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Research Paper

Linking process-based potato models with light reflectance data: Does model complexity enhance yield prediction accuracy?

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ABSTRACT

Data acquisition for parameterization is one of the most important limitations for the use of potato crop growth models. Non-destructive techniques such as remote sensing for gathering required data could circumvent this limitation. Our goal was to analyze the effects of incorporating ground-based spectral canopy reflectance data into two light interception models with different complexity. A dynamic- hourly scale- canopy photosynthesis model (DCPM), based on a non-rectangular hyperbola applied to sunlit and shaded leaf layers and considering carbon losses by respiration, was implemented (complex model). Parameters included the light extinction coefficient, the proportion of light transmitted by leaves, the fraction of incident diffuse photosynthetically active radiation and leaf area index. On the other hand, a simple crop growth model (CGM) based on daily scale of light interception, light use efficiency (*LUE*) and harvest index was parameterized using either canopy cover (CGM_{CC}) or the weighted difference vegetation index (CGM_{WDVI}). A spectroradiometer, a chlorophyll meter and a multispectral camera were used to derive the required parameters. CGM_{WDVI} improved yield prediction compared to CGM_{CC}. Both CGM_{WDVI} and DCPM showed high degree of accuracy in the yield prediction. Since large *LUE* variations were detected depending on the diffuse component of radiation, the improvement of simple CGM using remotely sensed data is contingent on an appropriate *LUE* estimation. Our study suggests that the incorporation of remotely sensed data in models with different temporal resolution and level of complexity improves yield prediction in potato.

Abbreviations: *D*, duration of leaf senescence; DCPM, dynamic- hourly scale- canopy photosynthesis model; DTY, dry tuber yield; *LUE*, light use efficiency; CGM, crop growth model; CGM_{CC}, crop growth model parameterized using canopy cover; CGM_{WDVI}, crop growth model parameterized using weighted difference vegetation index; *Chl*, total chlorophyll concentration per leaf area; Chl_{max}, maximum total chlorophyll concentration per leaf area; f_i, biomass fraction of organ i; F_{LINT}, fraction of *PAR* intercepted by the foliage; *G*, growth respiration; G_i, glucose requirement of organ i (leaves stems tubers roots); I_0, *PAR* on a horizontal plane; I_{leaf}, incident *PAR* on a leaf; *k*, light extinction coefficient; K_i, maintenance respiration coefficient of the plant organ i; *LAI*, leaf area index; *M*, asymptotic maximum of the harvest index; *m*, leaf transmittance; *MAE*, mean absolute error; *MCC*, maximum canopy cover; *NIR*, near-infrared band; *NDMA*, net dry matter assimilation rate; P_{leaf}, leaf photosynthetic rate; P_{canopy}, gross canopy primary productivity; P_{max}, photosynthesis at light-saturated conditions; *PAR*, photosynthetically active radiation; PAR_0, *PAR* extra-terrestrial irradiance on a plane; Q_{10}, temperature sensitivity factor; *R*, red band; R_m, maintenance respiration; *RMSE*, root mean square error; RS, remote sensing; *RRMSE*, relative *RMSE*; S_{df}, diffuse flux of global radiation; *T*, daily average temperature; t_e, beginning of senescence; t_m, time at maximum *WDVI* increment; T_r, reference temperature; TT, thermal time; t_{50}, time when light interception is reduced to 50%; VI, vegetation index; *WDVI*, weighted difference vegetation index; W_i, dry biomass of organ i; W_t, total dry biomass in the current day; Y_m, maximum value of *WDVI*; α, photosynthetic efficiency; ε, sharpness of the knee of the curve P_{max} vs. I_{leaf}; θ, solar zenithal angle; θ_Z, sun angle above the horizon; ΣP_{canopy}, balance of the assimilated carbon via daily P_{canopy}.

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1. Introduction

Crop growth modeling is an important tool for yield prediction under different management and environmental conditions (Boote et al., 1996; Murthy, 2004). The integration of biomass accumulation into yield along high time resolutions is an advantage of crop growth models (CGM). However, these models are confined to short spatial scales (field or local scales) since there is no mechanistic approach developed for the incorporation of spatial heterogeneity (Moulin et al., 1998). Ground, air- and space-borne remote sensing (RS) data have been used to reduce the bias generated by the scale dependency of modeled attributes (Moulin et al., 1998; Fischer et al., 1997). Thus, the incorporation of RS to CGM to improve yield predictions has produced reliable results in crops like sugar beet (Guérif and Duke, 2000; Launay and Guerif, 2005), wheat (Clevers et al., 2002; Oppelt, 2010), rice (Wang et al., 2014) and maize (Jongschaap, 2007). If some drawbacks (atmospheric corrections, soil interferences, among others) are overcome (Delécolle et al., 1992), RS is a very useful tool to describe some biophysical characteristics of the vegetation, like plant chlorophyll concentration and leaf area index (*LAI*), which are crucial components of CGM (Jongschaap, 2006, 2007; Dorigo et al., 2007). Chlorophyll concentration is a plant trait related to light absorption-interception, N content and photosynthesis. Vegetation indexes (VI), determined through RS, have been related to chlorophyll concentration (Gitelson et al., 2003; Almeida and De Souza, 2004; Jongschaap, 2006, 2007; Cammarano et al., 2011; Shrestha et al., 2012; Schlemmer et al., 2013) and these indexes have been incorporated into CGM with important improvements in the prediction of yield (Jongschaap, 2007; Oppelt, 2010; Wang et al., 2014). *LAI*, i.e. the leaf area per unit ground surface area, has been broadly related with VI using statistical approaches despite the limitation imposed by the near-infrared reflectance saturation occurring at below the maximum *LAI* values (Dorigo et al., 2007). Using statistical (Jongschaap, 2007) and physical (Fischer et al., 1997; Guérif and Duk, 2000; Launay and Guerif, 2005) approaches this variable has been simulated through a run-time calibration procedure and radiative transfer model respectively, and incorporated to CGM.

