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A spatially explicit crop planting initiation and progression model for the conterminous United States

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ABSTRACT

The ability to accurately estimate crop planting date and planting progression has major implications in crop management, crop model applications, and in developing adaptation strategies for future climate change. The objectives of this study are: 1) identify major factors that determine planting initiation and progression of six major crops in the U.S. and 2) develop a spatially explicit planting initiation and progression model. The crops that were evaluated are maize (*Zea mays*), cotton (*Gossypium hirsutum*), rice (*Oryza sativa*), sorghum (*Sorghum bicolor*), soybean (*Glycine max*), and winter wheat (*Triticum aestivum*). County-level daily planting data from 2005 to 2015 for representative states were obtained from USDA Risk Management Agency. For the five summer crops, the earliest planting gradually shifts to later dates with increasing latitude and elevation. The trend is reversed for winter wheat, with planting initiation shifting to earlier dates from south to north and from low to high elevation. A minimum planting temperature threshold was established for the five summer crops, which decreases from south to north and from low to high elevation. A maximum planting temperature threshold was established for winter wheat, which decreases from south to north but increases from low to high elevation. A spatially explicit temperature model as a function of latitude, longitude and elevation was established to predict planting initiation, while a soil texture-based soil wetness index predicts planting delays due to excessive precipitation. The model was calibrated with 2005–2009 data and validated with 2010–2015 data; it provided sound goodness of fit for planting initiation and weekly planting progression. The spatially explicit model for planting initiation and progression could be used to guide crop production planning and to improve the planting date and progression algorithms in crop models for regional simulation analysis.

1. Introduction

Crop planting dates are mostly constrained by rainfall, irrigation, soil temperature and soil moisture (Hodges et al., 1987; Lauer et al., 1999; Meyer and Dutcher, 1998; Pathak et al., 2012), and are usually determined based on crop calendar from historic planting practices and current weather and soil conditions, especially soil temperature and moisture (Bondeau et al., 2007; Dobor et al., 2016; Leenhardt and Lemaire, 2002; Maton et al., 2007; Pathak et al., 2012; Sacks et al., 2010). Planting usually starts when soil temperature is sufficient to support rapid seedling emergence and when soil contains sufficient moisture or soil condition does not hinder field operations (Kucharik, 2008).

Waha et al. (2012) developed a climate-driven algorithm to simulate the sowing dates of 11 major annual crops at the global scale, based on annual temperature and precipitation variation coefficients and crop-specific temperature requirements. Since their algorithm uses average monthly climatology variables and assumes a global crop-specific temperature threshold, its applicability at local scales remains to be tested. Dobor et al. (2016) evaluated a number of existing and new methods, based on soil temperature and moisture, for predicting planting dates for maize and winter wheat in Hungary, but none of the methods explicitly include geographic information that impacts planting dates, and thus their applicability to broader geographic regions outside Hungary remains to be evaluated.

In addition to soil temperature and moisture based methods, crop models are also used to estimate planting dates that maximize yields (Dobor et al., 2016; Waongo et al., 2014). Stehfest et al. (2007) simulated global production of maize, rice, soybean, and wheat and chose the month with the highest simulated yield as the optimal planting date for each crop. Laux et al. (2010) estimated planting dates for maize and groundnut based on predicted onset of the raining season in Cameroon, Africa, using fuzzy logic; they combined rainfall amounts, number of rainy days, and the occurrence of dry spells following the onset of the raining season and used the resulting planting date estimates as inputs to the CropSyst model to simulate maize and groundnut yields. In a

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study on the impact of climate change on sorghum yields, Niu et al. (2009) estimated the date having the greatest likelihood of planting based on cumulative heat units. Folberth et al. (2012) used a spatially explicit version of EPIC to estimate optimal planting dates for maize in sub-Saharan Africa, constrained by observed earliest and latest planting dates. The authors concluded that accurate simulation of yields require accurate planting date estimates, particularly for areas having seasonally bimodal rainfall patterns (Folberth et al., 2012).

In crop production, the decision on when to plant has major impacts on subsequent crop management, yield and quality (Bannayan et al., 2013; Dobor et al., 2016; Kucharik, 2006, 2008; Singh et al., 2010). Early planting can expose a crop to cold spells, which reduce seedling growth, favor development of seedling diseases and pests, and increase competition from weeds. On the other hand, late planted crops flower and mature later, which can expose plants to hot weather that can reduce pollination and grain filling (Bannayan et al., 2013) and to higher pest pressure (Pettigrew, 2010). In addition, crop planting does not simply occur on an optimal date and is usually spread over a span of one to several months, due to unfavorable weather and/or equipment constraints. For example in Texas, rice is usually planted over a 1–2 month planting window at the county level (Wilson et al., 2017). At the state level, the planting window is even wider with earlier planting in the southwestern rice counties and progressively later planting in the southeastern and northern rice counties (Wilson et al., 2017). At the national level, the spread is even greater (NASS, 2016a). Unfortunately, region-specific and spatially explicit algorithms for planting initiation and progression are not available. The objectives of this study are: 1) identify major factors that determine planting initiation and progression for six major crops in the U.S. and 2) develop a spatially explicit planting initiation and progression model for crop production planning and regional simulation analysis.

