SPECIAL SMAP COLLECTION

Modeling Regional Crop Yield and Irrigation Demand Using SMAP Type of Soil Moisture Data

HUSAYN EL SHARIF, JINGFENG WANG, AND ARIS P. GEORGAKAKOS

School of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, Georgia

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ABSTRACT

Agricultural models, such as the Decision Support System for Agrotechnology Transfer cropping system model (DSSAT-CSM), have been developed for predicting crop yield at field and regional scales and to provide useful information for water resources management. A potentially valuable input to agricultural models is soil moisture. Presently, no observations of soil moisture exist covering the entire United States at adequate time (daily) and space (~10 km or less) resolutions desired for crop yield assessments. Data products from NASA's upcoming Soil Moisture Active Passive (SMAP) mission will fill the gap. The objective of this study is to demonstrate the usefulness of the SMAP soil moisture data in modeling and forecasting crop yields and irrigation amount. A simple, efficient data assimilation algorithm is presented in which the agricultural crop model DSSAT-CSM is constrained to produce modeled crop yield and irrigation amounts that are consistent with SMAP-type data. Numerical experiments demonstrate that incorporating the SMAP data into the agricultural model provides an added benefit of reducing the uncertainty of modeled crop yields when the weather input data to the crop model are subject to large uncertainty.

1. Introduction

a. Background

Agricultural production systems have evolved significantly in recent years to address a growing national and global demand for food supply. The advent of modern measurement technologies, such as geographic information systems (GIS), global positioning systems (GPS), and other remote sensing tools at finer spatiotemporal resolutions, and crop system models have provided the opportunity to guide agricultural-related water resources management at both field and regional scales with reduced dependency on costly and uncertain in situ field experiments. Precision agriculture has been largely focused on maximizing field and regional crop yields and associated economic benefits. The tools involved in precision agriculture may also guide regional water resources management, as more accurate modeling and forecasting of water demand for crop production would lead to a more efficient allocation of limited water supplies. Careful monitoring and provision of water resources for agricultural use is critical as agriculture demands a large fraction of total water use in the United States and the world. In 2005, irrigation in the United States consumed 128 billion gallons per day, accounting for 37% of all freshwater withdrawals and 62% of all freshwater withdrawals excluding thermoelectric withdrawals (Kenny et al. 2009). The 2013 National Climate Assessment (NCA) indicates that under the A2 emissions scenario, U.S. freshwater withdrawals will increase by 25%–35% in the coming 50 years, with three-fourths of this increase due to irrigation and one-fourth due to landscape watering and power generation (Brown et al. 2013; Georgakakos et al. 2014). Because of these and other stresses, a key message of the 2014 NCA is that "in most U.S. regions, water resources managers and planners will encounter new risks, vulnerabilities, and opportunities that may not be properly managed within existing practices" (Georgakakos et al. 2014, p. 70). The information of space–time distribution of soil moisture is critical for irrigation decisions and for more efficient use of water resources across multiple sectors.

Corresponding author address: Husayn El Sharif, School of Civil and Environmental Engineering, Georgia Institute of Technology, 790 Atlantic Dr., Atlanta, GA 30332.
E-mail: helsharif@gatech.edu

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Agricultural models, such as Decision Support System for Agrotechnology Transfer cropping system model (DSSAT-CSM; Tsuji et al. 1994), have been developed to predict the yield of various crops at field and regional scales. Crop yield modeling and prediction provide essential information for water resources management. One key output of the agricultural models is soil moisture. Presently, no soil moisture observations covering the entire United States exist with adequate time (daily) and space (~10 km or less) resolutions preferred for crop yield assessments. Instead, estimates of soil moisture at fine spatial scales are commonly derived from downscaling remotely sensed soil moisture data (Cheng et al. 2008; El-Sharkawy 2011; NCDC 2006; NRCS 2014; WRF 2013). The NASA Soil Moisture Active Passive (SMAP) mission satellite was launched on 31 January 2015 and aims to measure soil moisture from space at fine (down to 9 km for the combined active radar and passive radiometer product) spatial and temporal (2–3 days global coverage) resolution for the first time. The depth of soil moisture retrieval will be the topmost 5 cm of the soil profile. Incorporating SMAP soil moisture data products into crop system models such as DSSAT-CSM has the potential to improve the accuracy of crop yield prediction, especially with regard to regional irrigation forecasting and water resources management. Although agricultural water use dominates consumption of water in many parts of the world, reliable estimates of historical and future agricultural water demand are lacking for some times and regions. In the southeastern U.S., for example, individual farmers do not routinely monitor or record their water usage, and they are not obligated to report their water use to any governing body. This situation presents significant challenges for retrospective analysis of interannual and seasonal water demand. Irrigation practice is strongly dependent on soil moisture conditions, and accurate fine-resolution soil moisture data are vital to regional water resources managers and related stakeholders who strive to efficiently and equitably allocate limited water resources, especially in the face of a changing climate.

b. *Problem statement*

Crop yield and water demand estimates depend on accurate, high-resolution spatiotemporal data of weather and/or soil moisture that are not available at sufficient resolutions for all regions. NASA's SMAP mission will provide much needed soil moisture data at relatively high spatiotemporal resolution with global coverage. These data can potentially support more accurate crop yield and irrigation demand forecasts, which would be particularly useful in regions where observed weather or soil moisture data are sparse or unavailable. In the developing world, for example, where food security is a major concern, the current and historical weather data critical to forecasting crop yield and irrigation demand are subject to substantial uncertainty (WFP/IFAD 2011), leading to large uncertainty in the modeled crop yield and irrigation demand. A potential benefit of SMAP-type data is to reduce the uncertainty in modeled crop yield and irrigation demand by constraining model simulations to be consistent with the remotely sensed top soil moisture data.

c. *Objectives*

The objectives of this study are to 1) develop an algorithm by which daily SMAP-type top soil moisture data can be assimilated into the DSSAT-CSM for modeling of crop yield and irrigation amount at the ~10-km spatial scale and 2) reduce the uncertainty in the forecast of crop yield and irrigation demand by combining SMAP-type remotely sensed soil moisture data with other weather measurement data products.

