pumped wells to withdraw groundwater; (3) building the drainage engineering; (4) flattening the soil hampers in the field where salt was accumulated; and (5) afforesting the landscape. Afforestation assists the regional environment in two ways: firstly increasing transpiration from forests with deep roots reduces the groundwater table over the region and secondly reducing the wind velocity, lowering the air temperature and increasing air humidity over the fields, which subsequently decrease the field evaporation and is useful to hinder the salt accumulation in the surface layer of the fields. Currently, when sufficient water is available, crop productivity from the lowland plain is as high as that achieved in the traditionally high-yielding western piedmont plain (e.g., Jin et al., 1999). However, limited surface water resources often results in low productivities being attained over much of the lower plain. Limited surface water resources is due to precipitation in

![Fig. 5. Maps of simulated crop yield for (a) winter wheat in 1993 and (b) summer maize in 1992.](image)
this area being the lowest in the NCP, with the Tai Yi Shan mountains in the south (see Fig. 1) acting as a barrier to the moist from southern air movement.

Fig. 5b shows that the spatial pattern of summer maize yield corresponds to the location of irrigation and rainfed fields shown in Fig. 2. Areas of high productivity were located in the north, south and piedmont areas; and areas of low productivity were found in the lowland and seashore plains where rainfall during the summer of 1992 was only about 200 mm; usually in rainfed areas the productivity can reach 4800 kg ha\(^{-1}\). Although there is enough summer-dominated rainfall to meet most of the maize’s water demand, the temporal distribution of rainfall is often irregular. This may cause severe crop water stress in one or two of maize growth and development stages in rainfed condition. In addition, the dates of fertilizer application may be non-optimum, due to waiting for adequate rainfall; consequently maize yield may be distinctly lower in rainfed areas when compared with irrigated areas.

The yield data over each grid of the study area show an interesting bimodal distribution (Fig. 6) corresponding to rainfed field and irrigated field, respectively. The yield of wheat ranges from 3900 to 7200 kg ha\(^{-1}\) in the irrigated field with the maximum frequency at 5900 kg ha\(^{-1}\), whereas rainfed fields produce from 100 to 2600 kg ha\(^{-1}\) with the maximum frequency at 600 kg ha\(^{-1}\). For summer maize, the yield ranges from 5800 to 8600 kg ha\(^{-1}\) with the maximum frequency at 7400 kg ha\(^{-1}\) in the irrigated field, whereas that of rainfed field is from 1400 to 4800 kg ha\(^{-1}\) with a bimodal distribution, with local maxima located at 2800 and 4100 kg ha\(^{-1}\). The bimodal distribution in rainfed maize fields shows the strong spatial variability of crop yield in the focus region. The great difference between the rainfed and irrigated yields indicates that there is a great potential for yield increment in this region if sufficient irrigation water is supplied. However, given that water is currently over allocated, and that competition for water resources, from economic and population growth, and for environmental flows, is increasing, it seems unlikely this water will become readily available for the agricultural producers of the NCP.

5.4. Water consumption (ET)

Both wheat and maize growing seasonal ET patterns, i.e., the water consumption pattern, show noticeably spatial variability (Fig. 7). For irrigated wheat, seasonal ET mostly ranges from 400 to 450 mm; 70% is from irrigation. For rainfed wheat, most seasonal ET is less than 250 mm, most is from rainfall, with limited residual soil moisture carried over from the previous maize growing season. The reason for low ET for rainfed wheat is that summer rainfall is almost entirely consumed by the previous maize crop; hence the available soil moisture is low when wheat is seeded in October and rainfall during the winter wheat growing season is low. In maize fields, seasonal ET mostly ranges from 350 to 450 mm; about 20% is from irrigation. Seasonal ET ranges widely from 140 to 350 mm for rainfed maize, all of which is from summer rain during the maize growing period. Our field experiments show that following the wheat-growing period there is some residual moisture in the soil layer for root uptake at the start of the maize season. This part of soil water is usually deposited under the soil plough pan layer, a compacted layer 0.2–0.35 m below the soil surface on the NCP as a result of ploughing or cultivation activity, across which soil water moves very slowly. For both
irrigated wheat and maize fields, $E_T$ is about 30–40% of growing seasonal ET. Potential ET ($ET_0$) calculated using a Penman–Monteith formula (Monteith, 1965) in the wheat and maize growing periods are about 560 and 500 mm, respectively. Our simulation results, see Fig. 7, are comparable with those presented in other studies in the NCP. Liu et al. (2002) presented the observed seasonal ET values of 400 to 480 mm for wheat and 395–450 mm for maize measured by a large scale weighing lysimeter. Zhang et al. (1999) reported seasonally observed ET values ranging from 305 to 455 mm at four winter wheat sites with different irrigation volumes applied.

