

Evaluation of an ecosystem model for a wheat–maize double cropping system over the North China Plain

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ARTICLE INFO

Article history:

Received 13 February 2011

Received in revised form

3 July 2011

Accepted 3 July 2011

Available online 23 August 2011

Keywords:

VIP model

Net ecosystem production

Evapotranspiration

Eddy covariance

Uncertainty

ABSTRACT

A process-based ecosystem model (Vegetation–atmosphere Interface Processes (VIP) model) is expanded, and then validated against three years' biometric, soil moisture and eddy-covariance fluxes data over a winter wheat–summer maize cropping system in the North China Plain (NCP). The results show that the model is capable of simulating satisfactorily the evolution of crop biomass, phenological development and soil moisture. The computed 30-min estimates of CO₂, water and heat fluxes agree well with the eddy-covariance measurements. At daily scale, the root mean square errors (RMSEs) of net radiation, latent heat flux and net ecosystem productivity (NEP) are 1.0 MJ m⁻² day⁻¹, 1.8 MJ m⁻² day⁻¹ and 2.6 gC m⁻² day⁻¹, respectively. However, systematic errors in sensible heat flux estimates are identified in times of season when daily sensible heat flux is negative due to the horizontal advection. Annually, about 55% of evapotranspiration (ET) is emanated from winter wheat and 45% from maize. The annual NEP varies noticeably, with relative biases of 18, 9 and –29% in each year from 2003 to 2005, respectively. Sensitivity analysis illustrates that ET is quite sensitive to soil resistance parameters contributing to soil evaporation, and NEP to quantum efficiency of photosynthesis. The uncertainties of annual ET and NEP are 16.5% and 35.6% respectively when the key parameters are randomly sampled in their uncertainty ranges. Errors on eddy-covariance measurements and uncertainty on the model parameters may partly explain the discrepancy between the simulations and the measurements.

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1. Introduction

Recently, much attention has been paid to terrestrial ecosystem dynamics. It is recognized that terrestrial ecosystem dynamics exerts great control on energy and carbon exchange between land surface and atmosphere at time scales spanning from hours, days, seasons, years to decades, and at spatial scales from leaf, canopy to landscape (Grant et al., 1999; Baldocchi and Wilson, 2001; Anderson et al., 2003; Turner et al., 2004). These exchanged fluxes significantly modify climate at both local and regional scales, and in turn affect vegetation structure and function, as well as ecosystem carbon cycling as feedbacks (Cayrol et al., 2000; Montaldo et al., 2005). Besides, interactions among climate, hydrology and vegetation physiology dominate the ecosystem responses to seasonal and inter-annual climate variability, through regulating the magnitudes of water vapor, heat and carbon fluxes between land surface and the atmosphere.

As an important component of terrestrial ecosystem, agro-ecosystem covers a large portion of land surface on the Earth and is influenced by both management and natural factors. The productivities of intensive agro-ecosystems are usually higher than natural ecosystems, due to the inputs of chemical fertilizers, irrigation, pesticides and new cultivars. At the same time, CO₂ exchange between the agro-ecosystem and the atmosphere is a regulator of air CO₂ fluctuation at annual and inter-annual scales. Agro-ecosystem may take an important role in global carbon budget, as reports show that crop fields have a great potential to sequester carbon dioxide with some agronomical managements, such as no-tillage and the return of crop residues to soil practices, which may increase soil organic carbon storage and mitigate the global greenhouse effect (Smith, 2004; Anthoni et al., 2004; Moureaux et al., 2008). There are also concerns of agro-ecosystem about the inadvertent, detrimental impacts on physical environment and river system, resulted from the export of nutrients and pesticides, over-withdrawals from river and groundwater, degradation of soil quality, as well as greenhouse gases emission (Tilman et al., 2002).

Great achievements have been obtained on physically based modeling the behaviors of terrestrial ecosystems, including

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physiologically controlling mechanisms of leaf stomata (Jarvis, 1976; Ball et al., 1987; Leuning, 1995), the physics of evapotranspiration (Monteith, 1965; Shuttleworth and Wallace, 1985; Fisher et al., 2005), the biochemistry of photosynthesis (Farquhar et al., 1980; Collatz et al., 1992), and the soil organic decomposition and respiration (Parton et al., 1987). So far, the integrated ecosystem dynamic models that couple soil–vegetation–atmosphere transfer (SVAT), vegetation dynamics, soil biogeochemistry and biogeography components into a more or less similar framework have been developed to predict water balance, vegetation productivity and carbon budget for assessment of land use and climate change impacts (Running and Hunt, 1993; Foley et al., 1996; Friend et al., 1997; Krysanova et al., 1999; Cramer et al., 2001; Grant et al., 2001; Dickinson et al., 2002; Kuchment and Demidov, 2006; Liu, 2009). By adopting the knowledge of terrestrial ecosystems and integrating the ecological processes for optimization of agricultural production and environmental cost, agro-ecosystem dynamic models have been developed or extended from the natural ecosystem models that focus on crop growth, water consumption and carbon budget, as well as management (Ritchie et al., 1985; Jones and Kiniry, 1986; Sharpley and Williams, 1990; Supit, 1994; Abrahamsen and Hansen, 2000; Kothavala et al., 2005; Wang et al., 2005; Adiku et al., 2006; Bechini et al., 2006; Stehfest et al., 2007; Kucharik and Twine, 2007; Bondeau et al., 2007; Post et al., 2008). These models have generally been used to investigate the effects of changing land management, climate and chemistry on crop yield, water consumption and carbon budget (Zhang et al., 2002; Izaurralde et al., 2006; Kucharik and Twine, 2007; Thomson et al., 2006), as well as on mechanistic understandings of the ecosystem functions that are hard to be tested with field methods (Schimel et al., 1996; Miao et al., 2011).

In general, there have been limited testing and validation of the ecosystem models on both energy partitioning and carbon turnover aspects with long term fluxes and biometric data, which is necessary for quantifying the model uncertainty under a variety of management practices, crop cultivars, local climate and soil conditions. In this study, a terrestrial ecosystem model, which is called as the vegetation–atmosphere interface processes (VIP) model is updated from its previous versions (Mo and Liu, 2001; Mo et al., 2005) to its new version for the simulation of water vapor, energy and CO₂ fluxes between the ecosystem and the atmosphere. In the new version, the heat storage terms of vegetation and surface soil layer are accounted for in the prognostic equations of canopy and soil surface energy balances. Also, water stress on stomatal conductance is related with leaf water potential which indicates the competing demand of water vapor from the atmosphere and supply of water to leaves by the soil via the roots and xylem. A soil organic matter decomposition component is developed and the crop growth module is improved. For model evaluation and uncertainty analysis purposes, eddy-covariance fluxes and biometric measurements are used, which were collected over a winter wheat (*Triticum aestivum* L.)–summer maize (*Zea mays* L.) double cropping field from 2003 to 2005 in the North China Plain by China Ecosystem Research Network (CERN).

In addition to testing the model capacity for tracing the rapid exchange of energy, water and CO₂ over the crop growing periods, the predictions of phenological development, carbon accumulation and soil moisture are also evaluated. Given the large number of input parameters of the model, sensitivity experiments are conducted to determine the key parameters and the effects of their uncertainties on the predicted fluxes.

2. Model description

In the original VIP model, energy partitioning, photosynthesis and soil hydrothermal processes are the mainly concerns, in which

crop growth is simplified as an accumulation process of net photosynthesis production with prescribed leaf area index. In the present version of the VIP model, both vegetation dynamics and soil organic matter decomposition processes are coupled to the early model version. The prognostic scheme for soil moisture is based on Richards equation and temperature on thermal diffusion equation, in which soil root zone is divided into six layers. Here only a brief description is given of the main assumptions and equations used in the new version. For the early version of the model, details can be found in Mo and Liu (2001).

2.1. Energy transfer

The irradiative energy absorbed by soil–canopy system is partitioned into turbulent and storage energy. The later consists of energy fixed by photosynthesis and heat stored in biomass and ground. Individually, the storage terms are generally a small fraction of net radiation. However the total heat storages in canopy and soil layer above the heat flux plates may comprise roughly 10% of the total available energy during the morning times under fully developed crop canopy (Meyers and Hollinger, 2004). By considering terms of storage energy in canopy biomass and soil surface layer, the energy budgets of canopy and soil surface are calculated with the following prognostic equations (Sellers et al., 1986; Acs, 1994), respectively,

$$C_v \frac{\partial T_v}{\partial t} = R_{nv} - H_v - LE_v \quad (1)$$

$$C_{g1} \frac{\partial T_g}{\partial t} = R_{ng} - H_g - LE_g - G \quad (2)$$

where the left terms in Eqs. (1) and (2) are respectively referred to as the terms of heat storage in canopy biomass and soil layer above the heat flux plates; C_v is the bulk heat capacity per unit area of canopy ($J m^{-2} K^{-1}$); C_{g1} is the bulk heat capacity per unit area of the upper soil layer ($J m^{-2} K^{-1}$), T_v is the canopy temperature (K), T_g is the soil surface temperature (K); R_n , LE and H are the net radiation, latent and sensible heat fluxes ($W m^{-2}$), with subscripts v and g referring to canopy and ground respectively; G is the soil heat flux ($W m^{-2}$), t is the time (s).

