Development and application of process-based simulation models for cotton production: A review of past, present, and future directions

Discipline: Agronomy & Soils

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Abbreviations: Full list appears at the end of the document.

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Abstract

The development and application of cropping system simulation models for cotton production has a long and rich history, beginning in the southeastern United States in the 1960's and now expanded to major cotton production regions globally. This paper briefly reviews the history of cotton simulation models, examines applications of the models since the turn of the century, and identifies opportunities for improving models and their use in cotton research and decision support. Cotton models reviewed include those specific to cotton (GOSSYM, Cotton2K, COTCO2, OZCOT, and CROPGRO-Cotton) and generic crop models that have been applied to cotton production (EPIC, WOFOST, SUCROS, GRAMI, CropSyst, and AquaCrop). Model application areas included crop water use and irrigation water management, nitrogen dynamics and fertilizer management, genetics and crop improvement, climatology, global climate change, precision agriculture, model integration with sensor data, economics, and classroom instruction. Generally, the literature demonstrated increased emphasis on cotton model development in the previous century and on cotton model application in the current century. Although efforts to develop cotton models have a 40-year history, no comparisons among cotton models were reported. Such efforts would be advisable as an initial step to evaluate current cotton simulation strategies. Increasingly, cotton simulation models are being applied by non-traditional crop modelers, who are not trained agronomists but wish to use the models for broad economic or life cycle analyses. While this trend demonstrates the growing interest in the models and their potential utility for a variety of applications, it necessitates the development of models with appropriate complexity and ease-of-use for a given application, and improved documentation and teaching materials are needed to educate potential model users. Spatial scaling issues are also increasingly prominent, as models originally developed for use at the field scale are being implemented for regional simulations over large geographic areas. Research steadily progresses toward the advanced goal of model integration with variable-rate control systems, which use real-time crop status and environmental information to spatially and temporally optimize applications of crop inputs, while also considering potential environmental impacts, resource limitations, and climate forecasts. Overall, the review demonstrates a languished effort in cotton simulation model development, but the application of existing models in a variety of research areas remains strong and continues to grow.

Keywords: agriculture, computer, cotton, model, simulation

1. Introduction

Cotton (*Gossypium hirsutum* and *Gossypium barbadense*) is an important commodity crop globally, providing sources of fiber, feed, food, and potentially fuel for diverse industries. Cotton fiber is used in products ranging from textiles to paper, coffee filters, and fishing nets. Cottonseed meal and hulls are used mainly for ruminant livestock feed. Cottonseed oil is currently refined as a vegetable oil for human consumption and has potential as a biofuel. From 2008 to 2012, China was the top cotton producer and averaged 33.1 million bales annually (USDA-FAS, 2013), followed by India (25.1 million bales), the United States (14.7 million bales), Pakistan (9.3 million bales), Brazil (7.2 million bales), Uzbekistan (4.2 million bales), and Australia (3.2 million bales). One bale contains 218 kg (480 lbs) of cotton fiber. In the 2010-2011 growing season, average global cotton fiber yield was 757 kg ha^{-1} and ranged from 1681 kg ha^{-1} in Australia to 200 kg ha^{-1} in some resource limited countries. A main issue for cotton in the developed world is the high cost of production, and improvements in cotton production practices are needed to keep cotton economically competitive with other commodity crops and fiber sources. For cotton production to be sustainable, water and energy resource limitations must also be considered. These goals for improved cotton production can be realized with smarter irrigation and nitrogen (N) fertilizer management, better understanding of climate impacts on cotton yield, further advancement in cotton breeding and genetics, greater adoption of precision agriculture technologies, and increased knowledge of cotton genetics by environment by management (GEM) interactions.

Many of the issues facing cotton industries can be better understood and perhaps mitigated by implementing process-based cropping system simulation models (Boote et al., 1996; Reddy et al., 1997a), which are important and powerful computer-based tools for guiding cotton management and research. Developers of these models synthesized the knowledge gained from decades of field, laboratory, and controlled-environment experiments and produced computer algorithms that simulate fundamental cropping system processes, including evapotranspiration (ET), soil water redistribution, nutrient dynamics, energy transfer, and crop growth and development. Past model applications include assessing irrigation and N management alternatives for cotton (Hearn and Bange, 2002), analyzing potential global warming impacts on cotton production (Reddy et al., 2002a), and forecasting seed cotton yield (seed plus fiber) from satellite remote sensing images (Hebbar et al., 2008).