The frequency distribution of ET (Fig. 8) is consistent with the distribution of crop yield, showing also the obvious differences between the irrigated and rainfed fields. However, the distribution of ET is more normally distributed than that for wheat yield (compare Fig. 8a with Fig. 6a). The ET of wheat ranges from 330 to 500 mm in the irrigated field with the maximum frequency at 430 mm, whereas ET from rainfed fields ranges from 70 to 280 mm with the maximum frequency at 130 mm. There is a high agreement between the low ET and low wheat yield; according to Zhang et al. (1999), if there is less than 110–120 mm of seasonal ET then there is no wheat yield in the rainfed areas. The distribution of ET for summer maize is different from that of the crop yield in that there is not an obvious difference between the irrigated field and rainfed field; or we say that the two populations for ET from summer maize overlap (Fig. 8b), with the ET primarily being above 140 mm and less than 520 mm for both the rainfed and irrigated fields. From Fig. 8b it seems that the maximum frequency for irrigated fields is about 420 mm and the maximum frequency for rainfed field is also 420 mm. However, comparing with the spatial distribution of ET in maize fields shown in the map of Fig. 7b, the ET from summer maize in irrigated field mostly ranges from 350 to 520 and 140 to 350 mm in rainfed conditions.

Fig. 7. Maps of simulated growing season ET for (a) winter wheat in 1993 and (b) summer maize in 1992.

Fig. 8. Histograms of simulated ET for (a) winter wheat in 1993 and (b) summer maize in 1992.
5.5. WUE

The spatial patterns of WUE for winter wheat and summer maize are presented in Fig. 9a and 9b, respectively. For winter wheat (Fig. 9a) the pattern of WUE is similar to that of yield, namely high WUE (greater than 11 kg ha\(^{-1}\) mm\(^{-1}\)) occurred in areas irrigated and low WUE (less than 8.5 kg ha\(^{-1}\) mm\(^{-1}\)) was experienced in rainfed areas. For summer maize, most WUE is greater than 16 kg ha\(^{-1}\) mm\(^{-1}\) with irrigation and less than 8.5 kg ha\(^{-1}\) mm\(^{-1}\) under rainfed conditions. The simulated WUE mostly is less than 18 kg ha\(^{-1}\) mm\(^{-1}\) for wheat and less than 21 kg ha\(^{-1}\) mm\(^{-1}\) for maize. In the same region, McVicar et al. (2002) developed a county-level ‘input–output’ GIS approach, and reported winter wheat WUEs from 1.2 to 21.5 kg ha\(^{-1}\) mm\(^{-1}\) and summer maize WUEs from 1.7 to 39 kg ha\(^{-1}\) mm\(^{-1}\) and over 85% of their observations for winter wheat (summer maize) WUE less than 15 (20) kg ha\(^{-1}\) mm\(^{-1}\). The high values (summer maize WUE > 30 kg ha\(^{-1}\) mm\(^{-1}\)) reported by McVicar et al. (2002) were attributed to errors in China’s agricultural statistics; providing weight to the use of a remote sensing-based approach, as developed here. In the 49 counties, for the winter wheat and the two-summer maize growing seasons, Fig. 10 presents the comparison of the WUEs developed here with those reported by McVicar et al. (2002). It is found that the WUE-values are agreeable in most of counties, except those with very high WUEs in McVicar et al. (2002). Additionally, our simulated WUE values are also comparable with those reported in the literature for the NCP, other areas in China as well as some international sites, see Table 3.

