Environmental Modelling & Software 62 (2014) 454–464

Contents lists available at ScienceDirect

Environmental Modelling & Software

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

Dynamic assessment of the impact of drought on agricultural yield and scale-dependent return periods over large geographic regions☆

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ARTICLE INFO

Article history:
Received 30 September 2013
Received in revised form
8 July 2014
Accepted 7 August 2014
Available online 4 September 2014

Keywords:
Drought
Yield prediction
Dynamic
Return period
Scale

ABSTRACT

Agricultural droughts can create serious threats to food security. Tools for dynamic prediction of drought impacts on yields over large geographical regions can provide valuable information for drought management. Based on the DeNitrification-DeComposition (DNDC) model, the current research proposes a Drought Risk Analysis System (DRAS) that allows for the scenario-based analysis of drought-induced yield losses. We assess impacts on corn yields using two case studies, the 2012 U.S.A. drought and the 2000 and 2009 droughts in Liaoning Province, China. The results show that the system is able to perform daily simulations of corn growth and to dynamically evaluate the large-scale grain production in both regions. It is also capable of mapping the up-to-date yield losses on a daily basis, the additional losses under different drought development scenarios, and the yield-based drought return periods at multiple scales of geographic regions. In addition, detailed information about the water-stress process, biomass development, and the uncertainty of drought impacts on crop growth at a specific site can be displayed in the system. Remote sensing data were used to map the areas of drought-affected crops for comparison with the modeling results. Beyond the conventional drought information from meteorological and hydrological data, this system can provide comprehensive and predictive yield information for various end-users, including farmers, decision makers, insurance agencies, and food consumers.

1. Introduction

Drought is a recurring natural hazard (Wilhite and Buchanan-Smith, 2005) that can cause widespread damage to agricultural production. Although studies in quantitative drought evaluations have been conducted for almost a century (e.g., Munger, 1916; Kincer, 1919; Marcovitch, 1930), the capacity for decision support in actual drought management is still limited. For example, during an agricultural drought before harvest, questions frequently asked by decision makers include: how much yield reduction the drought has caused to date; how severe it is in relation to previous droughts (return periods); and what the consequences would be if the drought continues? There is no current body of literature that seeks to fully address these questions in a quantitative way, especially in large-scale agricultural droughts.

The underlying challenge behind these questions is how to address the uncertainty of drought development and quantify its impacts on grain yields. The stochastic nature of drought is an inherent cause of uncertainty (Refsgaard et al., 2007). It is difficult to achieve a deterministic prediction of changes in drought severity because droughts develop slowly and last a long time. Another important source of uncertainty is from the epistemic constraints. Drought is often a phenomenon without a clearly defined beginning or end (Whilhite, 2005). The complex mechanisms of how the drought affects the processes of water, soil, and crop growth are not well understood. Although there are multiple approaches that are relevant to agricultural drought management for the quantitative evaluation of drought severity and effects, the dynamic evaluation of the uncertainties in predicting the drought impacts on yield losses has not been well studied.

☆ Thematic Issue on Agricultural Systems Modeling & Software.

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http://dx.doi.org/10.1016/j.envsoft.2014.08.004
1364-8152/

The primary methods available for quantifying drought severity and yield impacts include agricultural surveys, drought severity indices, remote sensing and crop modeling. Agricultural surveys are still the basic means for obtaining information on crop-growth status and for predicting grain yield in most countries. For instance, in the U.S.A., the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture (USDA) makes monthly predictions of agricultural yields based on statistical analyses of routine survey data. The survey includes in-field observations of crop conditions in major crop-producing states, as well as interviews with 5500–27,000 farm operators via mail or phone calls (NASS, 2009a). Due to independent and unbiased data collection for decades, the monthly yield projection based on regression analysis produce accurate results when compared to final yield reports. However, in places lacking reliable and consistent long-term historical data, this approach is not feasible.

Various drought indicators have been developed to automatically classify drought severity since the 20th century (Heim Jr. 2002). The indices relevant to agricultural drought are usually based on the parameters of precipitation, soil moisture, and transpiration. These indices include MAI (moisture adequacy index, McGuire and Palmer, 1957), CMI (crop moisture index, Palmer, 1968), CWSI (crop water stress index, Idso et al., 1981), SPI (standard precipitation index, McKee et al., 1993), SMDI (soil moisture deficit index, Narasimhan and Srinivasan, 2005), SMI (soil moisture index, Hunt et al., 2009), and ARID (the Agricultural Reference Index for Drought, Woli et al., 2012). Comprehensive drought indices such as PDSI (Palmer Drought Severity Index, Palmer, 1965) and DM (Drought Monitor, Svoboda, 2000) also provide important information for agricultural drought management. There are multiple drought indices that are based on information from remote sensing data, such as VCI (vegetation condition index, Kogan, 1995), and NDWI (the normalized difference water index, Gao, 1996) for classifying drought severity. Remote sensing has also been applied to crop yield predictions (NASS, 2009b). The methods usually relate historical records of crop yields to vegetation indices derived from remote sensing data (Murthy et al., 1996; Kogan et al., 2005; Sakamoto et al., 2013). However, this approach is constrained to the time frame and geographical area of the study. Though some regression-based models have been successfully generalized to new areas, the nature of these methods is empirical, and they are unlikely to predict crop yields under extreme conditions that are beyond historical records (Moulin et al., 1998; Becker-Reshef et al., 2010; Bolton and Friedl, 2013).