2.2. Carbon assimilation

Generally, photosynthetic rates of canopy leaves respond to irradiance in a nonlinear way. While photosynthesis in a sunfleck has been light saturated, photosynthesis of shaded leaves is still increasing with irradiance. It is reasonable and effective to simplify the canopy leaves into two classes, namely the sunlit and shaded for photosynthesis estimation at canopy scale (De Pury and Farquhar, 1997; Wang and Leuning, 1998). To account for the light extinction in a canopy, a multilayer scheme for both sunlit and shaded groups is developed to upscale the leaf photosynthesis to the whole canopy (Mo and Beven, 2004).

The scheme of C₃ and C₄ plant photosynthetic rates followed Farquhar et al. (1980) and Collatz et al. (1991, 1992). For both sunlit and shaded leaves, assimilation rates are limited by the efficiency of the photosynthetic enzyme system (Rubisco-limited), the amount of PAR captured by leaf chlorophyll, and the capacity of leaf to export (for C₃ crop) or PEP-carboxylase limitation (for C₄ species). The CO₂ assimilation rate, A_n ($\mu mol CO_2 m^{-2} s^{-1}$), for both C₃ and C₄ leaves is expressed as

$$A_n = \min(A_v, A_e, A_s) - R_d \quad (3)$$

where A_v , A_e and A_s , all in the unit of $\mu mol CO_2 m^{-2} s^{-1}$ are the Rubisco limited, potential electron transport limited, and export limited rate

of carboxylation (for C_3 crop) or the PEP-carboxylase limited rates of carboxylation (for C_4 crop), respectively; R_d is the dark respiration ($\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$). A_w , A_e and A_s are estimated according to Mo and Beven (2004) for C_3 and Collatz et al. (1992) for C_4 species.

A_v is calculated as,

$$A_v = V_{\text{cmax}} \frac{c_i - \Gamma}{c_i + K_c(1 + o_i/K_o)} \quad (C_3) \quad (4)$$

$$A_v = V_{\text{cmax}} \quad (C_4) \quad (5)$$

A_e is calculated as,

$$A_e = \frac{J}{4} \frac{c_i - \Gamma}{c_i + 2\Gamma} \quad (C_3) \quad (6)$$

$$A_e = \varepsilon Q_{\text{par}} \quad (C_4) \quad (7)$$

A_s is calculated as,

$$A_s = 0.5V_{\text{cmax}} \quad (C_3) \quad (8)$$

$$A_s = 1.8 \times 10^4 V_{\text{cmax}} \frac{c_i}{p_{\text{atm}}} \quad (C_4) \quad (9)$$

where V_{cmax} ($\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$) is the maximum catalytic activity of Rubisco; J is the electron transport rate ($\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$); c_i and o_i represent respectively the intercellular CO_2 and O_2 concentration (Pa) in the chloroplasts; K_c and K_o are the Michaelis–Menten coefficient (Pa) for CO_2 and O_2 , respectively; Γ is the CO_2 compensation point (Pa); ε is the intrinsic quantum efficiency ($\mu\text{mol CO}_2 \mu\text{mol}^{-1} \text{ Photons}$); Q_{par} is the absorbed photosynthetically active radiation ($\mu\text{mol photons m}^{-2} \text{ s}^{-1}$); p_{atm} is the atmospheric pressure (Pa).

Leaf stomatal conductance is related to assimilation rate that accounts for the effects of CO_2 concentration and relative humidity or vapor pressure deficit at leaf surface (Ball et al., 1987; Leuning, 1995) for the estimation of latent and sensible heat fluxes. In order to reliably calculate the stomatal conductance, the interactions among photosynthesis, transpiration and plant hydraulics are included, which regulate the supply and the demand of water in the soil–vegetation–atmosphere continuum. Since leaf water potential is mechanically linked to soil water potential in the root zone by the water flux across hydraulic resistance in the stem xylem and status of the stomatal guard cells, it is taken as an indicator accounting for water stress in stomatal functioning. It is reported that stomatal conductance is controlled by water potential at leaf epidermis (De Ridder and Schayes, 1997; Katul et al., 2003; Tuzet et al., 2003), which reflects the effects of supply and demand for water at the evaporating sites on guard cells and epidermal turgor. That using leaf water potential may remove the explicit dependence of stomatal conductance on atmospheric humidity and soil moisture. Hence, the following relationship between the stomatal conductance for CO_2 , g_s ($\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$), and the assimilation rate is adopted, based on De Ridder and Schayes (1997) and Katul et al. (2003),

$$g_s = m \frac{A_n p_{\text{atm}}}{c_s} \left(1 - \frac{\psi_v}{\psi_c}\right) \quad (10)$$

where c_s is the CO_2 concentration at the leaf surface (Pa); ψ_v is the leaf water potential (m); ψ_c is the critical water potential at which total stomatal closure occurs (-250 m); m is the dimensionless empirical coefficient.

Soil resistance for water vapor diffusion from soil pores to the above near surface air is parameterized using the relationship of Sellers et al. (1992),

$$r_s = \exp\left(a - b \frac{\vartheta_1}{\vartheta_s}\right) \quad (11)$$

where r_s is the soil resistance (s m^{-1}); ϑ_1 , ϑ_s are the surface (2 cm) and its saturated moisture content ($\text{m}^3 \text{ m}^{-3}$), respectively; a and b are the dimensionless empirical coefficients.

2.3. Decomposition and respiration of soil organic matter

Following the organic carbon pool concept in Century model (Parton et al., 1987), crop litter and soil organic matter are split into eight compartments (e.g., surface structural litter, surface metabolic litter, soil structural litter, soil metabolic litter, surface microbe, soil microbe, slow humus and passive or inertial humus).

Heterotrophic respiration, R_h ($\text{gC m}^{-2} \text{ s}^{-1}$), stems from four litter compartments and four soil carbon compartments, i.e.

$$R_h = \sum_{j=1}^8 \tau_j \kappa_j C_j \quad (12)$$

where τ_j is the respiration coefficient (gC gC^{-1}) which equals to the percentage of decomposed carbon released to the atmosphere; κ_j is the decomposition rate (d^{-1}) of a carbon compartment, affected by several environmental and biochemical factors, such as temperature, moisture, lignin fraction and soil texture; C_j is the carbon pool size (gC m^{-2}). The respiration fractions in turnover processes of the compartments are adopted from Parton et al. (1993) and Izaurralde et al. (2006).

2.4. Crop dynamics

The evolutions of foliage, stem, root biomass and leaf area index (LAI) are expressed as,

$$\frac{dM_i}{dt_d} = a_i P_g - R_{g,i} - R_{m,i} - D_i \quad (13)$$

$$\text{LAI} = S_{\text{LA}} M_l \quad (14)$$

where M_i is the biomass of vegetation compartment (gC m^{-2}) and subscript $i = l, s, r, g$ represents the foliage, stem, root and grain biomass of the crop, respectively; P_g is the daily gross primary production ($\text{gC m}^{-2} \text{ d}^{-1}$) derived via accumulation of net assimilation; a_i is the allocation coefficient (dimensionless); R_m and R_g are the maintenance and growth respiration rates respectively ($\text{gC m}^{-2} \text{ d}^{-1}$); D is the senescent rate ($\text{gC m}^{-2} \text{ d}^{-1}$); t_d is the time (d); S_{LA} is the leaf specific area ($\text{m}^2 \text{ gC}^{-1}$).

The above allocation coefficients depend on plant functional type and phenological properties. They are also regulated by the availability of soil moisture and light in canopy. It is assumed that photosynthetic product is preferentially used to expand the leaf area in the vegetative period, so the allocation coefficient of leaf with exponential form is adopted from Ji (1995) and Dickinson et al. (1998); coefficients to stem and root are expressed respectively as (Arora et al., 2005),

$$a_l = \exp(-k_c \text{LAI}) \quad (15)$$

$$a_r = \frac{B_p + P_w(1 - W)}{1 + P_w(1 - W)} (1 - a_l) \quad (16)$$

$$a_s = 1 - a_r - a_l \quad (17)$$

where k_c is an empirical coefficient; B_p and P_w are the empirical coefficients, W is the factor representing the availability of soil moisture in root zone. These four coefficients are all dimensionless.

The allocation coefficient of grain (a_g) is linearly related to the index of crop developmental stage represented as growing degree days (GDD) after flowering (Li et al., 2009).