d. *Outline*

The article is organized as follows. Section 1 introduces the value of precision agriculture models—models designed to explore site-specific, high-efficiency, sustainable agriculture with the help of detailed, modern datasets (McLoud and Gronwald 2007; Shibusawa 1998; Zhang et al. 2002)—and the potential benefit the upcoming SMAP remotely sensed soil moisture data products can provide in forecasting crop yield and irrigation demand. The objectives of this study are also stated. An overview of previous studies on crop system models, in particular DSSAT-CSM, the role of soil moisture data in such models, and the description of the upcoming SMAP mission and its data products are also provided. Section 2 presents the methodology for developing a synthetic ground-truth soil moisture sequence using observed weather data and DSSAT-CSM top soil moisture output and describes how the SMAP data product is expected to be within a specified error tolerance of the synthetic soil moisture dataset. SMAP-derived information on soil moisture is then combined with supplementary data and incorporated into the DSSAT-CSM agricultural model to simulate crop yield and irrigation demand. Section 3 describes the study region for which the methodology is applied and identifies relevant data sources. Results and conclusions are presented in sections 4 and 5, respectively.

e. *Literature review*

1) DSSAT-CSM

The DSSAT-CSM is a widely used biophysical model for simulating the phenology, growth, development, and yield of various crops and cultivars given inputs of soil,

TABLE 1. Description of DSSAT-CSM modules and submodules.

Modules	Sub modules	Behavior
Main program (DSSAT-CSM)		Controls time loops, determines which modules to call based on user input switches, and controls print timing for all modules.
Land unit		Provides a single interface between cropping system behavior and applications that control the use of the cropping system. It serves as a collection point for all components that interact on a homogenous area of land.
Weather		Reads or generates daily weather parameters used by the model. Adjusts daily values if required, and computes hourly values.
Soil	Soil dynamics	Computes soil structure characteristics by layer. This module currently reads values from a file, but future versions can modify soil properties in response to tillage, etc.
	Soil temp module	Computes soil temp by layer.
	Soil water module	Computes soil water processes including snow accumulation and melt, runoff, infiltration, saturated flow, and water-table depth. Volumetric soil water content is updated daily for all soil layers. Tipping-bucket approach is used.
	Soil nitrogen and carbon module	Computes soil nitrogen and carbon processes, including organic and inorganic fertilizer and residue placement, decomposition rates, and nutrient fluxes between various pools and soil layers. Soil nitrate and ammonium concentrations are updated on a daily basis for each layer.
SPAM		Resolves competition for resources in soil–plant–atmosphere system. Current version computes partitioning of energy and resolves energy balance processes for soil evaporation, transpiration, and root water extraction.
CROPGRO crop template module		Computes crop growth processes including phenology, photosynthesis, plant nitrogen and carbon demand, growth partitioning, and pest and disease damage for crops modeled using the CROPGRO model crop template (soybean, peanut, dry bean, chickpea, cowpea, faba bean, tomato, Macuna, Brachiaria, and Bahiagrass).
Individual plant growth modules	CERES-maize, CERES-wheat, CERES-rice, SubStor-potato, and other plant models	Modules that simulate growth and yield for individual species. Each is a separate module that simulates phenology, daily growth and partitioning, plant nitrogen and carbon demands, senescence of plant material, etc.
Management operations module	Planting	Determines planting date based on read-in value or simulated using an input planting window, soil, and weather conditions.
	Harvesting	Determines harvest date, based on maturity, read-in value, or on a harvesting window along with soil and weather conditions.
	Irrigation	Determines daily irrigation, based on read-in values or automatic applications based on soil water depletion.
	Fertilizer	Determines fertilizer additions, based on read-in values or automatic conditions.
	Residue	Application of residues and other organic material (plant, animal) as read-in values or simulated in crop rotations.

weather, and management conditions (Jones et al. 2003). DSSAT-CSM, version 4.5 (Hoogenboom et al. 2012), includes 29 crops and fallow fields (Daroub et al. 2003; Hoogenboom et al. 1999; Jones et al. 2001, 2003; Liu et al. 2011; Tsuji et al. 1994). DSSAT-CSM is composed of a main driver program, a land unit module, and modules of weather, soil, plant, soil–plant–atmosphere interaction, and management. The main driver program controls each of the primary modules and allows each module to read inputs, initialize variables, compute rates, integrate variables, and write outputs independent of other modules (Jones et al. 2003). A brief description of the modules included in DSSAT-CSM is presented in Table 1 (Jones et al. 2003).