6. Discussions

There are several sources of uncertainty in the crop yield simulation developed here. For example, we have used a constant HI for each crop (0.48 for winter wheat
and 0.38 for summer maize), however Bastiaanssen and Ali (2003), summarizing previous studies, reported that the HI varies (ranging from 0.10 to 0.65 for winter wheat and 0.30 to 0.47 for summer maize). Consequently changes from the constant used here will affect the accuracy of the predicted yield; a spatially varying HI is detailed information currently not available. Management factors, such as cultivar’s genetic characteristics, tillage, use of fertilizers, and irrigation timing and amount will also affect crop yield significantly. Exceptional events such as pests, unseasonably hot winds, frosts or flooding are site-specific factors that may greatly reduce the crop yields. These events, especially if they occur late in the growing season, when a large biomass has already been observed using remotely sensed data, can significantly reduce final grain yield, causing large discrepancies in modelled and measured county yields.

The retrieval of crop canopy LAI may also result in prediction uncertainty. LAI can be either calculated from logistic functions, as shown in Eqs. (A.1) and (A.2), or retrieved from remotely sensed SVI, such as the SR and NDVI. Practically, logistic function can represent approximately the LAI curve, whereas the relationship between LAI and SVI is non-linear as the LAI retrieved from remote sensing is insensitive to fully canopy cover; hence decreasing the relationship reliabilities when LAI is greater than 3. Lu et al. (2003), using validation data and a review of previous research, found that a linear calibration was not supported between LAI and NDVI. Although the linear relationships were found between LAI and SR, however they were not identical (assuming a linear relationship in one case implies a slightly non-linear relationship in the other). To date, no commonly accepted SVI-LAI relation has been developed. Choudhury (1987) reported that using NDVI in Eq. (15) resulted in more accurate estimates of \( F_{\text{PAR}} \) (hence LAI) than using SR to estimate LAI. Based on the simulated ET and assimilation amounts by using the \( D_v \)-LAI logistic functions (Eqs. (A.1) and (A.2)) with \( L_{\text{t max}} \) being 6.0 (4.0) for wheat (maize) under irrigated condition, we compared the simulated ET and assimilation amounts by using NDVI and SR data in Eq. (15) respectively. We found that the predictions using NDVI were very close to that by using logistic relations (less than 2%), whereas that by using SR was 16% lower than that by the logistic relations. This is why in this paper we used the NDVI to estimate LAI; the method to calculate LAI from logistic functions is only for the estimation of potential crop yield.

Five model parameters (\( V_{\text{c max}}, \alpha, A_1, A_2 \) and \( L_{\text{t max}} \)) are important to crop yield and ET (and hence WUE) and the method to calculate LAI from logistic functions is only for the estimation of potential crop yield. Five model parameters (\( V_{\text{c max}}, \alpha, A_1, A_2 \) and \( L_{\text{t max}} \)) are important to crop yield and ET (and hence WUE) and were selected to assess the model sensitivity. For both wheat and maize, each parameter was perturbed, in turn, by \( \pm 10\% \) from the initial value; percentage differences in yield, ET and WUE from the results using the initial value are presented in Table 4. This shows that \( \alpha \) is the most sensitive parameter, with the model being moderately sensitive to \( V_{\text{c max}}, L_{\text{t max}} \) and

![Fig. 10. Cross plots of simulated WUE from this study with those reported by McVicar et al. (2002) for (a) wheat in 1993; (b) maize in 1992; and (c) maize in 1993. On (a) three dubious points are identified by hollow circles and have been removed for some statistical analysis.](image)
Table 3
Documented results of WUE in NCP, other areas of China and international sites