Growth respiration is set as 0.25 of the gross photosynthesis (Ruimy et al., 1996; Nouvellon et al., 2000; Montaldo et al., 2005).

The maintenance respiration is estimated on the basis of a specified respiration rate β , which is taken as $0.3 \text{ kg C kg N}^{-1} \text{ d}^{-1}$ and a Q_{10} temperature function (Tjoelker et al., 2001),

$$R_{m,i} = \beta \frac{M_i}{\text{cn}_i} (3.22 - 0.046T_v)^{(T_v-20)/10} \quad (18)$$

where cn_i is the C:N ratio of the plant compartments. Eq. (13) is rearranged with Eq. (18) for M_i calculation.

Under chilling or water stress conditions and late stage of crop growth, the leaves will senesce gradually. The senescence of crop leaves attributed to life expectation occurs after flowering stage. The senescent rate is expressed as an exponential function,

$$D_i = \alpha \exp(\eta(v_s - 1)) \quad (19)$$

where D is the death rate of leaves ($\text{gCm}^{-2} \text{ d}^{-1}$); α and η are the empirical constants fitted by the observed data; v_s , which ranges from 0 to 2, is the index of crop developmental stage depending on the sum of daily temperature above 0°C and daylight length, or GDD. Here v_s is divided into two periods, namely from the seedling to flowering (0–1) and from the flowering to maturity (1–2).

2.5. Net ecosystem production (NEP)

The net ecosystem production, NEP ($\text{gC m}^{-2} \text{ s}^{-1}$), is the difference between net photosynthesis and ecosystem respiration which is split as autotrophic and heterotrophic respirations, namely,

$$\text{NEP} = A_n - R_a - R_h \quad (20)$$

where R_a is the autotrophic respiration, consisting of growth and maintenance respirations. At the daily or larger time scale, units of the variables in the right hand of Eq. (20) are converted from $\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$ to $\text{gC m}^{-2} \text{ d}^{-1}$ or $\text{gC m}^{-2} \text{ yr}^{-1}$.

3. Site and data

3.1. Site

The study site is located at Yucheng agro-ecosystem experimental station ($115^\circ 53' \text{E}$, $37^\circ 41' \text{N}$) in the North China Plain formed by alluvial sediment. It belongs to sub-humid warm temperate and monsoon climate zone with 70% precipitation occurring in summer. The soil texture is classified as silty loam with granular structure. Total soil organic content is 1.21% and the soil bulk density in root layer is 1.3 g cm^{-3} . Crop production is a winter wheat–summer maize double cropping system, in which winter wheat is sown in early October and harvested in early June next year, thereafter summer maize is planted, which grows in summer and is generally harvested at the end of September.

3.2. Data

The field measurements in this study were conducted from 2002 to 2005 by China-Flux of CERN (Chinese Ecosystem Research Network) during winter wheat and summer maize growing season. Wheat is irrigated 2–3 times with 70 mm each, whereas no irrigation is applied to maize. A flux tower with a fetch more than 500 m was established to continuously monitor the atmospheric variables and turbulent fluxes at a half-hourly interval. The

monitoring equipments were installed 2 m above the crop canopy. In the eddy-covariance system, air temperature and relative humidity were measured with HMP45C (Vector, Instruments, Denbighshire, UK), wind speed and direction with cup anemometer and wind vane (models A100R and W200P, Vector Instruments, Denbighshire, UK). Global and reflected shortwave radiation (CM11, Kipp & Zonen, NL), net radiation (CNR-1, Kipp & Zonen, NL) and soil heat flux with two flats (HFP01, Hukseflux) at 5 cm depth were also measured. Turbulent fluxes of CO_2 , latent and sensible heat fluxes were measured by the eddy-covariance system, in which CO_2 and water vapor fluxes were gathered with an open-path $\text{CO}_2/\text{H}_2\text{O}$ gas analyzer (Li-7500, Li-COR, USA), and wind and temperature variances were also recorded at the same height with a sonic anemometer (CSAT-3, Campbell Scientific Inc., Logan, UT, USA) at 20 Hz sampling rate.

Periodic soil moisture was measured in the profile of 0–200 cm with neutron probes. From planting to harvest, above ground biomasses of different components (leaf, stem and ear) and leaf area (Leaf area analyzer, Li-Cor Inc., USA) on $0.25 \times 0.25 \text{ m}^2$ plots were measured every 10 days.

3.3. Flux data quality and uncertainty

The turbulent fluxes have been processed with the WPL correction (Webb et al., 1980). Only the short data gaps of turbulent fluxes up to 3–4 h are filled by the linear interpolation. The longer gaps (a few days long) of global radiation and atmospheric variables are filled with data from the nearby automatic weather station. The quality of flux data is usually evaluated with the “goodness” of energy balance closure. Here half-hourly measurements of $R_n - G$ (net radiation minus ground heat fluxes) against $\text{LE} + H$ (latent plus sensible turbulent fluxes) are plotted, that for 2003 is shown in Fig. 1. From 2003 to 2005, the slopes of regression lines are 0.77, 0.75, 0.64, the intercepts are 10.0, 6.6 and 12.2 W m^{-2} and the correlation coefficients are 0.91, 0.84 and 0.66, respectively. The above slope values explicit that the actual turbulent fluxes may have been 23, 25 and 36% larger than those measured in the respective years. It is considered that uncertainty in the measured fluxes may be attributed to gap filling, lack of energy closure, as well as flux underestimation during weak turbulence conditions (Wilson et al., 2002; Baldocchi, 2003; Anthoni et al., 2004). In addition, advection may be another source of errors in eddy-covariance fluxes. It is found that daytime NEP is still positive even

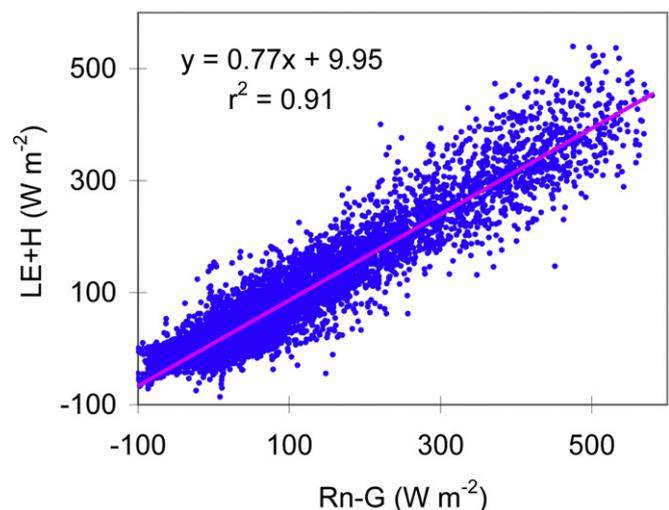


Fig. 1. Eddy-covariance fluxes closure between $R_n - G$ and $\text{LE} + H$ in 2003.

just after winter wheat is harvested, which very possibly is coming from up levee where other crops and windbreak trees are growing.

4. Model initialization and parameters

The simulated period is from Oct. 1st, 2002 to Dec. 31st, 2005 and the time step is set as 30 min. Half-hourly averaged meteorological observations are used to drive the model, which include air pressure, temperature, water vapor pressure, wind speed, precipitation, downward short and long wave radiation.

At present, no daily measurements of CO₂ concentration are available at Yucheng Station. According to the reported measurements of atmospheric CO₂ concentration above the vegetative surface (e.g., Wang et al., 2007; Zhang et al., 2008), its diurnal amplitude is around 20–30 ppm under clear sky during the growing season. With this amplitude of CO₂ concentration variation, the simulation of our model shows that the resulted change of NPP is about 2–3%, negligible at seasonal scale. Based on this analysis, free-air CO₂ concentrations are thus set as 375, 377 and 379 ppm for 2003, 2004 and 2005 for the study region respectively, referring to measurements at Mauna Loa in Hawaii as the global background. Under the same situation of the data scarce, Kothavala et al. (2005) and Kucharik and Twine (2007) also set a fixed value for their simulations. We use a gradual increasing value for each of the three years by matching the gradual annual increments observed at Mauna Loa in Hawaii.

Winter wheat is sown while daily mean air temperature is continuously lower than 18 °C for three days, whereas summer maize is set to be sown on the third day after wheat is harvested. It is assumed that there is not nutrition limitation for both wheat and maize, as sufficient synthetic fertilizers are supplied in due dates. Irrigation is supplied two to three times in the wheat growing period with an amount of 70 mm around each time. Additionally, distinctions in planting density and row spacing are not accounted for in the model. Removal of grain and leaving behind plant residue biomass in the field occur at the harvest dates. The model simulation is executed continuously to represent winter wheat–summer maize rotation and its impact on soil moisture and biogeochemistry, in which the initial soil carbon pools are derived with 50 year-running with historical climatic data. The key parameters for winter wheat and summer maize are provided in Table 1.