Throughout the paper, we refers to *Planting Initiation* as the earliest date of planting for a crop in a county, indicating the start of the planting season, and *Planting Progression* as the time-dependent cumulative proportion of fields that have been planted from the start of the planting season in the county, with 100% planting at the end of the planting season (NASS, 2016a; Wilson et al., 2017). In addition, we refers to *Planting Temperature* as the temperature threshold above or below which the earliest planting in a county is initiated.

2. Methodology

2.1. Data types and sources

Four major types of data were used in this study to develop the planting date algorithm, including crop planting dates, cropland distribution, soil, and weather data. Fig. 1 summarizes the data flow, spatial scale and usage of each data type, with detailed descriptions below.

The six major crops selected for this study are maize (*Zea mays*), cotton (*Gossypium hirsutum*), rice (*Oryza sativa*), sorghum (*Sorghum bicolor*), soybean (*Glycine max*), and winter wheat (*Triticum aestivum*). Sixteen states were selected for the analysis, including nine for maize (Georgia, Illinois, Kansas, Mississippi, North Carolina, Nebraska, Pennsylvania, South Dakota and Texas), six for cotton (Arizona, California, Georgia, Louisiana, North Carolina and Texas), six for rice (Arkansas, California, Louisiana, Mississippi, Missouri and Texas), four for sorghum (Kansas, Mississippi, South Dakota and Texas), seven for soybean (Arkansas, Illinois, Kansas, Louisiana, North Carolina, South Dakota and Texas), and five for winter wheat (Kansas, Montana, Ohio, South Dakota and Texas). The selection of states was based on U.S. cropland distributions (NASS, 2016b; Wilson et al., 2010; Yang et al., 2011) and was intended to represent the major geographic distribution of each crop in the U.S.

Daily data on the number of fields planted in each county from 2005 to 2015 for the selected states were obtained from the USDA Risk Management Agency (RMA, 2015) through a Freedom of Information Act request (FOIA, 2017). These planting date data are originally reported by crop producers to USDA Farm Service Agency (FSA) local county office or their participating crop insurance agent on behalf of the Risk Management Agency and are used by the Federal Crop Insurance Corporation under the Risk Management Agency to provide U.S. farmers with crop insurance protection (FSA, 2017).

Texas Rice Crop Survey (Wilson et al., 2017) is a program that collects and reports weekly planting progress and planting acreage data for all rice counties in Texas. For 2015, total rice acreage in Texas from the RMA data was 48,731 ha as compared to 52,843 ha from the Texas Rice Crop Survey, accounting for more than 92% of the acreage reported from Texas Rice Crop Survey. The rice planting progression in 2015 from the RMA data also closely matched the reported weekly planting progression from Texas Rice Crop Survey. These results suggest the RMA data for rice is representative of the reported rice acreage and planting progression. It is reasonable to assume the same high data quality for other years and other 5 crops. As a further illustration of the extensive data coverage, total acreage included in the 2015 RMA data are 12.4, 3.0, 1.0, 2.0, 8.4 and 7.8 million ha for maize, cotton, rice, sorghum, soybean, and winter wheat, respectively; the corresponding total number of field units are 498, 119, 22, 87, 366, and 261 thousands, respectively, indicating sufficient data volumes for the development of the planting date algorithm in this paper.

County-level planting initiation and progression for each crop in each year and county were extracted from the daily planting data (Fig. 1D). Crop field distribution in a county was based on NASS 2013 cropland data (NASS, 2016b) with field size reconciled using the method of Yang et al. (2014) (Fig. 1A). Daily weather data (max and min air temperatures, precipitation, and solar radiation) for each field were obtained from the closest weather station in the *iAIMS* (Integrated Agriculture Information Management System) climatic database (Wilson et al., 2007; Yang et al., 2010) (Fig. 1C). Soil data for each field was based on Soil Survey Geographic (SSURGO) database (NRCS, 2010), which is integrated into *iAIMS* soil database (Yang et al., 2011) (Fig. 1B).

The Soil Climate Analysis Network (SCAN), administered by the NRCS National Water and Climate Center, consists of approximately 200 stations across the U.S. that automatically collect hourly data on soil moistures and temperatures (NRCS, 2017). But the density of the stations is rather low as compared to the number of climatic stations with air temperatures in *iAIMS* climatic database (more than 10,000 stations in the U.S.). Daily soil temperature at 10 cm depth was thus estimated based on daily air temperature from *iAIMS* weather stations using the method of Potter and Williams (1994), which first calculates soil surface temperature as a function of daily max and min air temperatures, plant biomass and residue, and total daily solar radiation using equations (12–16) and then calculates soil temperature at a specific depth as a function of yesterday's soil temperature, current soil surface temperature, soil bulk density and water content using equations (6–11) in Potter and Williams (1994). Since soil is usually bare at the time of planting, no plant biomass and residue were assumed. It was also assumed that soil water content was at its 50% holding capacity. Since the Potter and Williams (1994) method usually underestimates soil temperatures at very low air temperatures, the following equation was developed to correct the underestimation

$$T_{Under\ Estimation} = -13.6262/(1 + \exp((T + 14.4569)/5.7745))\ (R^2 = 0.63),$$

where $T_{Under\ Estimation}$ (°C) is the correction for underestimation for soil temperature T (°C) using the Potter and Williams (1994) method, and R^2 is the proportion of total variation that is explained by the fitted regression (Zar, 1984). The underestimation was based on observed soil temperature data in 2010 at 10 cm depth for Bushland, Texas and Mason, Illinois (NRCS, 2017). Daily soil temperatures at the county