<table>
<thead>
<tr>
<th>Reference</th>
<th>Site</th>
<th>WUE values (kg ha$^{-1}$ mm$^{-1}$)</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zhu et al. (1994)</td>
<td>NCP</td>
<td>14.8</td>
<td>Wheat</td>
</tr>
<tr>
<td>Zhang et al. (1999)</td>
<td>NCP</td>
<td>11.8–14.0</td>
<td>Irrigated wheat</td>
</tr>
<tr>
<td>Jin et al. (1999)</td>
<td>NCP</td>
<td>14.9–23.0</td>
<td>Wheat mulch, fertilizer application and irrigation treatment</td>
</tr>
<tr>
<td>McVicar et al. (2002)</td>
<td>Hebei portion of NCP</td>
<td>1.2–21.5</td>
<td>Wheat</td>
</tr>
<tr>
<td>This paper</td>
<td>Hebei portion of NCP</td>
<td>12.25–15.75</td>
<td>Irrigated wheat</td>
</tr>
<tr>
<td>Zhang et al. (1998)</td>
<td>Beijing, NCP</td>
<td>9.3–15.5</td>
<td>Wheat</td>
</tr>
<tr>
<td>Li et al. (2000)</td>
<td>Northwest China</td>
<td>6.5–12.1</td>
<td>Wheat</td>
</tr>
<tr>
<td>Kang et al. (2002)</td>
<td>Northwest China</td>
<td>7.7–14.6</td>
<td>Irrigated wheat</td>
</tr>
<tr>
<td>Regan et al. (1997)</td>
<td>Australia</td>
<td>5.5–16.5</td>
<td>Wheat</td>
</tr>
<tr>
<td>Zhang and Oweis (1999)</td>
<td>North America</td>
<td>2.5–16.0</td>
<td>Wheat</td>
</tr>
<tr>
<td>Howell et al. (1995)</td>
<td>USA</td>
<td>4.4–8.8</td>
<td>Wheat</td>
</tr>
<tr>
<td>Mosteck et al. (1994)</td>
<td>USA</td>
<td>0.84</td>
<td>Wheat</td>
</tr>
<tr>
<td>Colberci et al. (1998)</td>
<td>Morocco</td>
<td>0.1–11.5</td>
<td>Wheat</td>
</tr>
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<td>Zhu et al. (1994)</td>
<td>NCP</td>
<td>19.4</td>
<td>Maize</td>
</tr>
<tr>
<td>Jin et al. (1999)</td>
<td>NCP</td>
<td>20.6–23.4</td>
<td>Maize, with mulching and irrigation treatments</td>
</tr>
<tr>
<td>McVicar et al. (2002)</td>
<td>Hebei portion of NCP</td>
<td>1.7–39</td>
<td>Maize</td>
</tr>
<tr>
<td>This paper</td>
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<td>11.1–19.25</td>
<td>Irrigated maize</td>
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<tr>
<td>Zhang et al. (1998)</td>
<td>Hebei portion of NCP</td>
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<td>Rainfed maize</td>
</tr>
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<td>Li et al. (2000)</td>
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<td>Maize</td>
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<tr>
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<td>Semi-arid central and southern high plain of USA</td>
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<td>Maize</td>
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<td>Lebanon</td>
<td>13.4–18.8</td>
<td>Maize</td>
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<td>Karam et al. (2003)</td>
<td>USA</td>
<td>16.5</td>
<td>Maize</td>
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<td>Howell et al. (1998)</td>
<td>USA</td>
<td>12.5–14.6</td>
<td>Maize</td>
</tr>
<tr>
<td>Mosteck and Dusek (1980)</td>
<td>USA</td>
<td>12.4–13.8</td>
<td>Maize</td>
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</tbody>
</table>

Fig. 11. Histograms of simulated WUE for (a) winter wheat in 1993 and (b) summer maize in 1992.
Table 4
Percent sensitivity (calculated as reference minus perturbed) of yield, ET and WUE to perturbing the parameters listed by ±10%.

<table>
<thead>
<tr>
<th></th>
<th>Yield</th>
<th>ET</th>
<th>WUE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheat</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>−10%</td>
<td>+10%</td>
<td></td>
</tr>
<tr>
<td>V_{cmax}</td>
<td>−3</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>α</td>
<td>−9</td>
<td>−9</td>
<td>−2</td>
</tr>
<tr>
<td>A_1</td>
<td>−1</td>
<td>1</td>
<td>−1</td>
</tr>
<tr>
<td>A_2</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>−10%</td>
<td>+10%</td>
<td></td>
</tr>
<tr>
<td>Maize</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>−10%</td>
<td>+10%</td>
<td></td>
</tr>
<tr>
<td>V_{cmax}</td>
<td>−2</td>
<td>3</td>
<td>−2</td>
</tr>
<tr>
<td>α</td>
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<td>1</td>
</tr>
<tr>
<td>A_2</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>−10%</td>
<td>+10%</td>
<td></td>
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</table>

A_1, with no sensitivity to A_2. Overall, perturbing the parameters V_{cmax} and α changes the crop yield response greater than ET. The reason for this is that ET consists of canopy transpiration, intercepted water evaporation and soil evaporation; V_{cmax} and α are only indirectly related with the latter; Transpiration is controlled not only by canopy physiological factors, but also by available energy. The crop yield, however, is closely related with these two parameters.