In the United States, early development and application of crop growth models was historically linked with the cotton industry. By the mid-1970's, fundamental equations were developed to describe cotton growth and development (Baker et al., 1972; McKinion et al., 1975; Wanjura et al., 1973), cotton plant N balance (Jones et al., 1974), and ET and soil water balance (Ritchie, 1972; Shirazi et al., 1976). Also, the effects of leaf angle and leaf area vertical distribution on light penetration and cotton canopy photosynthesis had been examined using computer models (Fukai and Loomis, 1976). Approaches for simulating the development of cotton fruits, including squares, bolls, seed, and fiber, were investigated later (Jackson et al., 1988; Wanjura and Newton, 1981). Notably, these initial efforts led to the development of the GOSSYM simulation model (Table 1) and the accompanying CrOp MAnagement eXpert system (COMAX), which was used across the United States Cotton Belt to guide on-farm cotton management in the 1980's (McKinion et al., 1989; Whisler et al., 1986).

In addition to GOSSYM/COMAX, other simulation models for cotton production systems were developed more recently (Table 1): Cotton2K (Marani, 2004), COTCO2 (Wall et al., 1994), OZCOT (Hearn, 1994), and CROPGRO-Cotton (Jones et al., 2003; Pathak et al., 2007; 2012). A variety of generic cropping system models, with reduced complexity for simulating a variety of crop types, were also recently evaluated for cotton production (Farahani et al., 2009; Sommer et al., 2008; Zhang et al., 2008). The models vary greatly in details and approaches for simulating various plant and soil processes and management practices, and none have yet reached their full potential. Landivar et al. (2010) provided an excellent review of strategies for physiological simulation of cotton growth and development; however, "it [was] not the purpose of this chapter to compare cotton models." Landivar et al. (2010) mainly described model development approaches and did not contrast existing cotton models or review recent advances in cotton model applications.

The objective of this article was to review the state-of-the-art in development and application of computer simulation models for cotton production systems. Because of its comprehensive scope, cotton researchers with diverse interests and levels of expertise should find useful information herein. Given the trend for new cotton modeling efforts beyond traditional analyses of agronomic field experiments, the review also provides a resource for non-traditional and beginning modelers to learn about past and present cotton modeling efforts. A brief history is presented of cotton model development and applications in the last century, from 1960 to 2000. Descriptions and qualitative comparisons of existing cotton models are emphasized in this section. Next, the review describes cotton model development and applications in the current century thus far. Since year 2000, the literature has demonstrated a marked increase in articles that describe applications of the cotton models previously developed, and fewer articles focus on development of new models. Finally, considering the reviewed literature holistically, a perspective is provided on anticipated future challenges and opportunities for the application of process-based simulation models to cotton production.

2. Past Directions: 1960-2000

2.1. Overview of simulation approaches

The cotton models discussed herein are classified as mechanistic, dynamic, and deterministic. The models are mechanistic as they describe processes with some level of understanding (e.g., plant growth based on calculations of intercepted radiation). They are dynamic, because the time variable is explicit. Thus, the models use partial differential equations to calculate how quantities vary with time (e.g., transpiration and plant growth). The models are deterministic rather than stochastic, because the calculations are made without any associated probability distribution. Although most cotton simulation models share these characteristics, different model design strategies have been explored. For example, the cotton model of Plant et al. (1998) used qualitative categorical variables (e.g., HIGH, MODERATE, or LOW) rather than quantitative variables to describe plant and soil states. The coarseness of the Plant et al. (1998) model improved simulation robustness at the expense of precision, but the model was arguably less mechanistic and dynamic than traditional cotton models. Most cotton simulation models have simulated soil and plant processes explicitly and quantitatively in a mechanistic, dynamic, and deterministic fashion.