2) HISTORY OF INCORPORATING SOIL MOISTURE DATA INTO AGRICULTURAL MODELS

Improving agricultural models by incorporating soil moisture measurements and/or remote sensing data has become a growing field of study. Baier and Robertson (1968) found that wheat yields from 39 plantings in Canada over five seasons were more closely related to soil moisture conditions than rainfall and maximum and minimum temperatures, a significant finding as the DSSAT-CSM soil water balance algorithm still uses precipitation and maximum and minimum temperatures as model input (Jones et al. 2003). Batts and Kaleita (2008) investigated the impact of synthetic top 5-cm soil moisture data on the DSSAT-CSM simulations in a series of modeling experiments for a maize field in Ames, Iowa. Differences in modeled yield using their assimilation method in some cases were greater than 10% depending on year, soil type, and nitrogen fertilizer application rate of the synthetic experiments. Groenendyk et al. (2011) investigated assimilation of in situ soil moisture data into DSSAT-CSM through a Kalman filter to simulate the winter-wheat crop growing seasons of 2003–05 in Maricopa, Arizona. Model improvement (defined by closer agreement with field measurements of crop yield and canopy biomass) occurred when soil moisture data were assimilated into the top 3 cm and top 5 cm of the soil layer. Ines et al. (2013) utilized an ensemble Kalman filter to assimilate remotely sensed AMSR-E soil moisture and MODIS leaf area index (LAI) data products into DSSAT-CSM to model year 2003–09 maize yields in Story County, Iowa. Data assimilation improves the correlation between modeled and observed crop yield from 0.47 (no data assimilation) to 0.65 (with combined assimilation of soil moisture and LAI data). Maas (1988) explored four techniques for incorporating remotely sensed data into a simulation of a white-maize monoculture at a U.S. Department of Agriculture (USDA) research farm in Texas, with direct input of remotely sensed data being the simplest of data assimilation methods under testing. However, the direct input method required frequent observations that were not available. Moulin et al. (1998) addressed challenges in incorporating coarse-resolution remote sensing data to estimate regional crop yields using a similar approach. Delécolle et al. (1992) also used remote sensing data assimilation techniques for several categories of crop models and recommended that regional analysis may be performed by aggregating simulated crop yields from individual fields. Mo et al. (2005) used remotely sensed data of crop canopy LAI with a process-based soil–vegetation–atmosphere transfer (SVAT) model to predict crop yield, water consumption, and water use efficiency for a subregion of the North China Plain. Mishra et al. (2012) have tested the Atmosphere–Land Exchange Inverse (ALEXI) satellite-derived soil moisture estimates as a surrogate for precipitation data in DSSAT-CSM for crop yield simulation for two climatically contrasting locations in Alabama and Indiana. The soil moisture data with the required resolutions are often obtained through downscaling. Blöschl et al. (2009) provide a statistical technique for downscaling 25-km remotely sensed soil moisture data to 1-km resolution over Europe. Lin et al. (2011) used the coupled WRF–Triangulated Irregular Network (TIN)-based Real-Time Integrated Basin Simulator (tRIBS) with Vegetation Generator for Interactive Evolution (VEGGIE) hydrologic model to downscale early adopter SMAP data products. Use of high spatiotemporal resolution soil moisture data for modeling crop yields is an active field of research.

3) SMAP and other soil moisture measurement missions

Remote sensing soil moisture datasets have been derived from signals of active and passive microwave sensors on satellites (Bartalis et al. 2007; Njoku et al. 2003; Owe et al. 2008) since the early 1980s. Without such observations, soil moisture estimates often depend on reanalysis data subject to large uncertainties (Dorigo et al. 2012; Ferguson and Wood 2011). Satellite missions include Skylab (Entekhabi et al. 2010), *ERS-1*, *ERS-2*, AMSR-E, SMMR, SSM/I, TMI, Advanced Scatterometer (ASCAT), and SMOS (Dorigo et al. 2010). These soil moisture data products have spatial resolutions ranging from 12 to 50 km and daily, weekly, and monthly temporal resolutions covering various regions of the earth.

According to the National Research Council's (NRC) decadal survey (NRC 2007), the data product of the SMAP mission, whose satellite was launched on 31 January 2015, was characterized with high scientific and practical applications value in multiscale hydrologic and environmental studies (Entekhabi et al. 2010). The SMAP mission will measure the top 5-cm-layer soil moisture and soil freeze–thaw state from space at fine (down to 9 km) spatial and temporal (2–3 days global coverage) resolution using (the first spaceborne) L-band (active) radar and an L-band (passive) radiometer instrumentation (Entekhabi et al. 2010). It is specified that one standard deviation about true soil moisture in the level-2 (9 km) SMAP data product shall not exceed $0.04\,\mathrm{cm^3\,cm^{-3}}$. Incorporating SMAP soil moisture data into crop system models such as DSSAT-CSM has the potential to improve the accuracy of crop yield simulations related to regional irrigation forecasting and water resources management.

2. Methodology and data

The purpose of this study is to quantify the impact of SMAP-like remote sensing soil moisture data on DSSAT-CSM agricultural model forecasts of agricultural yield and irrigation demand using synthetically generated datasets with statistical characteristics (uncertainty) similar to those of the upcoming SMAP products. This soil moisture data product is then used to ''filter'' an ensemble of

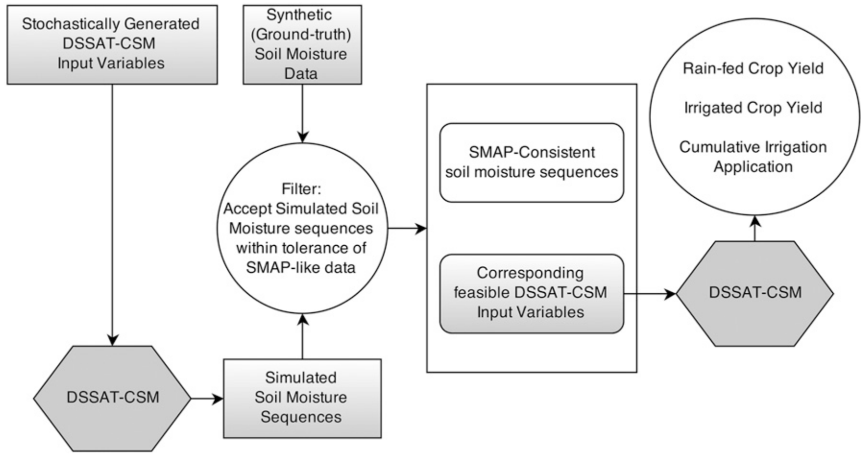

FIG. 1. Flowchart describing process of using ground-truth soil moisture data and SMAP-derived error tolerances in modeled top-layer soil moisture to filter through DSSAT-CSM runs.

DSSAT-CSM runs using synthetic weather input data. In this study, stochastic forcing is introduced by adding measurement noise to daily weather inputs. The ''control'' scenario refers to DSSAT-CSM results using the entire ensemble of synthetic input data in DSSAT-CSM runs. The ''SMAP'' scenario refers to DSSAT-CSM runs in which modeled top soil moisture is consistent with the SMAP-like data. Agreement is assessed via the absolute difference between modeled and the ground-truth top-layer soil moisture content for each day of the simulated growing season. Model runs in which the SMAP-derived error tolerance criteria for soil moisture content is violated less than 5% of the growing season are selected as ''feasible'' or ''SMAP consistent'' model runs. The SMAP-derived absolute difference threshold is assumed to be a function of the ''true'' soil moisture for the current day of simulation. SMAP-consistent model runs are used to generate samples of simulated rain-fed and irrigated crop yield and irrigation demand. Under the irrigation scenarios, the DSSAT-CSM is programed to automatically irrigate the top soil layer to saturation when the modeled top-layer soil moisture drops below a user-specified threshold. An overview of the filtering procedure is illustrated in Fig. 1. Details regarding the acceptance criteria for a model run to be considered either feasible (SMAP consistent) or infeasible are shown in the Fig. 2 flowchart. Metrics used to assess the usefulness of soil moisture data include the reduction in the standard deviation of modeled crop yield and year-end irrigation application depth after the soil moisture data filter is applied. It is also of interest to record whether incorporation of SMAP-like data impacts the mean modeled crop yield and irrigation amount.