5. Model evaluation

5.1. Seasonal patterns of LAI and biomass

The simulated LAI series of winter wheat and summer maize are evaluated with field measurements during the crop growing periods from 2003 to 2005. As shown in Fig. 2a, the model can successfully capture the seasonal LAI patterns of both winter wheat and summer maize, including the rapid expansion in the vegetative stage and the senescent period after flowering. The differences between the simulated and the observed maximum LAI are within 10% of the observed values except for wheat in 2004. The model can explain 84% of the LAI variance with root mean square error (RMSE) of 0.75, close to the general standard deviation of crop LAI measurements (about 0.5). For example, Pauwels et al. (2007) reported RMSE values between the simulated and the observed LAI are ranged from 0.27 to 1.09 in 18 fields. The maximum LAI of wheat canopy in 2004 is a bit higher than that in the other two years, probably resulted from biases in plant density measurements. As the leaf duration of wheat is regulated by the senescent rate in chilling winter, and the re-vegetative starting date in spring, as well as the parameters related to senescent rate in the late growing stage, the accuracy of LAI estimates is determined by these parameters.

Table 1

The main eco-physiological and soil physical parameters in the VIP model.

Description	Symbol	Wheat	Maize
Maximum carboxylation capacity, ($\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$)	V_{cmax}	85	50
$J_{\text{max}}/V_{\text{cmax}}$		2	
Stomatal conductance coefficient	m	9	3
Quantum yield	ϵ	0.385	0.060
C:N of leaf	cn_l	30	30
C:N of stem	cn_s	40	40
C:N of root	cn_r	30	30
C:N of grain	cn_g	30	30
*Field capacity (m^3/m^3)	θ_f	0.255	0.255
Saturation (m^3/m^3)	θ_s	0.485	0.485
*Saturated hydraulic conductivity (cm/s)	K_{sat}	$7.2\text{e}-4$	$7.2\text{e}-4$
GDD from seeding to seedling ($^\circ\text{C}$)	GDD_0	110	100
GDD from seedling to flowering ($^\circ\text{C}$)	GDD_1	1050	1300
GDD from flowering to maturity ($^\circ\text{C}$)	GDD_2	950	1200
Specific leaf area ($\text{m}^2 \text{ g C}^{-1}$)	S_{LA}	0.055	0.05
*Fraction of lignin to nitrogen in litter	CN	18	18
Decomposition rate of structural litter at 30 °C (d^{-1})	k_1	0.0107	0.0107
Decomposition rate of metabolic litter at 30 °C (d^{-1})	k_2	0.0405	0.0405
Decomposition rate of slow humus at 30 °C (d^{-1})	K_7	0.0005	0.0005
Decomposition rate of inertial humus at 30 °C (d^{-1})	K_8	0.000012	0.000012
Empirical constant in soil resistance scheme	a	8.2	8.2
Empirical constant in soil resistance scheme	b	4.255	4.255
*Wind extinction coefficient in canopy	α_w	2	2

Note: those parameters marked with * were used in the model, but not mentioned in the text in this paper.

The simulated above ground biomass traces the measured quite well from 2003 to 2005 (Fig. 2b). The correlation coefficient (r^2) is 0.92 and RMSE is 160 g DM m^{-2} (DM is dry mass) between the simulated and the measured above ground biomass. Relative biases

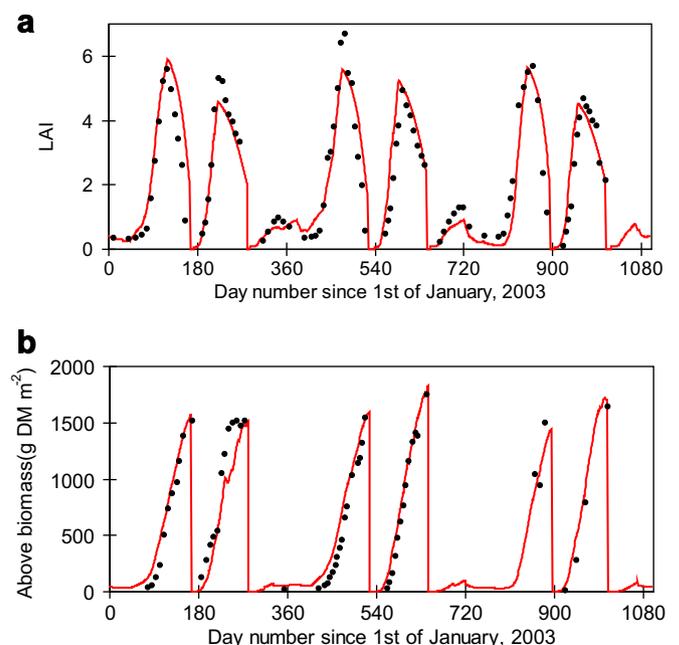


Fig. 2. The simulated and the measured leaf area index (a) and above biomass (b) during 2003–2005.

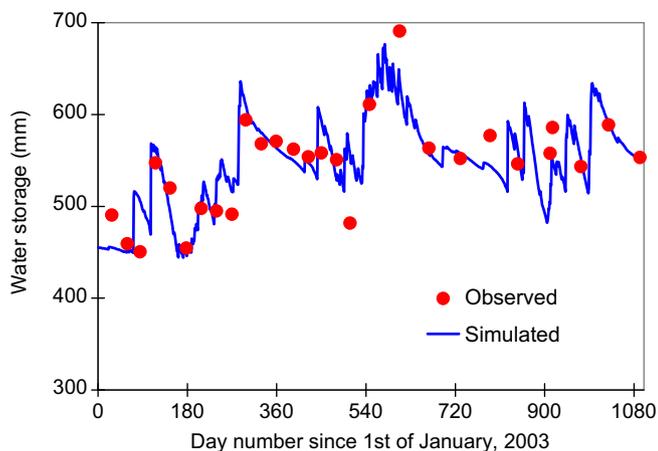


Fig. 3. The simulated and the measured soil water storage in 0–150 cm profile during 2003–2005.

of the above ground biomass at harvest stage between the simulated and the measured are less than 6%. Comparing Fig. 2a with Fig. 2b, it can be seen that the agreement of biomass is a bit higher than that of LAI. The predicted fraction of root to above ground biomass is around 13–15% at the harvest time, which is in consistent with the field measurements (10–15%) (Zhang, 1999).

5.2. Seasonal variation of soil moisture

Soil moisture is a key regulator of evapotranspiration, carbon assimilation and soil respiration. The predicted moisture is validated with the measured water storage within 0–150 cm profile (Fig. 3). Over the simulated period, the observed mean storage is 543 ± 63 mm. It is shown that the simulated water storages coincide with the measurements quite well ($r^2 = 0.69$ and $RMSE = 29$ mm). Since the groundwater level is fluctuating around 1.5–3 m in response to precipitation/irrigation and evapotranspiration at the study site, soil moisture content is quite high in the profile underneath the plowing pan (about 0.5 m under land surface) and the drainage from the bottom boundary (2 m) is weak. Hence, crop water uptake and soil surface evaporation are the dominant ways of the depletion of soil moisture.

5.3. Energy balance

5.3.1. Half-hourly time scale

Half-hourly energy fluxes of net radiation (R_n), latent heat (LE), sensible heat (H) and soil heat (G) are employed to validate the model predictions. Regressive results are listed in Table 2, including Pearson correlation coefficient (r^2), slope of best linear fit (a , slope), intercept (b) and root mean square error (RMSE). It is seen that net radiation is predicted quite satisfactorily. For the heat components,

the agreements of LE are obviously better than H and G , and vary slightly in different years. Since soil moisture in root zone is always sufficient for transpiring demand due to irrigation, latent heat flux is the dominant component of energy balance and the evaporative fraction of available energy is quite steady during daytime, resulting in LE patterns to be traced more easily. However, as sensible heat flux is usually low and fluctuates irregularly over the canopy, it is usually less efficient to capture its variation. The model efficiencies of H prediction are better in 2003 and 2004 than 2005, corresponding to a higher energy balance closure error in 2005. The lower agreement of G is possibly caused by the heterogeneity of soil heat flux, being related to such factors as canopy shading, soil texture and soil–canopy interactions.