Crop models are considered to be valuable tools for improving agricultural management and decision making. Most crop models predict yields based on simulating physiological processes during crop growth. These models include ELCROS (de Wit, 1965), CERES (Jones and Kiniry, 1986), EPIC (Williams and Singh, 1995), APSIM (McCown et al., 1996), ALMANAC (Kiniry et al., 1996), WOFOST (Boogaard et al., 1998; Eitzinger et al., 2004), and AquaCrop (Steduto et al., 2009). Another branch of models have been developed for simulating the biogeochemical processes such as carbon, hydrogen, oxygen, nitrogen, and phosphorus cycles in agro-ecosystems. Simulating crop growth to predict yields is also an essential part of these biogeochemical models, such as DNDC (Li et al., 2006; Zhang et al., 2002) and Century (Gilmanov et al., 1997). Many of these models have been developed and evaluated at the field scale rather than for large geographic regions (Palosuo et al., 2011). Most existing crop models are complex, and require a large number of input parameters that are not readily available (Steduto et al., 2009). Without establishing detailed agricultural databases, it is difficult to apply these models for large-scale simulations of crop growth.

One strength of using crop models for yield prediction is that the models allow for a sensitivity analysis (Saltelli and Annoni, 2010; Pogson et al., 2012; Wang et al., 2013) of how single input parameters affect crop growth and yield formation. For supporting drought management, if the weather data can be input into crop models, the drought-induced changes of soil moisture and yield losses can be estimated. Most of the existing methods of providing future weather data as model inputs are based on historical data. For example, Du Toit and Du Toit (2003) compared the current weather conditions with historical data to identify the five best fitting years, and used the daily data for the rest of growing season from these five analogue years. Bannayan et al. (2003) applied a weather generator to create future weather data based on the stochastic analysis of multiple-year historical data, and later they (Bannayan and Hoogenboom, 2008) developed a weather analogue tool for predicting daily weather data based on a modification of the k-nearest neighbor approach. In the current research, in addition to historical weather data, we applied a scenario analysis approach to address the uncertainties of drought development (Refsgaard et al., 2007; Warmink et al., 2010) and to provide information about the potential consequences for decision makers if a given drought scenario is realized.

Beyond the efforts in yield forecasting, there is a need to facilitate analysis of past drought probability and permit dynamic analysis of future drought scenarios. First, a stochastic analysis of the drought probability is fundamental in risk management because risk generally is considered as a combination of probability and damage (Haynes et al., 2008). Second, using return periods (e.g., a 100-year drought) for evaluating the severity of a natural hazard is a widely accepted measurement for the public and decision makers. Quantitative analyses of drought return periods date to work of Yevjevich (1967), who proposed the run concept for identifying drought events and their statistical characteristics. Most of these research efforts have been to derive drought return periods based on hydrological series (Sen, 1980; Sharma, 1997; Clausen and Pearson, 1995; Shiau and Shen, 2001; Shiau et al., 2007; Tarawneh and Salas, 2009) or meteorological data (Gabriel and Neumann, 1962; Serinaldi et al., 2009; Mirakbari et al., 2010; Núñez et al., 2011). For decision support of agricultural drought, however, it is necessary to evaluate return periods based on drought-induced yield losses. In addition, return periods are geographically scale-dependent. For example, if a 100-year drought occurs in a state, it does not imply the same severity for each county within this state; instead, the county-level drought may be more or less severe than the 100-year event. Quantitative evaluations of such scale-dependent return periods have rarely been reported.

The objectives of the current paper are to describe a Drought Risk Analysis System (DRAS) that allows the dynamic evaluation of large-scale yield losses and the calculation of scale-dependent return periods for agricultural droughts based on yield prediction. Using scenario analysis approaches, we applied the proposed system to quantify drought impacts on corn yields during the 2012 drought in the U.S.A. and to the 2000 and 2009 droughts in Liaoning Province, China. Remote sensing data were also used for dynamic verification of the modeled results.

Section 2 introduces the methodology of the dynamic evaluation and prediction of drought-induced yield losses, as well as the software tool for supporting dynamic agricultural drought management. Section 3 demonstrates applications of the tool for evaluating the daily impacts of the 2012 drought on corn in the U.S.A., which applications are associated with remotely sensed information. Section 4 illustrates the case of the droughts in Liaoning Province, China, with a focus on the dynamic quantification of spatially scale-dependent drought return periods based on yield losses. The dynamic evaluation of the uncertainty of