The experiments involved in this study are listed in Table 2. Experiment 1 explores how daily soil moisture data can reduce uncertainty in modeled crop yield under the scenario in which daily precipitation is subject to random measurement errors. Experiment 2 builds on this premise and subjects all required daily weather variables—precipitation, maximum and minimum air temperature, and solar radiation—to measurement errors. These two experiments represent scenarios in which field data on weather are available but are subject to modest uncertainties because of measurement error or spatial interpolation/extrapolation of weather data, as may be the case in data-scarce regions. The method of generating the surrogate ground-truth soil moisture dataset and weather measurement sequences for a case study region and incorporating them into DSSAT-CSM experiments mentioned in Table 2 is described below.

a. SMAP-like soil moisture data

In this study, DSSAT-CSM soil moisture driven by observed weather input is referred to as ground truth. The SMAP-like 9-km spatial and daily temporal resolution data product is assumed to be within a specified error tolerance of the synthetic ground-truth dataset. Operating over a SMAP 9-km pixel, the DSSAT-CSM point-scale model simulates crop yield and irrigation amount assuming homogeneous field, soil, crop, and weather conditions. DSSAT-CSM is then constrained to keep modeled top-layer soil moisture within SMAP-derived error tolerances for each day of the growing season while measurement errors are introduced into daily weather inputs. When these constraints are fulfilled for at least 95% of the growing season, it is concluded that DSSAT-CSM has ''assimilated'' SMAP-like data.

While the upper bound of the error (1σ) in the SMAP level-2 (combined radar and radiometer) data product is $0.04\,cm^3\,cm^{-3}$, prelaunch tests of the SMAP retrieval

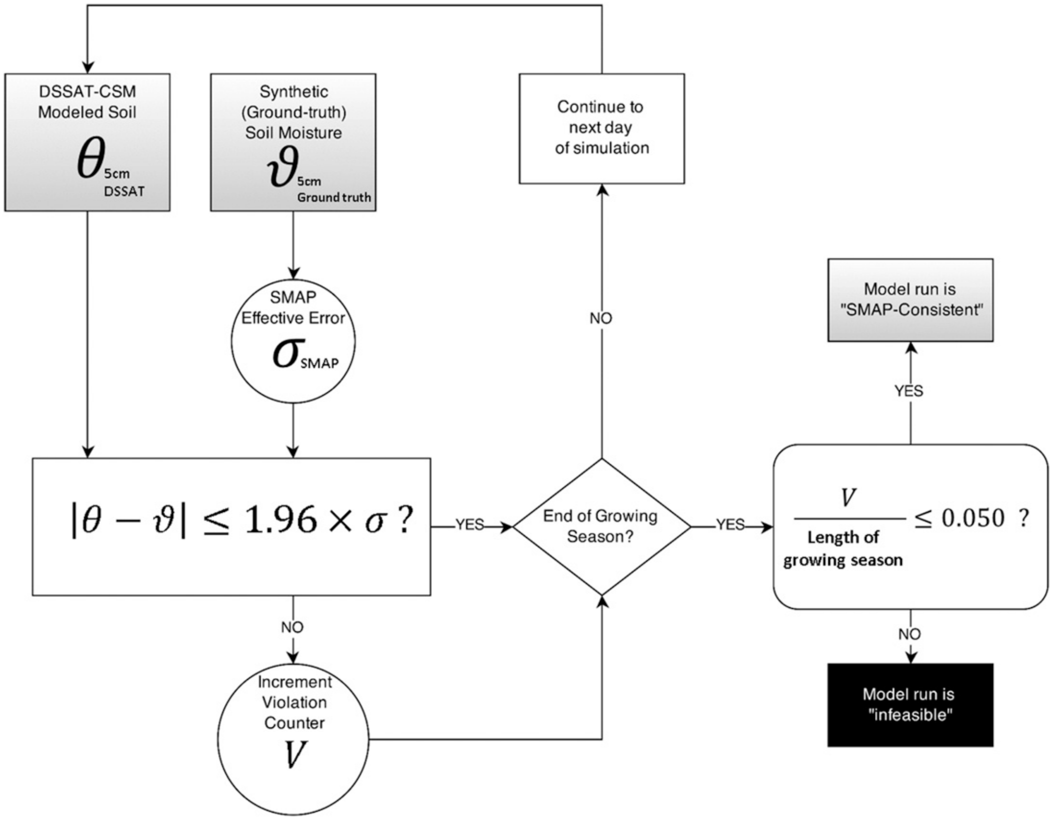

FIG. 2. Flowchart detailing the process of determining the SMAP consistency (feasibility) of a DSSAT-CSM run. For each day of the growing season, the absolute difference between the DSSAT-CSM soil moisture θ and the ground-truth synthetic soil moisture ϑ is compared to the effective error in SMAP-like measurement σ. A violation counter V is incremented each day the acceptance criteria are not fulfilled. If acceptance criteria are violated more than 5% of the days of the growing season, then the model run is deemed as infeasible, and if otherwise, then it is deemed SMAP consistent.

algorithm suggest that the actual error is expected to be smaller (e.g., approximately 0.03 cm^3 cm^{-3}; Das et al. 2011). The error may be further reduced through constraining SMAP-like data by the information of the case study site. Under this condition, we suggest that the actual, or ''effective,'' error for the SMAP product varies with true soil moisture, peaking halfway between wilting point and saturation and diminishing near wilting point and saturation. Figure 3 illustrates a characterization of σ in the SMAP data product with a wilting point near zero and saturation water content of 0.361 cm^3 cm^{-3}. The maximum effective error is set at 0.025 cm^3 cm^{-3} according to our analysis of SMAP calibration mission results from Das et al. (2011). For each day of the DSSAT-CSM simulated growing season, modeled soil moisture content for a feasible model run must remain within 1.96 times the effective error (representing two standard deviations) of the synthetic ground-truth soil moisture dataset for at least 95% of the modeled growing season. If this acceptance criterion is achieved, then the model run is considered to be ''feasible'' and consistent with SMAP-like data.