Fig. 4 presents the averaged monthly composite diurnal variations for energy budget components. For all the three years, the simulated R_n captures the diurnal processes quite well in most months; however R_n is underestimated in several months with the maximum bias of 50 W m^{-2} at noon. The simulated LE also captures the diurnal processes quite well, except some obvious over-estimation in June of 2003 and 2005 when wheat is harvested and soil surface is covered by residues. For H and G , agreements between the simulated and the observed are not as satisfactory as LE. This kind of situation is also reported by Baker et al. (2003), in which the modeled H is generally larger than the observed values between 8:00 and 12:00 in the morning by 85–100% and more than 40% in the afternoon. The model underestimates the quite negative values of H at night in both July and August of 2004 and 2005, in which the turbulent fluxes from eddy covariance are nearly 40% less than the available energy, approximately equaling to the predicted biases. Hence it is very possible that the measuring errors are more related to sensible heat flux while turbulence is weak. For ground heat flux, it is reasonably estimated at daytime, except the first three months in each year when the measured G values are high, whereas the simulated values of G flux are noticeably lower than the measured at night. Bearing in mind that the measured G flux is sampled at 5 cm below ground surface, its diurnal amplitude should be smaller than that at soil surface due to soil heat storage above the heat flux plates. At the study site, from our calculation the heat storage can be as high as 30 W m^{-2} at noon. It is found that ground heat flux is the key energy budget component at the soil surface, while turbulence is suppressed under stable atmospheric condition. The biases between the simulated and the measured energy fluxes may be partly attributed to the overall energy imbalance of eddy-covariance flux measurements (i.e., the difference between R_n and the sum of H , LE and G) that is about -15% of yearly summation of net radiation. Overall, the agreements of sensible and soil heat fluxes are acceptable, compared with other reports (e.g. Hanan et al., 2005; Kothavala et al., 2005; Kucharik and Twine, 2007; Casanova and Judge, 2008), for example, Kucharik and Twine (2007) presented that the simulated error of H is around 60.3–81.6% in three sites over a three-year period; Casanova and Judge (2008) showed RMSE of $46\text{--}62 \text{ W m}^{-2}$ for heat fluxes between the simulated and the observed values.

Table 2
Regression results between the measured and the simulated half-hourly fluxes during 2003–2005 (best fit linear equation: $Y_{\text{obs}} = aX_{\text{sim}} + b$; unit: R_n , LE, H and G : W m^{-2} ; NEP: $\mu\text{mol C m}^{-2} \text{ s}^{-1}$).

	2003						2004						2005					
	Y_{obs}	X_{sim}	r^2	a	b	RMSE	Y_{obs}	X_{sim}	r^2	a	b	RMSE	Y_{obs}	X_{sim}	r^2	a	b	RMSE
R_n	55.87	56.03	0.98	0.95	3.81	21.1	65.96	65.21	0.98	0.99	0.82	24.3	73.17	71.89	0.98	0.99	2.68	24.2
LE	37.23	43.00	0.82	1.00	5.78	34.4	45.36	53.86	0.84	0.99	9.10	36.1	50.69	55.3	0.70	0.86	11.69	50.6
H	15.64	21.2	0.64	0.98	5.83	33.2	8.90	20.19	0.60	0.92	12.09	41.5	6.56	23.21	0.30	0.60	19.27	68.4
G	0.42	-7.01	0.35	0.74	-8.83	37.1	3.067	-8.4	0.40	0.73	10.82	48.2	2.87	-6.29	0.41	0.81	-8.73	52.3
NEP	0.99	1.11	0.76	1.13	0.03	5.7	1.85	1.92	0.77	1.14	-0.20	6.1	2.28	1.59	0.65	0.84	-0.33	7.2

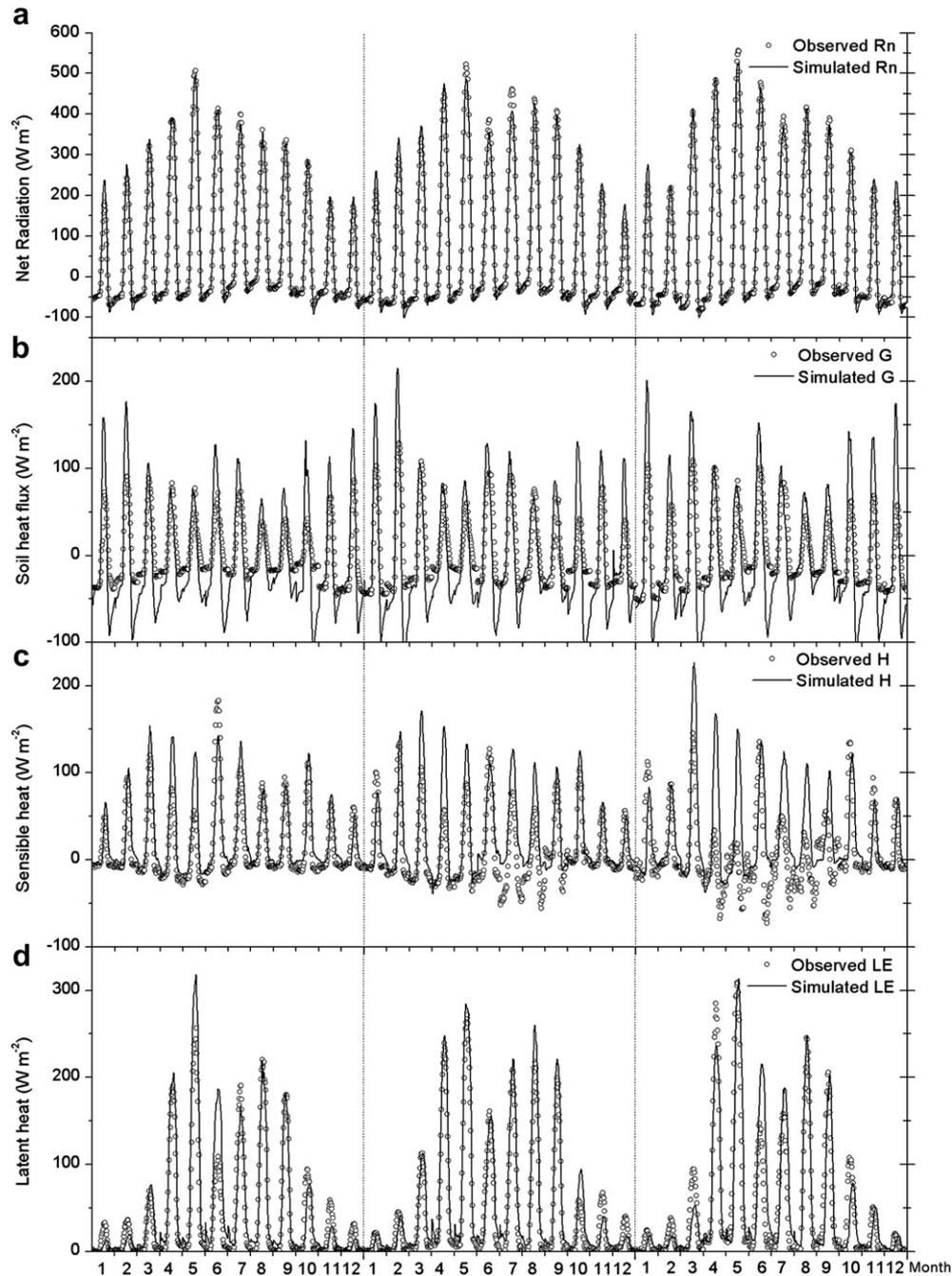


Fig. 4. Monthly diurnal composites of the modeled and the observed net radiation (R_n), soil heat (G), sensible heat (H) and latent heat (LE) fluxes during the years 2003–2005.

5.3.2. Daily time scale and seasonal pattern

Seasonal variations of daily energy budgets are presented in Fig. 5a–d. At daily scale, the agreements of R_n and LE between the simulated and the measured are quite good with correlation coefficients (r^2) of 0.96 and 0.83, and RMSE values of 1.0 and $1.8 \text{ MJ m}^{-2} \text{ d}^{-1}$ respectively. Annually, the relative error of R_n is about 5%. The noticeable biases of R_n are seen in June when wheat is harvested and maize is sown afterward. At this period, land surface is dominated by residues that significantly alter its albedo and thermal properties, consequently changing the energy partitioning. It is seen from Fig. 5b that there are two peaks of latent heat flux in wheat–maize double cropping field at annual scale, occurring respectively in May and August with fully developed canopies;

whereas high sensible heat flux is seen in June with sparse crop covers (Fig. 5c). It is demonstrated that the model is able to trace the seasonal evapotranspiration process quite well. The fractions of annual water amount consumed by wheat and maize are about 55 and 45%, respectively, indicating more water consumed by wheat with 60% through transpiration. At daily scale, the amounts of H and G are similar, most of which are ranging from -5 to $5 \text{ MJ m}^{-2} \text{ d}^{-1}$ (Fig. 5c, d). At daily scale, the model can only explain 27% of the observed H variance in the simulated period. The lower agreements of daily H and G fluxes may be attributed to offset of daytime and nighttime values. In summer time, systematic errors in sensible heat flux estimates are identified with daily sensible heat flux being negative due to the horizontal advection.

