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Predicting crop growth under different cropping and fertilizing management practices

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ABSTRACT

Simulation models are widely used to make predictions of crop growth and yield, and soil carbon and nutrient dynamics under various agricultural practices and soil-climatic conditions. An analytical model of soil carbon and nutrient dynamics, K-model, was expanded to include a plant sub-model (K-Model-P). This allows for the prediction of short- and long-term crop growth, and soil carbon and nitrogen dynamics. The simulations for a short-term experiment (2 growing seasons) with three nitrogen application rates showed that K-Model-P correctly predicted the growth processes of above-ground plant biomass and grain yields. Predicted and measured daily accumulative biomass were significantly correlated, and differences were statistically insignificant. The simulation results for long-term experiments (70 years) of two crop rotations with three soil amendments showed that predicted and measured annual straw and grain yields were significantly correlated, with the differences of less than 13%. Annual crop straw and grain yields can be estimated by the model without significant errors. The agreement between the predicted daily growth and annual yields and experimental data illustrated that the K-Model-P can be used to produce reliable predictions for daily and annual crop growth.

1. Introduction

Effects of agricultural management practices on crop growth, soil carbon and nutrient dynamics, and greenhouse gas emission have been studied for several decades. It is widely accepted that changes in agricultural practices, such as crop rotation, conservation tillage, organic fertilizer, and complete return of crop residues, will result in changes in the crop yield as well as soil organic carbon content (Basamba et al., 2006; Cai and Qin, 2006; Cherr et al., 2007; Dolan et al., 2006; Fliebbach et al., 2007; Koch and Stockfisch, 2006; Meyer-Aurich et al., 2006; Moret et al., 2007; Sainju et al., 2006; Sieling et al., 2006). However, experimental evidences on these effects are somewhat inconsistent. Soil and climate conditions also strongly influence these effects (Baker et al., 2007). The short-term effects are often inconsistent with long-term effects (Grant et al., 2001; Meyer-Aurich et al., 2006; Sainju et al., 2006). Therefore, there is a demand for information of both the short- and long-term effects of agricultural practices on crop production and soil carbon dynamics that may be used to help select optimal management options that maximize long-term sustainability of crop production and soil carbon sequestration.

Field experiments are the most reliable source of this information, and can help resolve the observed inconsistency between long- and short-term effects. However, site-specific influences on these effects constrain extrapolation of experimental results, and well-designed and documented long-term experiments are rare and difficult to maintain. They are also limited by time and cost. Simulation models with demonstrated accuracy and reliability provide an alternative method of assessing both short and long-term agricultural practices with low time requirements and cost (Farage et al., 2007; Farahbakhshazad et al., 2007; Janssen and van Ittersum, 2007; Malone et al., 2007). Many models have been developed to describe the responses of crop growth to specific soil and climatic conditions and management practices (Chertov and Komarov, 1997; Grant et al., 2001; Jenkinson, 1990; Parton et al., 1987; Shaffer et al., 2001; Smith et al., 1997; Wallman et al., 2006; Wu and McGechan, 1998). Many models are not well suited for general use. For example, Ecosys (Grant et al., 2001) uses a very detailed, complex description of crop growth making parameterization a challenge. The model CERES (Godwin et al., 1989; Jones and Kiniry, 1986) have different versions for different crops, complicates its general use. Other models, such as CENTURY and DNDC, use many statistical functions to estimate crop growth. Generally speaking, the utility and prediction accuracy of these

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models are reduced when they are used beyond the conditions and length of time covered by the data from which these functions are developed.

The K-model (Feng and Li, 2002, 2001) is a semi-analytical soil carbon and nitrogen dynamics model. It integrates soil carbon and nutrient process functions and a geographic information system into a Microsoft Office Excel user interface to provide a flexible and user-friendly modeling tool over wide spatial and temporal scales. Its crop sub-model (K-Model-P) aims to effectively integrate the biophysical and numerical functions of crop growth to avoid the disadvantages discussed above. The K-Model-P is composed of simple algorithms of crop growth, linked to soil carbon and nutrient dynamics of the earlier version of the K-model, and provides a simple user-friendly tool for evaluating the effects of cropping and land management practices on productivity of agricultural crops and grassland.

The purpose of this paper is to present the analytical–biophysical crop growth sub-model of the K-model, K-Model-P, and to evaluate its performance on predicting crop growth by validating simulation results against data from two experimental sites with different soil/climate conditions and cropping/soil management practices.