Concerning potato, the fourth most important crop worldwide (FAOSTAT, 2013), there are 32 different CGMs reported, that simulate tuber yield under different conditions of water and N availability and CO_2 atmospheric levels (Raymundo et al., 2014). However, the difficulty of data acquisition remains as a major limitation for the widespread use of the models (Raymundo et al., 2014). As RS facilitates the monitoring of required vegetation variables, it could be an important aid to data acquisition. RS indexes in potato have been related to water status (Moller et al., 2006; Prashar et al., 2013), chlorophyll concentration through greenness (Zakaluk and Ranjan, 2006, 2008), canopy cover (Bouman et al., 1992a) and *LAI* (Islam and Bala, 2008; Bala and Islam, 2009; Papadavid et al., 2011; Duan et al., 2014; Fortin et al., 2014). Thus, Jongschaap (2006) has obtained acceptable predictions of *LAI* and canopy N content through the incorporation of RS data to a dynamic model in potato. However the assessment of whether tuber yield prediction can be improved by incorporating RS data into models is still a pending research issue although this incorporation is considered important to improve the performance of models (Raymundo et al., 2014). In the present study we use RS-derived parameters to drive some routines of two simulation models with different levels of complexity: i) an hourly-run dynamic canopy photosynthesis model (DCPM) based on the estimation of photosynthesis on sunlit and shaded leaf layers, factoring carbon losses by respiration (complex model); ii) a daily-run CGM based on light interception and light use efficiency using "big leaf" approach, and carbon partition (simple model). Our aims were: – to compare the accuracy of prediction of tuber yield by both models along the growing season; – to assess the improvement of tuber yield prediction using RS data as surrogate of actual chlorophyll concentration, canopy cover and *LAI* measurements; – to analyze the main drivers that affect tuber yield. We hypothesize obtaining a better tuber yield prediction through the complex model, driven by the incorporation of key parameters related to photosynthetic performance, bilayer light interception and photorespiration carbon losses. Since some authors suggest that RS data (reflectance) is more related to canopy light interception than canopy cover and *LAI* (Bouman et al., 1992b), we hypothesize an improvement in the prediction of tuber yield using RS-derived parameters.

2. Materials and methods

2.1. Dynamic canopy photosynthesis model (DCPM)

2.1.1. Original model formulation

The net primary productivity simulation model tested in this study is based on the instantaneous canopy photosynthesis concept developed by Thornley (2002), which describes mathematically the assimilation of atmospheric carbon dioxide into plant dry matter as driven by photon flow. Assuming that leaf photosynthetic response can be described by a non-rectangular hyperbola model, Thornley's model is formulated as (for a detailed description of this model see Thornley, 2002):

$$\varepsilon P_{leaf}^2 - P_{leaf}\left(\alpha I_{leaf} + P_{max}\right) + \alpha I_{leaf} P_{max} = 0 \quad (1)$$

$$I_{leaf}\left(LAI\right) = \frac{k}{1-m} I_0 e^{-kLAI} \quad (2)$$

Where P_{leaf} is leaf photosynthetic rate (kg $CO_2\,m^{-2}\,s^{-1}$), I_{leaf} is photosynthetically active radiation (*PAR*) incident on a leaf ($J\,m^{-2}\,s^{-1}$),P_{max} is photosynthesis at light-saturated conditions, α is photosynthetic efficiency, ε determines the sharpness of the knee of the curve P_{max} vs. I_{leaf}, $I_0$is *PAR* on a horizontal plane, kis the light extinction coefficient, *LAI* is the cumulative leaf area index, and m is leaf transmittance.

In our adapted model, the accumulation of photosynthates per leaf area unit was calculated using a numerical integration with hourly steps. Parameters such as *LAI*, *k*, *m* and the diffuse component of incident *PAR* –considered as constants in Thornley's model-were replaced with dynamic parameters that account for the temporal and spatial variability of the photosynthesis process. These parameters were approximated through remotely sensed data (see Section 2.3.2).

2.1.2. Incorporation of the dynamic parameters and respiration

Thornley's model was adapted by converting it from an instantaneous canopy photosynthesis calculator into a dynamic one. The modified model calculates the gross canopy primary productivity (P_{canopy}) by way of integrating CO_2 fixed from plant emergence to harvest.

k characterizes the light absorption by the canopy and depends on the type of light, the position and characteristics of the leaves; it varies during the day according to the solar zenithal angle (θ). Assuming a spherical angular distribution, with leaves distributed at random within the canopy volume, *k* varies between 0.5 at noon and 1 at dawn and sunset, and is defined as (Goudriaan, 1982):

$$k = \frac{1}{2\cos\left(\theta\right)} \quad (3)$$

m is calculated by integrating the *PAR* energy transmitted through the leaf mesophyll. The light transmittance characterizes the physiological state of the leaf and is an indicator of its pigment concentration. The transmittance usually represents 10% of the