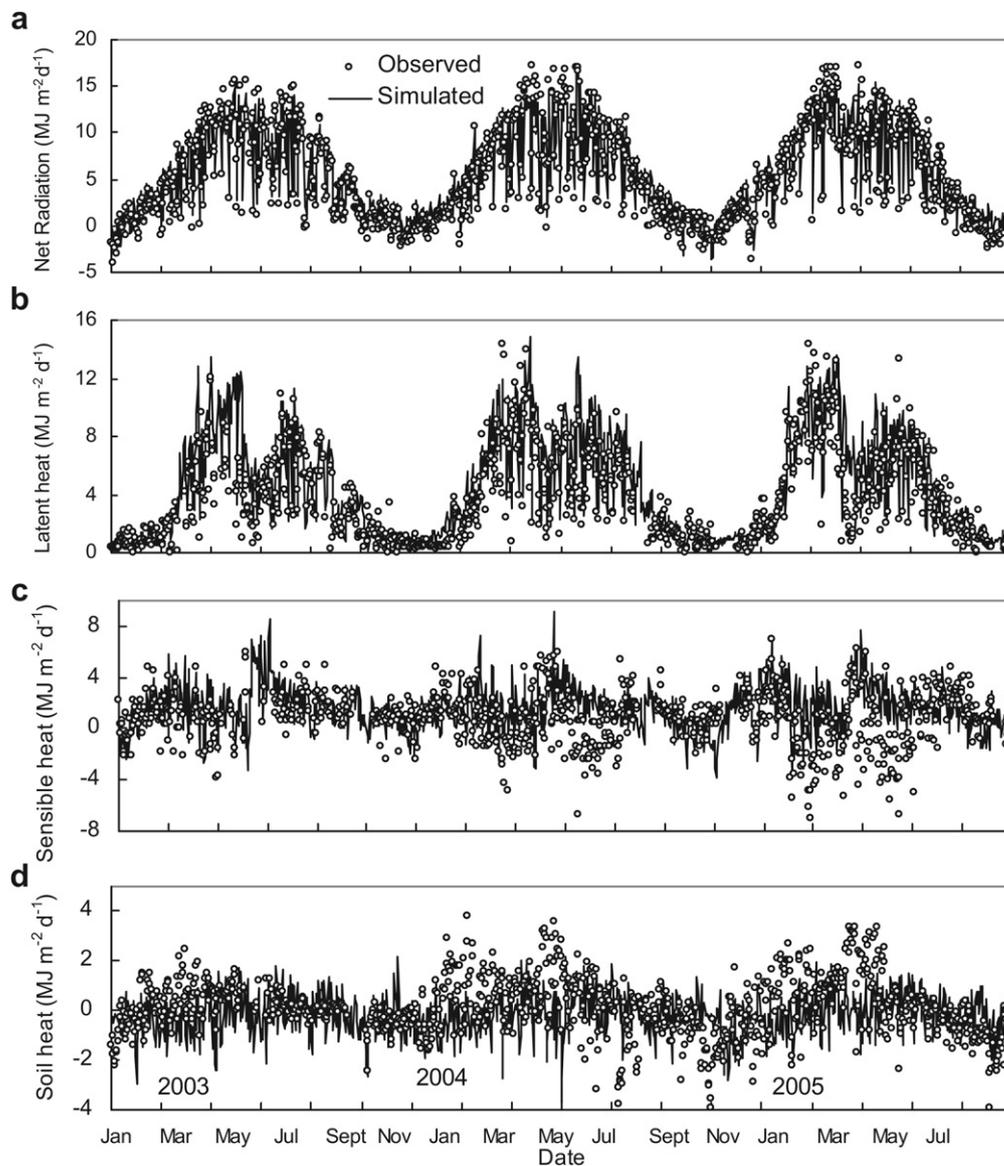


Fig. 5. Daily net radiation, latent heat, sensible heat and soil heat fluxes of eddy-covariance technique and the simulated during 2003–2005.

5.4. Net ecosystem productivity (NEP)

5.4.1. Half-hourly time scale

As shown in Table 2, the model can explain 76, 77 and 65% of the observed half-hourly NEP variances respectively in the three years. The NEP is overestimated in 2003 and 2004 respectively, whereas it is underestimated in 2005. As shown in Fig. 6, the model performs well in tracing the diurnal variation with carbon sequestering at daytime and releasing at nighttime, with a Pearson correlation coefficient of 0.91 in the study period. In the wintertime the average diurnal variation is quite small, when both leave photosynthesis and soil heterotrophic respiration are inhibited by low temperature. In March, as winter wheat is re-vegetative under warming weather, NEP arises above zero in the daytime with a peak value of $5 \mu\text{mol C m}^{-2} \text{s}^{-1}$ at noon. Then in April and May the most rapid growth of wheat occurs with the maximum NEP of $25 \mu\text{mol C m}^{-2} \text{s}^{-1}$, and the ecosystem respiration is also greatly intensified with a peak value of $5 \mu\text{mol C m}^{-2} \text{s}^{-1}$ at night. Thereafter, leaves senescence commences, and wheat grain reaches maturity in early June. The estimates of heterotrophic respiration

are a bit higher than the measurements in June, which may be relevant with the assumption of all plant residues being left in the field. The maize grows quickly in July–September with the maximum carbon assimilation rate of $35 \mu\text{mol C m}^{-2} \text{s}^{-1}$ at noon. After maize is harvested and wheat is sown, NEP is decreased with temperature declining.

5.4.2. Daily time scale and seasonal pattern

The seasonal pattern of daily NEP is consistent with wheat–maize rotation cropping, as shown in Fig. 7. The model can explain 69% of the measured NEP variance at daily scale with the best fit slope of 1.04 and RMSE of $2.6 \text{ gC m}^{-2} \text{ d}^{-1}$. It is confirmed that net CO_2 uptake is concentrated on the periods of maximal leaf area and physiological activity for both wheat and maize; whereas net CO_2 release is concentrated on the periods when crops are harvested and following crops are in seedling stage. The maximum daily NEP values are close to $10 \text{ gC m}^{-2} \text{ d}^{-1}$ and $15 \text{ gC m}^{-2} \text{ d}^{-1}$ for wheat and maize growth periods, respectively. The daily variation in maize growing period is more obvious than that of wheat, owing to the more cloudy or rainy weather conditions in the summer monsoon period.

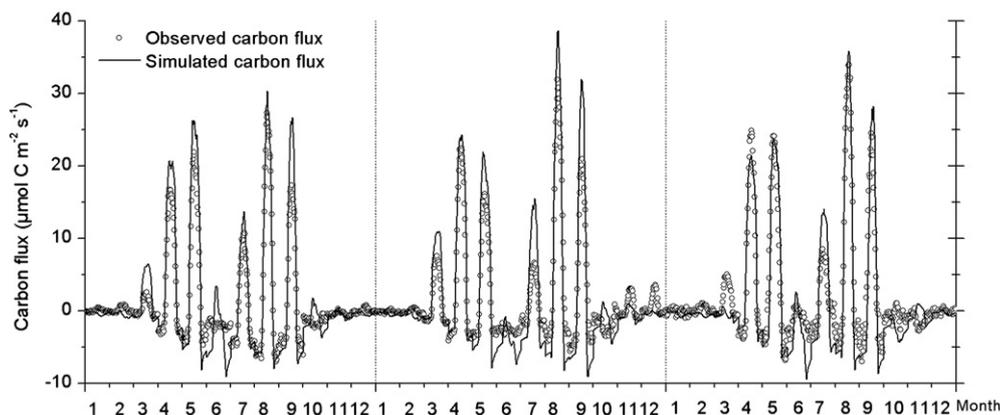


Fig. 6. Monthly diurnal composites of the modeled and the observed net ecosystem production (NEP) during 2003–2005.

There are 115 missing days in the observed daily NEP series from 2003 to 2005. In order to estimate the annual carbon budget, the missed data are replaced with the simulated values. The measured annual NEP values are 480, 624 and 750 $\text{gC m}^{-2} \text{yr}^{-1}$ and the biases of prediction are 18, 9 and -29% respectively from 2003 to 2005. These biases are reasonable, considering 30% uncertainty in eddy-covariance measurements of annual NEP (Anthoni et al., 2004). Simulation results present that the soil humus, which is the summation of slow and passive humus components, is increasing at a rate about $74 \text{gC m}^{-2} \text{yr}^{-1}$. The heterotrophic respiration consists of 25% gross primary production (GPP, or the summation of P_g over a year). The ratio of ecosystem respiration to gross primary production (GPP) is 0.80 and that of yearly NEP to NPP (the difference between GPP and the summation of R_a) is 0.44 at the study site.

6. Effect of parameter uncertainty on the predicted fluxes

Though the simulated energy fluxes and NEP are quite close to the observations at half hourly and daily scales, the deviations are still significant in some periods. They may be related to errors of both the observation and the model. As we know, the eddy-covariance technique does not always achieve energy budget closure, as reported by Wilson et al. (2002), although it can be adjusted to force energy closure by partitioning the energy imbalance into LE and H according to their observed ratios (Kucharik

et al., 2006). Except for the observational errors, there are also errors in model parameters and forcing variables, and inadequate representation of physical processes at appropriate temporal and spatial scales. Usually the model error is attributed to parameter uncertainty in the analysis of model sensitivity. Below three methods were used to analyze the effect of parameter uncertainty on the predicted fluxes.