2. Description of model

The K-Model-P is a daily crop growth sub-model of the K-model (Feng and Li, 2002, 2001). Most of the crop growth algorithms are adopted from DAICRO (Verdoodt et al., 2004), SUCROS (van Laar et al., 1992), CERES (Jones and Kiniry, 1986; Ritchie et al., 1988) and SPASS (Wang and Engel, 2000, 2002). It simulates plant biomass production, autorespiration loss, and below- and above-ground growth and senescence as functions of daily climate parameters and soil environmental conditions (Fig. 1, definitions of symbols in Fig. 1 are listed in Appendix A). Climate data inputs consist of incoming radiation, air temperature, wind speed and relative humidity. Soil input data include soil texture, soil organic carbon and nitrogen contents, mineral nitrogen content, soil water content and temperature, which are computed by the soil organic matter and water/energy transfer sub-models.

2.1. Photosynthesis

Daily rate of canopy CO_2 assimilation (e.g. Gross Primary Production, *GPP*) is dependent on the leaf photosynthetic capacity and various environmental factors (Goudriaan and van Laar, 1994). *GPP* is related to the maximum gross photosynthesis rate (p_m), and changes exponentially with the photosynthetically active radiation intercepted by the plant canopy (*PAR*) and light use efficiency (L_{eu}) (Wang and Engel, 2002).

$$GPP = \begin{cases} p_m\left(1-\exp\left(\dfrac{-L_{eu}PAR}{p_m}\right)\right) & p_m > 0 \\ 0 & p_m = 0 \end{cases} \tag{1}$$

PAR is exponentially related to the canopy light extinction coefficient (k) and leaf area index (*LAI*), and is reduced by the surface albedo (α) of the ecosystem.

$$PAR = 0.5R_a(1-\alpha_p)(1-\exp(-k \times LAI)) \tag{2}$$

We have assumed that approximately one half of the incoming solar radiation (R_a) is in the short-wave spectrum (photosynthetic), represented by the parameter 0.5.

Ecosystem albedo is approximated as the sum of soil (α_s) and vegetation (α_p) albedo weighted by radiation partitioning between soil and vegetation.

$$\alpha = \alpha_s \times \exp(-k \times LAI) + \alpha_p \times (1-\exp(-k \times LAI)) \tag{3}$$

The maximum photosynthesis rate, p_m, is modified by the ambient CO_2 concentration, air temperature, soil water and nutrient limitations ($f_{[CO_2]}$, S_T, S_w and S_N) from the daily maximum rate of photosynthesis at the reference CO_2 concentration of 340 ppm and the optimum temperature ($p_{\max 340}$) (Wang and Engel, 2002).

$$p_m = p_{\max 340} f_{[CO_2]} S_T \times \min(S_w, S_N) \times LAI \tag{4}$$

$p_{\max 340}$ is calculated from day light length (D_l) and hourly light-saturated gross photosynthesis rate at the CO_2 concentration of 340 ppm, optimal air temperature and no stress from soil water

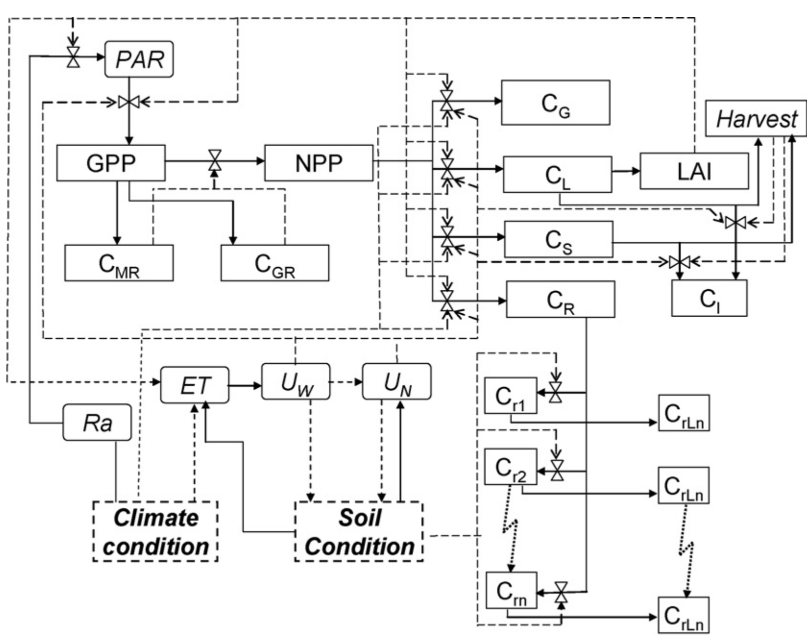

Fig. 1. Structure of the plant sub-model (K-Model-P) of the K-model. The boxes with solid frames indicate state variables, boxes with dashed frames are input conditions, and boxes with round corners are state variables computed by other sub-models. Valves represent conversion rate. Solid arrows show direction of mass and/or energy flow while dashed arrows represent flow of information controlling mass/energy transfer rates.