European Journal of Agronomy 92 (2018) 141–152

Contents lists available at ScienceDirect

European Journal of Agronomy

journal homepage: www.elsevier.com/locate/eja

Review article

A review of data assimilation of remote sensing and crop models

Xiuliang Jin[a,b,c,d,*], Lalit Kumar[e], Zhenhai Li[a,b,c,d], Haikuan Feng[a,b,c,d], Xingang Xu[a,b,c,d], Guijun Yang[a,b,c,d], Jihua Wang[f]

[a] Key Laboratory of Quantitative Remote Sensing in Agriculture of Ministry of Agriculture, China
[b] Beijing Research Center for Information Technology in Agriculture, Beijing 100097, China
[c] National Engineering Research Center for Information Technology in Agriculture, Beijing 100097, China
[d] Beijing Engineering Research Center for Agriculture Internet of Things, Beijing 100097, China
[e] Ecosystem Management, School of Environmental and Rural Science, University of New England, Armidale, NSW 2351, Australia
[f] Beijing Research Center for Agri-food Testing and Farmland Monitoring, Beijing 100097, China

ARTICLE INFO

Keywords:
Crop models
Remote sensing
Canopy state variables
Data assimilation
Yield

ABSTRACT

Timely and accurate estimation of crop yield before harvest to allow crop yields management decision-making at a regional scale is crucial for national food policy and security assessments. Modeling dynamic change of crop growth is of great help because it allows researchers to determine crop management strategies for maximizing crop yield. Remote sensing is often used to provide information about important canopy state variables for crop models of large regions. Crop models and remote sensing techniques have been combined and applied in crop yield estimation on a regional scale or worldwide based on the simultaneous development of crop models and remote sensing. Many studies have proposed models for estimating canopy state variables and soil properties based on remote sensing data and assimilating these estimated canopy state variables into crop models. This paper, firstly, summarizes recent developments of crop models, remote sensing technology, and data assimilation methods. Secondly, it compares the advantages and disadvantages of different data assimilation methods (calibration method, forcing method, and updating method) for assimilating remote sensing data into crop models and analyzes the impacts of different error sources on the different parts of the data assimilation chain in detail. Finally, it provides some methods that can be used to reduce the different errors of data assimilation and presents further opportunities and development direction of data assimilation for future studies. This paper presents a detailed overview of the comparative introduction, latest developments and applications of crop models, remote sensing techniques, and data assimilation methods in the growth status monitoring and yield estimation of crops. In particular, it discusses the impacts of different error sources on the different portions of the data assimilation chain in detail and analyzes how to reduce the different errors of data assimilation chain. The literature shows that many new satellite sensors and valuable methods have been developed for the retrieval of canopy state variables and soil properties from remote sensing data for assimilating the retrieved variables into crop models. Additionally, new proposed or modified crop models have been reported for improving the simulated canopy state variables and soil properties of crop models. In short, the data assimilation of remote sensing and crop models have the potential to improve the estimation accuracy of canopy state variables, soil properties and yield based on these new technologies and methods in the future.

1. Introduction

Crop yields play a vital role in agriculture development in the world, so it is necessary to accurately estimate crop yields before harvest to allow crop yield management decision-making. In the past several decades, increasing demand for agricultural products and a desire for a higher rate of profit have led to tremendous changes in traditional agriculture (Tilman, 1999). Pesticides, machinery, irrigation technology, new high-yielding varieties, and new field crop management methods have been proposed to meet agricultural production needs in different countries and regions.