6.1. By the method of mono-factor analysis

The key parameters directly related to processes of photosynthesis, energy partitioning and soil moisture movement in Table 1 are selected to conduct the sensitivity analysis by the method of mono-factor analysis. For the convenience, the changes of the parameters of maintenance respiration (cn_1 , cn_s , cn_r , cn_g) are represented as the change of one working parameter C_{Rm} , which is a unified adjusting ratio, or multiplier, to all the parameters of maintenance respiration. Similarly, the changes of the parameters of heterotrophic respiration are represented as the change of one working parameter C_{Rh} , which is also a unified adjusting ratio, or multiplier, to all the parameters of heterotrophic respiration.

These parameters are systematically increased or decreased by 10% of their reference values to diagnose the responses of model outputs. Surely the uncertainty of these parameters may be more than this range. The parameters that result in more than 1% change

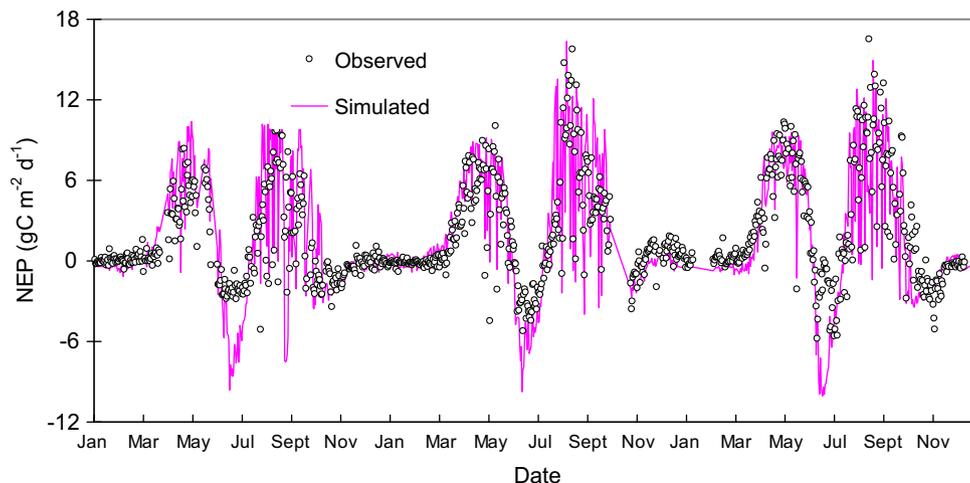


Fig. 7. Daily NEP measured by eddy-covariance technique and the simulated during 2003–2005.

of annual ET and NEP are shown in Fig. 8a and b, respectively. It is seen that ET is sensitive to six of the selected parameters, among which the coefficient of soil resistance (a) in Eq. (9) is the most sensitive one with 7% change of ET, then the parameter of stomatal conductance–photosynthesis relationship (m) and specific leaf area (S_{LA}) with 1–3% changes of ET. Since soil evaporation is a significant component of ET at annual scale, the parameterization of soil resistance will exert noticeable influence on ET prediction. Further, NEP is sensitive to seven of the selected parameters which are related with characteristics of photosynthesis (v_{cmax} , ϵ), stomatal conductance (m), live biomass maintenance respiration (C_{Rm}), stalk residue quality (CN), soil organic decomposition (C_{Rh}) and leaf area (S_{LA}) respectively (Fig. 8b). Among these parameters, quantum efficiency for carbon assimilation (ϵ) is the most sensitive with 17% change of NEP, specific for maize (C_4 crop). Leaf area index plays an important role in regulating the exchanges between the land surface and the atmosphere. The bias in leaf area and its physiological activity prediction may be a significant source of error (Hanan et al., 2005). The model is thus also run with measured LAI to assess influences of LAI bias on the predicted fluxes. It is found that the correlation coefficient (r^2) of ET between the measured and

the simulated LAI is 0.99 and the uncertainty is 10%; correspondingly, the r^2 and uncertainty of GPP are 0.95 and 28% respectively, indicating that GPP is much more sensitive to LAI deviations than ET. In the entire simulated period, the differences are about 8% for both GPP and NEP between estimates with the measured and those with simulated LAI respectively, whereas the relative difference of seasonal ET is only about 2%.

To test the influence of LAI deviation on the predicted ET and GPP, the model is run with 20% biases of LAI, respectively. It is shown that ET of wheat will increase 1.4% and GPP 2.9%, and ET of maize will increase 3.5% and GPP 4.6%, illustrating that maize is a bit more sensitive to LAI bias than wheat in their growing seasons. As wheat experiences a much longer stage with low LAI than maize, the total ET of wheat is less dominated by LAI. Canopy transpiration and underneath evaporation, being the components of ET, are more sensitive to LAI bias than ET itself does, due to the compensating effect between transpiration and evaporation. This can be explained that increased LAI will intercept more radiation and then transpire more water, resulting in less solar energy available and lower evaporation rate on the underneath soil surface.

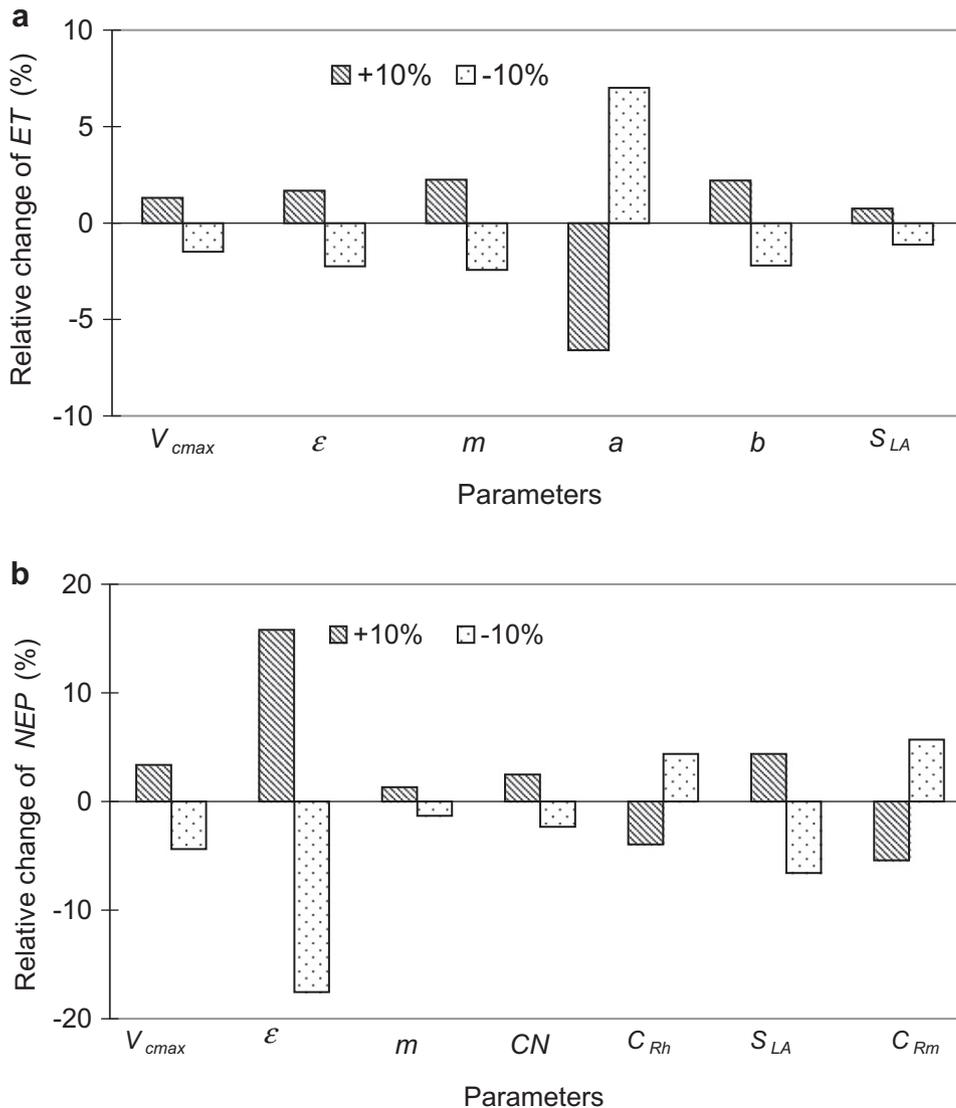


Fig. 8. Sensitivities of parameters to evapotranspiration (a) and to NEP (b).

