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Estimation of maize yield by using a process-based model and remote sensing data in the Northeast China Plain

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ABSTRACT

Climate change significantly impact on agriculture in recent year, the accurate estimation of crop yield is of great importance for the food security. In this study, a process-based mechanism model was modified to estimate yield of C_4 crop by modifying the carbon metabolic pathway in the photosynthesis submodule of the RS–P–YEC (Remote-Sensing–Photosynthesis–Yield estimation for Crops) model. The yield was calculated by multiplying net primary productivity (NPP) and the harvest index (HI) derived from the ratio of grain to stalk yield. The modified RS–P–YEC model was used to simulate maize yield in the Northeast China Plain during the period 2002–2011. The 111 statistical data of maize yield from study area was used to validate the simulated results at county-level. The results showed that the Pearson correlation coefficient (R) was 0.827 ($p < 0.01$) between the simulated yield and the statistical data, and the root mean square error (RMSE) was 712 kg/ha with a relative error (RE) of 9.3%. From 2002 to 2011, the yield of maize planting zone in the Northeast China Plain was increasing with smaller coefficient of variation (CV). The spatial pattern of simulated maize yield was consistent with the actual distribution in the Northeast China Plain, with an increasing trend from the northeast to the southwest. Hence the results demonstrated that the modified process-based model coupled with remote sensing data was suitable for yield prediction of maize in the Northeast China Plain at the spatial scale.

1. Introduction

Agriculture plays an important role in ensuring food security in developing countries. With population expansion, the demand for food is also increased and the climate change aggravates the volatility of yield. Making timely and accurate regional predictions of crop yield is of great importance for agricultural management and food security warning purposes (IPCC, 2007; Yao et al., 2007; Mo et al., 2005, 2009; Piao et al., 2010; Wang et al., 2011). The Northeast China Plain is one of the important grain production bases in China. This area accounts for nearly half of the national maize cultivated area with a yield of 30% (National Bureau of Statistics of China, 2009). In recent years, the crop yields have been significantly affected by the climate change in the Northeast China Plain (Chen et al., 2011). Therefore, the accurate estimation of crop yield for this area is of importance for national food security.

Over last decades, many models such as statistical models, light use efficiency models, and processed-based models have been used to estimate crop yield (Liu et al., 1997; Fraisse et al., 2001; Lobell et al., 2003; Kalfas et al., 2011; Hu and Mo, 2011; Qin et al., 2012; Mo et al., 2012). One kind of statistical models are based on field experiments, which are time-consuming, expensive, and prone to large errors for regional scale estimation (Reynolds et al., 2000). Other statistical models are based upon remote sensing technology to predict crop yield regionally. The inverse information derived from remote sensing, for example, normalized difference vegetation index which monitors well the crop growth, can be is used widely for crop yield estimation (Shanahan et al., 2001; Baez-Gonzalez et al., 2005; Prasad et al., 2006). The light use efficiency models use the proportional relation between net primary productivity derived from light energy utilization (ε) and crop biomass or yield to estimate crop yield spatially (Bastiaanssen and Ali, 2003; Lobell et al., 2003). However, it has a problem that the specific ε does not distinguish between crop types in the same region and changes in the crop growth stages (Turner et al., 2002). The proportional relation changes with

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regions and is east to be effected by other environmental factors (Gower et al., 1999), and lacks mechanistic explanation for the crop ecological processes and physiological changes.

Recently, process-based models have been developed to estimate crop yield. Crop growth simulation models at points developed earlier, are strong mechanistic, well quantifying the relationship between crop growth and environment (Pohlert, 2004; Yang et al., 2004; Marletto et al., 2007; Soler et al., 2007; Hu and Mo, 2011; Zhuang et al., 2013). Noting that crop models perform well at the field scale (Wu et al., 2008), there are limitations in the application at the regional scales. Because of spatial heterogeneity, the data for a wide range of crop parameters is difficult to obtain, which is a restriction for the site-based crop models in the simulation of regional yield. It is possible in estimation regional crop yield coupled with remote sensing information and process-based crop models (Wang et al., 2011). The simplest method is to use the remote sensing data, such as leaf area index (LAI) and land cover, through classification of crops to form a GIS database (Liu et al., 1997; Chiesi et al., 2002; Yun, 2003; Mo et al., 2009), and as input variables to drive the model, is namely the driving method. Assimilation method is another method to estimate the regional yield, but it is more complex and the improvement of simulation precision is still questionable (Launay and Guerif, 2005; Mo et al., 2005; de Wit and van Diepen, 2007; Dente et al., 2008; Ma et al., 2008; Fang et al., 2011).