To ensure optimum crop yields, many scholars have begun to study the relationship between crop growth and growth environment and to propose crop models to simulate crop growth status (Boogaard et al., 2011; Brisson et al., 2003; Franko et al., 2007; Jones et al., 2003; Keating et al., 2003; Nendel et al., 2011; Stöckle et al., 2003; Steduto

* Corresponding author at: Beijing Research Center for Information Technology in Agriculture, Beijing Academy of Agriculture and Forestry Sciences, Beijing 100097, China.
E-mail address: jinxiuxiuliang@126.com (X. Jin).

https://doi.org/10.1016/j.eja.2017.11.002
Received 19 May 2017; Received in revised form 13 October 2017; Accepted 5 November 2017

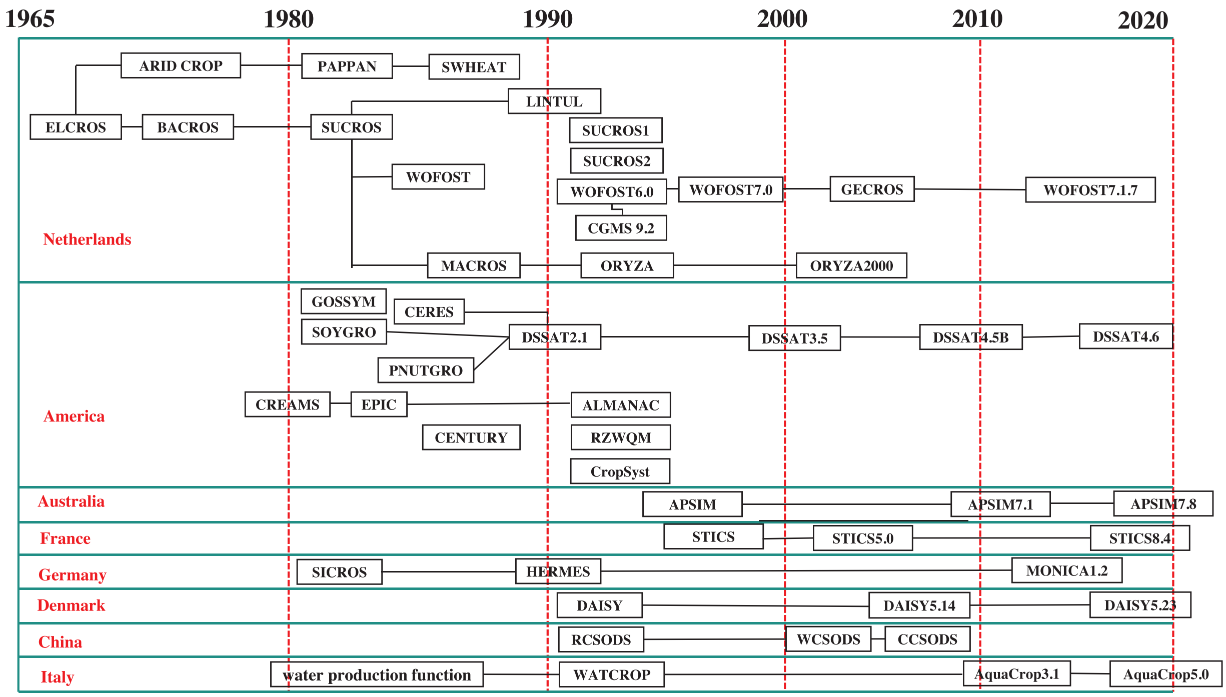

Fig. 1. Development of main crop models over time. Note: horizontal continuous lines indicate the development of new crop models.

et al., 2009). After nearly 40 years of development, crop models have advanced from the initial qualitative simulation of crop growth to quantitative simulation of crop growth and from simulation of single physiological and ecological growth processes to simulation of the whole growth process. Through the combination of crop models and a multidisciplinary approach, considerable progress has been attained. A timeline on the development of the main crop models is shown in Fig. 1. The figure shows that, over time, the WOFOST, DASSAT, APSIM, STICS, MONICA, DAISY and AquaCrop models have been refined and updated to better simulate crop growth status and crop yield. Further development of these crop models will provide better opportunities to analyze the response of crops to changes in the field management practices and environmental conditions worldwide.