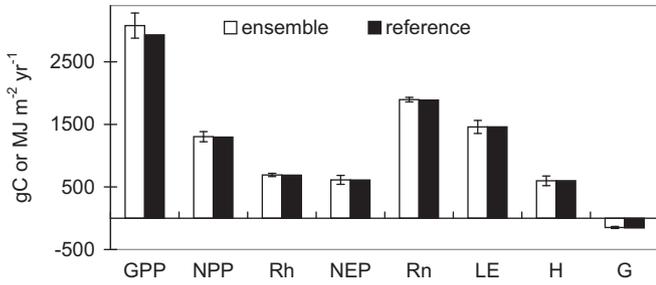


Fig. 9. Annual output variables simulated with mean parameter and the mean over 10,000 simulations with a random Gaussian noise on key parameters. Error bar represents the standard deviation. The output variables chosen are the gross primary production (GPP), the net primary production (NPP), the net ecosystem production (NEP), the heterotrophic respiration (R_h), the net radiation (R_n), latent heat (LE), sensible heat (H) and soil heat (G) fluxes.

Compared with the effects of the uncertainty of both the parameters and LAI on the predicted fluxes, it is found that even though the amplitude of LAI bias is larger than the amplitude of the change of the parameters chosen, the effects of LAI are smaller than the effects of those parameters which caused the prominent change of fluxes, such as coefficient of soil resistance (a) and quantum efficiency for carbon assimilation (ϵ).

6.2. By Monte–Carlo method

Monte–Carlo method is popularly used for evaluation of parameters uncertainty on the model outputs. Here the method is adopted from Dufrene et al. (2005), in which a normalized distribution is set for the parameter values around the references in Table 1. In the simulation, the summations of daily mean air temperature above zero Celsius degree for the three stages, namely planting to seedling, seedling to flowering and flowering to maturity respectively, are sampled within 5% of the references considering their actual influences on crop phenological processes, and the other parameters are sampled within 10%. The model is run with 10,000 randomly sampled parameter sets and the ensemble results of annual carbon budgets and energy budgets are given in Fig. 9. The results show that although the relative differences between the references and the ensemble mean values of energy components are diverse, they are all less than 9%. Similarly, the relative differences are less than 5% for annual carbon budgets. The uncertainties which are defined as the ratio of standard deviation (stdev) to the mean of annual gross primary production (GPP), net primary production (NPP), heterotrophic respiration (R_h) and NEP are 6.5, 6.2, 3.6 and 11.7%, respectively. Correspondingly, the

Table 3
Sampled ranges of the main parameters.

Symbol	Wheat	Maize
V_{cmax}	50–120	20–70
J_{max}/V_{cmax}	1.8–2.4	
m	6–12	3–9
ϵ	0.2–0.6	0.04–0.08
θ_f	0.15–0.35	
θ_s	1e–5 to 1e–3	
K_{sat}	7.2e–4	
GDD ₀	100–120	90–110
GDD ₁	950–1150	1200–1400
GDD ₂	850–1050	1100–1300
S_{LA}	0.039–0.072	0.035–0.065
α_w	1–3	1–3
C_{Rm}	0.7–1.3	0.7–1.3
C_{Rh}	0.5–1.5	0.5–1.5
Multiplier of a and b	0.7–1.3	0.7–1.3

uncertainties of energy components (R_n , LE, H and G) are 1.9, 7.1, 12.9 and 10.5% respectively, which are comparable to that of carbon fluxes. These differences are attributed to the highly nonlinear responses and interactions existing in the model processes.

6.3. By GLUE methodology

GLUE methodology (Beven and Binley, 1992) is also applied to analyze the model prediction performance caused by parameter uncertainty. The parameters sampled are listed in Table 3. 20,000 parameter sets are sampled for the model running. The measurements of CO₂ (NEP), latent heat fluxes are used to constrain the parameter values based on the multi-objective approach theory (Mo et al., 2006). The agreement index (R^2 , Willmott, 1981) is employed as an objective function for model performance evaluation and the likelihood measure for GLUE analysis:

$$L(Y|\zeta) \propto R^2 = \frac{\sum_{i=1}^N (Y_i - O_i)^2}{\sum_{i=1}^N (|Y_i - \bar{Y}| + |O_i - \bar{O}|)^2} \quad (21)$$

where Y is the predicted variable, ζ is the parameter set. O is the observed variable. The averages are noted with overbars.

The predicted uncertainties of daily ET and NEP with 10% and 90% quantiles with $R^2 > 0.6$ as behavior models are presented in Fig. 10, taken 2004 as an example. It is shown that the uncertainty bounds of the model predictions include most observed values and the parameter variability explains a great part of the bias between the measurements and the simulations. The width between upper and lower bound is becoming larger in June and October, caused by the prolonged or reduced growing seasons. In the extended growth period cases, field is covered by crops in these two months, whereas in shortened growth period cases, field is almost bare. Annually, the uncertainty of R_n , ET, GPP, NPP, R_h , NEP is 4.6, 16.5, 21.1, 25.5, 22.3 and 35.6% for all the model realizations, respectively. Comparatively, Dufrene et al. (2005) reported 30% uncertainty of annual NEP in a forest site, and Cervarolo et al. (2010) presented 27 and 89% uncertainty for latent heat and CO₂ fluxes respectively in their case.

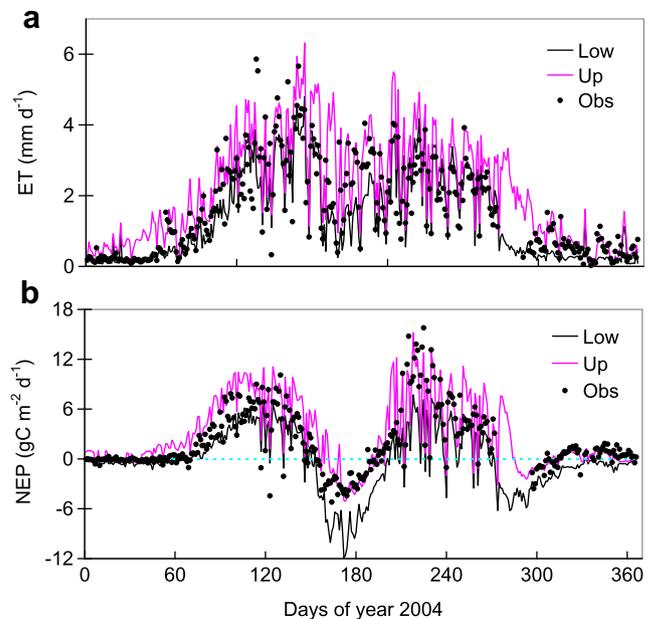


Fig. 10. 90% and 10% quantiles of the predicted and measured daily ET and NEP in 2004.

As a residual of GPP and ecosystem respiration, NEP is usually one order less than GPP and thus shows a higher uncertainty.

The above three methods give the results of the parameter sensitivity in different ways. Mono-factor analysis gives us a picture of the most sensitive parameter to flux prediction conveniently. Monte–Carlo method shows the result under a defined range scenario of parameter change. GLUE method produces the uncertainty by considering the possible practicable change for each of the parameters. There is no absolute rule for the choice of the analysis methods. However it is definitely necessary to jointly use of the multiple methods to explore the effects in a more comprehensive way.

7. Conclusion

The energy balance and carbon cycling processes in agro-ecosystem dominate crop water consumption, productivity and carbon sequestration. Physically process-based models that incorporate soil–vegetation–atmosphere transfer and crop growth dynamics are broadly used to simulate the fluxes between the ecosystem and the atmosphere. Here the updated VIP model is evaluated on estimation of energy, water vapor and CO₂ fluxes in a winter wheat–summer maize double cropping system over the North China Plain from 2003 to 2005. The results show that the VIP model reproduces net radiation, latent heat flux (evapotranspiration) and NEP above canopy quite well at diurnal, daily and seasonal scales, owing to strong coupling between crop physiological activities, water transpiring loss and carbon assimilation. This is also supported by the reasonable agreement between the measured and the simulated above ground live biomass and soil water storage.

Sensitivity analysis shows that ET is quite sensitive to empirical coefficients in soil resistance scheme, and NEP to quantum efficiency of photosynthesis. The uncertainties of ET and NEP are respectively 16.5% and 35.6% when the parameters are randomly sampled in their uncertainty ranges.

Since the complexity of ecosystem processes, there are still some mechanisms under exploring to improve the ecosystem model capacity, such as assimilated production allocation, leaf growth and senescence under water and temperature stresses, soil respiration that contributed by varied microbial groups. Data assimilation with measurements at local or remote sensing at large area should be crucial to improve the model performance. With improved evaluation of model uncertainty, long term prediction of ecosystem behavior will be more reliable under changing climate and land managements.

Acknowledgments

This study was jointly supported by the Chinese Ministry of Science and Technology Projects (2010CB428404, 0911) and the Natural Science Foundation of China (NSFC) grants (41071024, 40671033). Authors also thank CERN for providing eddy-covariance data and Dr. Zhao Fenghua from CERN providing part of the LAI data.

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