TABLE 2. Experiment description.

Expt	Description	Incoming solar radiation (MJ m^{-2})	Max and min air temp (°C)	Precipitation (mm)
1	Soil moisture data corrects errors in daily rainfall input.	Known	Known	Subject to 20% daily measurement error.
2	Soil moisture data corrects errors in daily weather input.	Subject to ±10% daily measurement error.	Subject to ±0.5°C daily measurement error.	Subject to 20% daily measurement error.

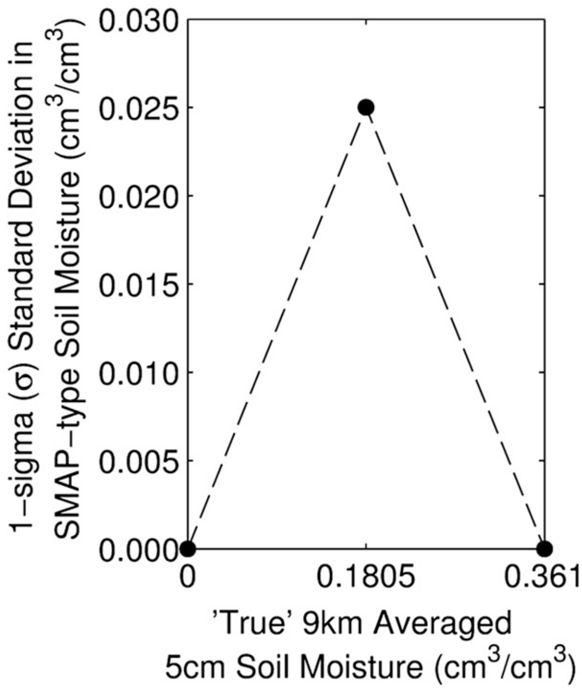

FIG. 3. Simple characterization of σ in the 9-km SMAP level-2 data product for a soil type with a wilting point near zero and saturation water content of 0.361 $cm^3 cm^{-3}$. Max error is assigned where the soil moisture has more freedom to vary; min error is assigned at the extremes of wilting point and saturation.

b. *Experiment 1: Soil moisture data corrects errors in daily rainfall input*

When precipitation observations are available with significant uncertainty, the DSSAT-CSM may be used to ‘‘correct’’ rainfall input through modeling the dynamics of top-layer soil moisture with soil moisture data used as a rainfall correction ‘‘filter.’’ Using information on the percent error in daily rainfall measurements, an ensemble of stochastic rainfall sequences is simulated. Each of these weather realizations are used as input into a model run of DSSAT-CSM. Whenever a weather realization results in a modeled daily time series of top soil moisture within the effective error threshold for at least 95% of the growing season, the model run is selected as SMAP consistent. Modeled rain-fed and irrigated crop yields are sampled from these feasible model runs. In this experiment, daily precipitation data are stochastically generated based on daily observations. For each day of simulation, 2000 samples of precipitation are generated from a truncated normal distribution with a mean equal to the observed precipitation and a standard deviation equal to 20% of the observation. The distribution is bounded by zero and 1.1 times the observation (to allow for both under- and overestimation errors). Introducing this type of noise into rainfall data mimics measurement and/or spatial interpolation/extrapolation errors. In this experiment, other daily weather variables (incoming solar radiation, maximum and minimum air temperatures) are assumed to be known and equivalent to observations, as mentioned in Table 2. In this study, the absolute error threshold for DSSAT-CSM daily top soil moisture is set at 1.96 times the daily effective SMAP error shown in Fig. 3.

c. *Experiment 2: Soil moisture data corrects errors in daily weather input*

When observed meteorological variables such as incoming solar radiation, precipitation, and maximum and minimum air temperatures are available with significant errors, incorporating SMAP-like top soil moisture data into DSSAT-CSM can mitigate model errors because of incorrect weather input. Error-contaminated measurement datasets are developed using different methods appropriate for each weather variable. The rainfall data are obtained using the method described in experiment 1. The daily solar radiation data are simulated using a truncated Gaussian distribution with a mean equal to the day's observation of solar radiation. The truncated distribution is bounded by zero and 1.2 times the historical data of radiation to cover the cases of both over- and underestimation. The standard deviation is set as 10% of each day's historically recorded solar radiation. Daily maximum and minimum temperatures were simulated from the observation data superimposed with a white noise following a truncated Gaussian distribution between $-1°$ and $+1°C$ with a mean of zero and a standard deviation of 0.5°C. Experiment 2 represents a practical scenario in which observations are available for multiple weather variables, all subject to measurement and/or interpolation/extrapolation error.

Each of these weather realizations are used as input to DSSAT-CSM runs. The synthetic soil moisture data, with the SMAP-derived effective error threshold, is used to select SMAP-consistent model runs just as in experiment 1. Similarly, modeled rain-fed and irrigated yields are sampled from these feasible model runs.

3. Data

a. *Ames, Iowa*

The case study site was Ames, Iowa, located at 42°1′N, 93°44′W (central Iowa, United States) at an elevation of 327 m (NRCS 2014). As published by the National Climatic Data Center (NCDC) Climate Services Branch (NCDC 2006), the Iowa terrain is mostly composed of rolling hills with a climate dominated by moist southerly wind from the Gulf of Mexico in the summer, northwesterly wind of cold, dry Canadian air in the winter, and occasional air masses from the Pacific Ocean and