7. Conclusions
A biophysically process-based model, combining a moderately complex crop growth model with a SVAT scheme, has been used to predict crop yield, water consumption ET and WUE using NDVI data from NOAA-AVHRR for C_3 and C_4 crops. The model was calibrated and validated for a portion of Hebei province, most of which located within the NCP. The purpose of the model is to trace crop yield and water consumption consistently and to present the spatial variations of crop yield, ET, and WUE regionally, which are strongly desirable for agriculture and water resources management.

Generally, the performance of the model for winter wheat and summer maize is successful with comparable deviations from previous international results. The low predicted deviation of maize is perhaps because 66% of the summer crop is maize. The dispersed presence of small-scale maize, cotton and sorghum fields within AVHRR pixels may introduce significant error in the summer integration of biomass. Additionally, the presence of varying amounts of water vapor in the atmosphere during the wetter summers, may also result in remnant noise in the remotely sensed data after atmosphere correction.

The simulated spatial patterns of crop yield, ET and WUE correspond to the irrigated/irrigated pattern. The predicted crop yield for irrigated winter wheat ranges from 3900 to 7200 kg ha$^{-1}$, and ranges from 100 to 2600 kg ha$^{-1}$ for rainfed conditions. The crop yield for irrigated summer maize is 5800–8600 and 1400–4800 kg ha$^{-1}$ for rainfed areas. The predicted ET ranges from 330 to 500 mm for irrigated winter wheat, and from 70 to 280 mm for rainfed conditions. The ET for irrigated summer maize is primarily from 350 to 520 and 140 to 350 mm in the rainfed fields. The WUE is from 12.25 to 15.75 kg ha$^{-1}$ mm$^{-1}$ for irrigated winter wheat and from 0.5 to 8.25 kg ha$^{-1}$ mm$^{-1}$ for rainfed fields. The WUE for summer maize mostly is from 11 to 20 kg ha$^{-1}$ mm$^{-1}$ when irrigated and from 5 to 11 kg ha$^{-1}$ mm$^{-1}$ in rainfed areas. The substantial gap between the irrigated and rainfed field reveals that the crop yield of this area can be significantly enhanced if irrigation efficiency is noticeably improved, more farms are irrigated and water resources and other resources are managed better.

To improve the accuracy and reliability of the crop yield prediction, more detail and timely agronomic information and higher resolution satellite images such as MODIS should be cheaply available, preferably free on-line access, globally.

Acknowledgements
This research was supported by the Chinese National Natural Science Foundation project 90211007 and the Chinese National Basic Research Key Projects 2002CB412500. Many thanks to Dr. Huiyi Zhu at Institute of Geographical Sciences and Natural Resources Research for providing the TM land use data. Dr. Tim McVicar’s involvement was funded by CSIRO Land and Water and the Australian Centre for Agricultural Research (ACIAR), specifically projects LWR1/1995/007 and LWR1/2002/018. We thank the anonymous reviewers and the editors of the journal for
their comments that improved an earlier draft of this paper.

Appendix A

A.1. Using logistic functions to estimate \( L_t \)

For estimation of potential crop yield, \( L_t \) is estimated by logarithmic functions with the thermal growing variable, \( D_v \), for wheat

\[
L_t = \frac{1.2011L_{t, \text{max}}}{1 + \exp(-1.1601 - 4.1194D_v - 0.8661)} + 7.9603(D_v - 0.8661)^2
\]

(A.1)

for maize

\[
L_t = \frac{1.11L_{t, \text{max}}}{1 + \exp(-12.399D_v + 5.1342D_v^2)}
\]

(A.2)

where \( L_{t, \text{max}} \) is the maximum \( L_t \) during the growing period (assumed to be 6.0 for winter wheat and 4.0 for summer maize).

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