Crop models need to account for spatial variation when crop yields are estimated over large regions, however, the spatial distribution of soil properties (soil moisture), canopy state variables (LAI, biomass, nitrogen content, etc.), and meteorological data are often uncertain (Hansen and Jones, 2000). These uncertainties mainly affect crop model physiological growth simulation processes, leading to larger errors in crop yield estimation when crop models are used.

The rapid development of remote sensing technology offers more potential for accurate and reliable quantitative estimates of soil properties and canopy state variables at regional scales. Many researchers have used remote sensing to estimate crop canopy state variables or soil properties over large areas, such as the fraction of absorbed photosynthetically active radiation (FAPAR) (Clevers, 1997; Gobron et al., 2000; Morel et al., 2014a), LAI (Abou-Ismail, 2004; Bouman, 1995; Fang et al., 2008; Jiang et al., 2014; Jongschaap and Schouten, 2005; Nearing et al., 2012; Yao et al., 2015), canopy cover (Bouman, 1995), biomass (Claverie et al., 2009; Jin et al., 2013a, 2015b), leaf nitrogen accumulation (Huang et al., 2013), evapotranspiration (Bastiaanssen and Ali, 2003; Huang et al., 2015; Hurtado et al., 1994), and soil properties (e.g., soil moisture, Bach and Mauser, 2003; Dente et al., 2008; Ines et al., 2013; Chakrabarti et al., 2014). These canopy state variables and soil property variables need to be integrated with crop models since they are important parameters at crop canopy growth stages. Crop models have been used in the past to simulate these canopy state variables. Canopy cover and LAI were used to drive crop biomass accumulation in different crop models (Brisson et al., 2003; Hansen et al., 1990; Jones et al., 2003; McCown et al., 1995; Nendel et al., 2011; Steduto et al., 2009) while remote sensing methods were used to estimate these canopy state variables and soil properties for input into crop models (Bouman, 1995; Fang et al., 2008; Huang et al., 2015; Jiang et al., 2014) and drive crop phenology information (Karnieli, 2003; Xin et al., 2002). Since phenology information controls crop matter distribution during the growth process, it is essential for all crop models. Therefore, remote sensing has been used to accurately monitor crop phenology for improving the results of crop models (Guyot, 1996; Sakamoto et al., 2005). In the last 10–15 years, optical sensor technology has seen a rapid development. More new satellite sensors have been launched to obtain more high spatial and temporal resolution remote sensing data (such as Sentinel-2; Landsat 8; RapidEye; WorldView-2; SPOT-6; GeoEye-1; Huanjing-1; Gaofen-1; Jilin-1, etc.). Kross et al. (2015) estimated LAI and biomass of corn and soybean using RapidEye multi-spectral data; the results indicated that the cumulative red-edge simple ratio performed best for estimating LAI and biomass. Li et al. (2017) comparatively analyzed Gaofen-1, Huanjing-1, and Landsat-8 multispectral data for estimating the leaf area index of winter wheat; the four spectral indices from the three sensors all showed to be highly correlated with LAI. Wei et al. (2017) estimated LAI of winter oilseed rape from high spatial resolution satellite data (SPOT-6 and WorldView-2) and the results showed the potential operational applicability of random forest regression for the retrieval of winter oilseed rape LAI values at field scales using multi-source and high spatial resolution optical remote sensing data. Clevers et al. (2017) estimated LAI of a potato crop with different fertilization levels using Sentinel-2 satellite images; the results demonstrated that the weighted difference vegetation index using bands at 10 m spatial resolution can be used for estimating the LAI.

Compared with optical satellite images, synthetic aperture radars (SARs) have some advantages for monitoring crop growth status owing to the fact that microwave sensors can penetrate crop canopies and are less influenced by weather conditions (Kim et al., 2012; Wiseman et al., 2014). Many scientists have exploited the capabilities of SAR image data in crop canopy state variables or soil properties over large areas, such as LAI (Inoue et al., 2002; Canisius and Fernandes, 2012; Capodici