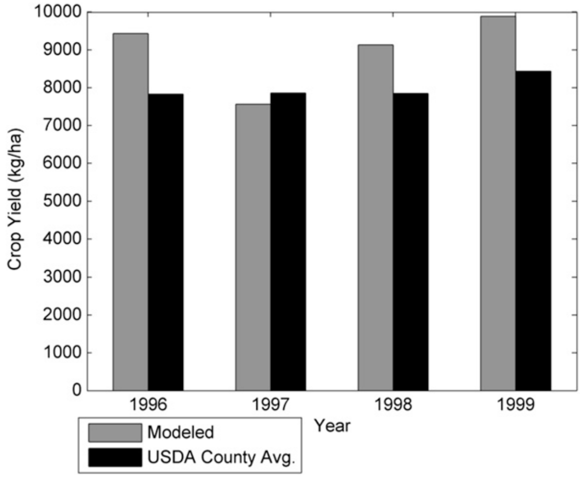

FIG. 4. Comparison of DSSAT-CSM crop yield to USDA NASS averaged county yield. Yield average reported for Boone and Story Counties near Ames, Iowa.

the Southwest desert. Summer daily high temperatures (July) reach 28°C and winter daily low temperatures (January) drop to −15.6°C. Statewide annual precipitation is 864 mm, with the majority of precipitation occurring during the late April to early October growing season. Iowa's climate and rich soils are ideal for rain-fed corn and soybean crops.

b. *Weather data*

This study uses 2003 weather data from station 2031 (Ames, Iowa) from the Soil Climate Analysis Network (SCAN) managed by the Natural Resources Conservation Service (NRCS) (NRCS 2014). Minimum weather inputs for DSSAT-CSM include daily data of incoming solar radiation, maximum and minimum temperatures, and precipitation. The SCAN station includes temperature probes and a rain gauge to provide the rainfall and temperature data. For daily measurement entries from the SCAN site containing erroneous or missing data, data entries were replaced with available data from the previous day. Only three days during 2003 had missing data at the SCAN site. Daily solar radiation data were taken from the NASA Prediction of Worldwide Energy Resource (POWER) agroclimatology (NASA 2014) dataset.

TABLE 3. DSSAT-CSM initialization. The asterisk indicates that crop nitrogen demand is assumed to be fully met throughout the growing season; nitrogen transport and nitrogen-deficit plant stress is not simulated.

Expt parameter	Description
Maize cultivar	DK 611
Plant population	4.7 m^{-2}
Nitrogen fertilizer application	Not applicable*
Soil type	Clarion loam
Planting date	27 May 2003
Harvest date	31 Oct 2003

c. *DSSAT-CSM initialization*

DSSAT-CSM simulations for 2003 in this study were based upon crop, soil type, and management parameters from a 1999 Ames, Iowa, rain-fed maize cropping scenario. The 1999 scenario data files were provided as one of the default maize experiments in DSSAT-CSM, version 4.5.0.0, and were developed by Drs. J. Lizaso and B. Batchelor of the Department of Agricultural and Biosystems Engineering, Iowa State University. Model results from the 1999 experiment agreed well with in situ measurements of crop yields. DSSAT-CSM simulation of Ames, Iowa, crop yields using weather observations from years 1996–99 are compared with averaged county-level crop yields reported by the USDA National Agricultural Statistics Service (NASS) as shown in Fig. 4. Modeled crop yields in these years were generally within 20% of the county average, suggesting that DSSAT-CSM reasonably simulates the region's hydrology, soil type, expected crop growth, and crop stresses, at least for the nondrought years of 1996–99. One of the required inputs for DSSAT-CSM initialization is the initial soil moisture profile. Initial conditions for 2003 soil moisture profile were obtained from a 2002 DSSAT-CSM run using a fallow crop. The soil moisture profile from 31 December 2002 was assigned to the soil water profile for 1 January 2003. Year 2003 model runs were initialized from 1 January 2003 with the simulated growing season from 27 May to 31 October 2003. Table 3 lists some management parameters

TABLE 4. Site-specific soil profile characteristics for Ames, Iowa.

Depth (cm)	Soil water lower limit	Drained upper limit	Saturated water content	Saturated hydrological conditions (cm h^{-1})	Organic carbon content (%)	Sand (%)	Clay (%)	Silt (%)
10	0.110	0.300	0.361	3.3	2.03	79	21	0
30	0.110	0.300	0.361	3.3	2.03	79	21	0
60	0.129	0.310	0.371	3.3	0.44	73	27	0
90	0.129	0.310	0.371	3.3	0.44	73	27	0
120	0.107	0.229	0.369	3.3	0.15	83	17	0

TABLE 5. USDA NASS year 2003 Iowa Maize yield.

Region	Dry yield (kg ha^{-1})
Story County	8725
Boone County	9038
Avg (Boone and Story Counties)	8882

used to initialize DSSAT-CSM simulations, and Table 4 lists soil layer and soil type parameters used in the study.

d. Crop yield statistics

Results from the numerical experiments are compared to the reported annual (growing season) maize yields for year 2003 from the USDA NASS. To facilitate comparison with USDA-reported yields, DSSAT-CSM calculated dry yields were reduced by 5% to account for mechanical losses during the harvest process. USDA-reported yields were converted to dry weight assuming a grain moisture content of 15.5%. Relevant county-level statistics are presented in Table 5 (USDA 2013). It is important to note that this study models crop yield at the scale of a single SMAP pixel (~10 km) and not county-level yield; comparison of model results to county-level data is done only for reference.

4. Results

As shown in Fig. 5, the soil moisture filtering procedure was able to reduce the uncertainty in modeled rain-fed crop yield for experiments 1 and 2 in which measurement uncertainties were introduced into daily weather variables. Simulated rain-fed crop yields in those experiments were brought closer to the modeled rain-fed crop yield from true weather input. The USDA county-level yield for year 2003 (an average of Boone and Story counties in Iowa) converted to dry weight is indicated in Fig. 5 for reference.

For experiment 1, in which only daily rainfall was subject to measurement error, the soil moisture filter selected 727 SMAP-consistent model runs from a pool of 2000. The mean modeled rain-fed crop yield did not change significantly after the soil moisture filter was applied (increasing by only 2%); however, the uncertainty (standard deviation) in the modeled crop yield was reduced by approximately 30%, as shown in Table 6. Similarly, when measurement error was introduced into all daily weather inputs (experiment 2), the soil moisture filter selected 872 SMAP-consistent model runs from a pool of 2000, and the standard deviation in modeled rain-fed crop yield was reduced by approximately 18%.