This study modifies a process model for the yield estimation of C_4 crops. The modified model is based on the Remote-Sensing–Photosynthesis–Yield Estimation for Crops (RS–P–YEC) model, which is based on the Boreal Ecosystem Productivity Simulator with the biggest advantage of the solution of scaling-up (Liu et al., 1997; Chen et al., 1999; Feng et al., 2007; Zhang et al., 2012a,b). The RS–P–YEC model can better represent crop canopy radiant process and convert NPP to biological yield using the harvest index for estimating C_3 crop yield (Wang et al., 2011; Ji et al., 2015). Taking the difference of carbon metabolic pathways of C_3 and C_4 crops into account (Von Caemmerer, 2000), the objectives of this study are: (1) to modify the carbon metabolic pathway in the photosynthesis sub-module of RS–P–YEC model and to make it suitable for yield simulation of the C_4 crops; (2) to quantitatively simulate the yield of maize (C_4 crop) in the Northeast China Plain and validate the adaptability of the developed model, and (3) to analyze the spatial distribution of maize yield in the Northeast China Plain.

2. Methods

2.1. Study area

The study area is located in the maize planting zone of the Northeast China Plain (118.83–135.09°E, 38.72–54.56°N), including Heilongjiang, Jilin and Liaoning provinces (Fig. 1). The total area is 78.7 million ha, with the arable land of 21,526,200 ha, accounting for 16.6% of the total arable land in China. As the largest plain in China, the Northeast China Plain belongs to continental monsoon climate with an average rainfall of 400–800 mm, mainly concentrated in July to September (Chen et al., 2012). The average annual temperature is from −3 to 11 °C, the accumulated temperature ⩾10 °C is 1600–3600 °C with the frost-free period at 155–257 days. Two main types of soil are black and chernozem, which is fertile and has a strong water-holding capacity.

2.2. Model description

As a basis for RS–P–YEC model, the Boreal Ecosystem Productivity Simulator (BEPS) model is a physically process-based remote sensing model (Liu et al., 1997; Chen et al., 1999; Feng et al., 2007; Zhou et al., 2007). In RS–P–YEC model, the advantage of BEPS is inherited, and a hypothesis with horizontally homogeneous and vertically laminar structure is made. The structure of two-big-leaf model is still retained derived from the BEPS model. The photosynthesis of each leaf layer was integrated to get the canopy photosynthesis and the autotrophic respiration was subtracted to get the biomass of crops. The crop yield is estimated according to the ratio of biomass and the yield with the correlation coefficient up to 0.9 (Wang et al., 2009, 2011).

In this study, the modified model was used to estimate the photosynthesis of C_4 crop. Based on the RS–P–YEC model and the harvest index derived from the ratio of the grain yield to the stalk yield for maize, the yield of maize is then calculated (see Fig. 2).

2.2.1. Solar radiation

The solar radiation received by leaves is a key factor to determine their photosynthetic rate. The radiation calculations were made by dividing leaves into N layers. The top of the canopy is the sunlit layer. The solar radiation received by the top sunlit leaves of the canopy includes the direct and scattered radiation from the sky. The radiation received by the lower layers is the sum of multi-scattered and reflected solar radiation from the canopy and soil surface, and the scattered radiation meets the radiation transfer equation (Huang, 1997).

$$S_{sun}(0) = S_{shade}(0) + S_0\mu_0 \tag{1}$$

$$-\mu\frac{dS_{in}}{dL} = -S_{in} + \frac{\omega}{2}\int_{-1}^{1} S_{in}(\mu')d\mu' + \frac{\omega S_0}{2}\exp\left(\frac{LG_0}{\mu_0}\right) \tag{2}$$

where $S_{sun}(0)$ is the photosynthesis available radiation received by the top leaves of the top of the canopy, $S_{shade}(0)$ is the scattered radiation, S_0 is the direct radiation on the underlying surface and μ_0 is the cosine of the zenith angle, S_{in} is the scattered radiation received by the internal of the canopy, L is the distance between internal leaves and the top of the canopy, μ is the cosine of the zenith in scattering direction, ω is the single scattering albedo of leaves and G_0 is the projection in the direction of the reflected radiation.

The scattered radiation in the horizontal direction of L could be expressed as (Wang et al., 2009):

$$S_{shade}(L) = 2\int_{0}^{1} S_{in}(L,\mu)\mu d\mu \tag{3}$$

where $S_{shade}(L)$ is the scattered radiation received by the shade leaves in L.

2.2.2. Photosynthetic rate

(1) Leaf photosynthetic rate (A, μmol m^{-2} s^{-1}).

Leaf photosynthesis rate is mainly limited by the efficiency of Rubisco and light (Liu et al., 1997; Chen et al., 1999). For C_4 crops, the leaf gross photosynthesis rate could be described as (Zhang et al., 2012a,b):

$$A = \min\{w_v, w_j\} - R_d \tag{4}$$

$$R_d = 0.015V_{cmax} \tag{5}$$

$$w_v = V_{cmax} \tag{6a}$$

$$w_j = J \tag{6b}$$

where A is the net CO_2 assimilation rate, w_v is the rate limited by Rubisco, w_j is the rate limited by photoelectron transfer rate, R_d is dark respiration, μmol m^{-2} s^{-1}; V_{cmax} is the maximum rate of