As evidenced by the uncertainty in the control modeled crop yields, measurement errors in weather input to DSSAT-CSM can introduce significant uncertainty in model results. Errors such as those introduced in experiment 1 directly influence the evolution of soil moisture in each layer of the soil profile. Water flux downward through the soil profile (via drainage) and upward (via

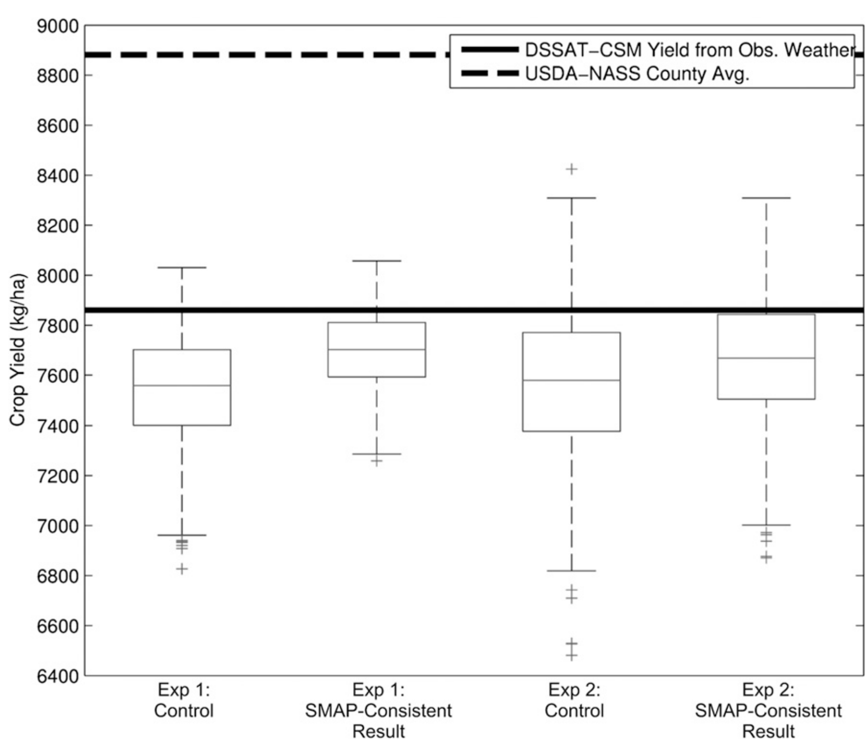

FIG. 5. Modeled rain-fed crop yields for experiments 1 and 2.

TABLE 6. Change in uncertainty of modeled rain-fed crop yield after applying daily soil moisture filter.

Expt	Description	Std dev in modeled rain-fed crop yield (kg ha^{-1})		Change (%)
		Before filter	After filter	
1	Soil moisture data corrects errors in daily rainfall input.	223	157	−30
2	Soil moisture data corrects errors in daily weather input.	302	249	−18

diffusion and root water uptake) is also affected. Lack of predictive skill, due to erroneous water input, would introduce errors with regard to modeling nutrient transport and would cause inaccurate yield estimates. Likewise, errors in solar radiation and temperature data, such as those included in experiment 2, cause errors in crop photosynthesis, soil evaporation, and crop transpiration, which, in turn, affect the transport of water and nutrients through the soil profile and lead to errors in crop growth and yield. Because of the highly nonlinear relationship between weather variables, soil water and nutrient transport dynamics, and crop growth, it is not entirely clear what type of error (over- or underestimation) would be introduced to crop yield because of combined (and/or competing) errors in precipitation, solar radiation, and air temperature. Overestimation of low precipitation events and underestimation of extreme (and rare) precipitation events could lead to water surpluses offsetting drought effects. However, when coupled with reduced photosynthesis and reduced evaporation due to underestimation of solar radiation, any benefit from the plentiful supply of water would be lost. Water surplus coupled with overestimation of solar radiation would obviously accelerate photosynthesis, leading to overestimation of crop yield. It is of interest to note that the errors introduced to rainfall input for experiment 1 and to weather inputs for experiment 2 resulted in modeled top soil moisture content that was outside of SMAP specifications for 65% and 56% of the crop yield simulations, respectively. Guiding the DSSAT-CSM to produce results consistent with the SMAP-type top soil moisture data, as accomplished by the novel soil moisture filtering procedure developed in this study, can correct some potentially dramatic model biases introduced by such input/measurement errors.

Under the automated irrigation scenario, drought stresses on photosynthesis and crop growth were virtually eliminated, and crop yield approached the modeled irrigated levels using true weather input as shown in

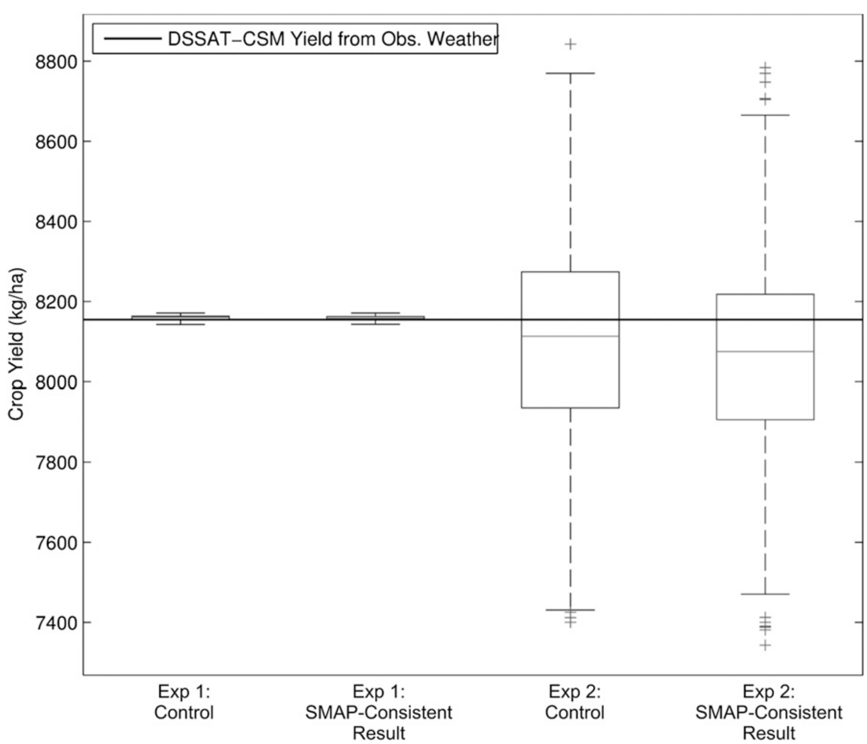

FIG. 6. Modeled irrigated crop yields for experiments 1 and 2.

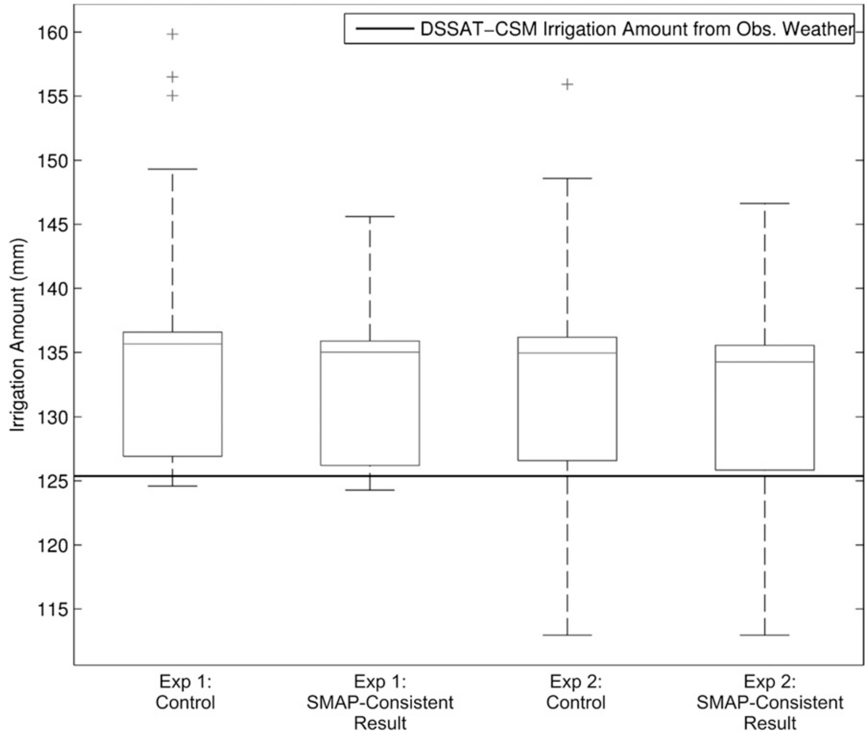

FIG. 7. Modeled cumulative irrigation amounts for experiments 1 and 2.

Fig. 6. This occurs regardless of whether external soil moisture data was available or not. Because of the achievement of potential production in the absence of water stresses, modeled crop yield variation was negligible in the irrigated crop simulations. Mean irrigated crop yield and mean irrigation amount for experiments 1 and 2 did not significantly change with application of the soil moisture filter as shown in Figs. 6 and 7; however, the standard deviation in irrigation amount was reduced (marginally) by 14% and 9% for experiments 1 and 2, respectively, as shown in Table 7.

5. Conclusions and ongoing research

This study introduces an efficient algorithm for assimilating SMAP top-layer daily soil moisture data into DSSAT-CSM. The soil moisture filtering procedure constrains the agricultural model to produce results consistent with SMAP-like remotely sensed soil moisture data, thereby reducing the uncertainty in forecasted crop yield and irrigation amount. Incorporating SMAP-like top-layer soil moisture data into DSSAT-CSM resulted in increased precision of modeled rain-fed crop yield, bringing model estimates of mean crop yield into closer agreement with DSSAT-CSM rain-fed yield using observed weather input. Furthermore, the data assimilation algorithm developed for this study mitigated the impact of measurement errors in critical weather inputs on modeled crop yield and irrigation amount, highlighting the potential utility of both this algorithm and of the SMAP top soil moisture data product.

This study is limited to a single site (an experimental "field" in Ames, Iowa) for a single growing season (2003). Further research will expand the case study spatially and temporally to the regional scale, multiple years, and for various rain-fed and irrigated crops. This study is also limited by the assumption that ground-truth 9-km soil moisture can be accurately determined from weather observations,

TABLE 7. Change in uncertainty of modeled cumulative irrigation amount after applying daily soil moisture filter.

Expt	Description	Std dev in modeled irrigation amount (mm)		Change (%)
		Before filter	After filter	
1	Soil moisture data corrects errors in daily rainfall input.	5.9	5.1	−14
2	Soil moisture data corrects errors in daily weather input.	6.1	5.6	−9

detailed site-specific soil properties, and the other required minimum input to the point-scale DSSAT-CSM.

As the SMAP satellite data products will not be available until early 2015 and reliable soil moisture observations at the Ames, Iowa, case study site were not available, DSSAT-CSM top-layer soil moisture driven by observed daily weather input served as a surrogate for ground-truth soil moisture and is assumed to mimic the SMAP soil moisture data product. Likewise, the potential to merge information on local physical constraints with SMAP data products to further reduce the error in SMAP remotely sensed beyond the $0.04\,cm^3\,cm^{-3}$ mission specification needs further investigation. It is of interest to validate the conclusions of this study as soon as soil moisture data from the SMAP mission are available.

Merging remotely sensed SMAP soil moisture data with DSSAT-CSM is a topic of ongoing research, and we look forward to conducting ongoing research on the following topics:

- the impact of lower effective error in top-layer soil moisture data, (e.g., $0.01\,cm^3\,cm^{-3}$) on precision in crop model output;
- how SMAP-like data can guide DSSAT-CSM runs in which other inputs such as crop cultivars, soil type, and soil hydraulic characteristics are uncertain;
- performing DSSAT-CSM simulation of drought years to further investigate the benefit of SMAP-type data to reduce uncertainty in irrigation forecasts; and
- incorporating the SMAP level-4 root-zone soil moisture product to further reduce uncertainties in DSSAT-CSM forecasts.

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