Process-based crop models share a common goal of estimating crop yield by simulating the contribution of soil water, nutrient, and plant growth and developmental processes to the formation of harvestable plant products. However, the approaches used to simulate these processes vary widely among existing crop models (Tables 2 and 3; Landivar et al., 2010). To simulate plant development, many crop models use a growing degree-day concept, where measured air temperature is assessed in relation to known functions of crop development rate with air temperature. Simulation details, such as the number of development stages considered, the treatment of leaf appearance, and the development of yield components, vary widely among models (Table 2). Carbon (C) assimilation and biomass accumulation are commonly simulated as a function of measured solar irradiance, using simulated leaf area index (LAI) to calculate the fraction of photosynthetically active radiation intercepted by the crop canopy. Simulations of water, nutrient, and temperature stresses and atmospheric carbon dioxide (CO_2) concentrations ([CO_2]) may further adjust energy to biomass conversions. Approaches for representing plant stress factors vary widely among models.

Perhaps the most important physiological difference among models is whether they use a radiation use efficiency approach to account for plant growth and maintenance respiration (Monteith, 1977) or whether they explicitly simulate photosynthesis and respiration as independent processes (Boote and Pickering, 1994; Farquhar et al., 1980; McCree, 1974; Mutsaers, 1982). Models also differ in simulation details for leaf area expansion, stem elongation, organ growth, and yield components. To simulate the soil water balance, several crop models implement the 'tipping bucket' method of Ritchie (1972; 1998), while others use numerical methods to solve the soil water balance. Simulations of ET are conducted using a variety of methods with varying complexity and data requirements: Priestley and

Taylor (1972); FAO-56 Penman-Monteith (Allen et al., 1998); or surface energy balance. Approaches to simulate N dynamics are also variable, while some models do not simulate any nutrient effect on plant growth (Table 3). Models also vary in their consideration of management impacts on cotton production, including irrigation, fertilization, sowing date, tillage, and defoliation events (Table 4). The time steps of calculations also vary among models, but hourly or daily time steps are common (Table 1). Given the diverse approaches for simulating cotton production systems, it is not the objective of this review to claim one approach as superior to the other, but rather it is to summarize and contrast the approaches currently implemented in existing cotton models. The appropriateness of a given model will depend mainly on the specific application.

2.2. Established crop simulation models for cotton

2.2.1. GOSSYM

The development, characteristics, and applications of the cotton model, GOSSYM, were previously described extensively (Baker et al., 1983; Hodges et al., 1998; Landivar et al., 2010; McKinion et al., 1989; Reddy et al., 1997a; 2002a). Briefly, GOSSYM uses mass balance principles to simulate water, C, and N processes in the plant and soil root zone. It requires environmental variables, such as solar irradiance, air temperature, precipitation, and wind, as well as information on soil physical properties and cultural practices, including variety-dependent parameters. The model estimates potential growth and developmental rates as a function of air temperature under optimum water and nutrient conditions, and it corrects the potential rates by the intensity of environmental stresses using environmental productivity indices (Baker et al., 1983; Reddy et al., 2008). Each day, the model simulates the birth and abscission of organs, their size and growth stage, and the intensity of stress factors. The user can assume certain future weather conditions (days, weeks, and years) to determine fiber yield estimates and impact of altered cultural practices on cotton maturity and fiber yield.

The GOSSYM model consists of several subroutines for various aspects of crop production (Hodges et al., 1998) and biology (Reddy et al., 1997a). A unique aspect is its treatment of the soil (Lambert et al., 1976) and the processes therein, as they influence the plant's physiological processes. In addition to plant and soil processes, an expert system known as COMAX was explicitly developed for the GOSSYM model (Hodges et al., 1998; Lemmon, 1986; McKinion et al., 1989).

The concept and development of GOSSYM started in the late 1960's with a meeting at the University of Arizona, sponsored by the Department of Agronomy and Agricultural Engineering (Baker et al., 1983; Hodges et al., 1998; Landivar et al., 2010; Reddy et al., 2002b). Significant contributions were made from several institutions (Baker et al., 1972; 1976; 1983; Hesketh and Baker, 1967; Hesketh et al., 1971; 1972; Lambert et al., 1976; McKinion et al., 1975; Wanjura et al., 1973) in the years after that first meeting.

With the construction of Soil-Plant-Atmosphere-Research facilities at several locations in the southeastern United States (Phene et al., 1978; Reddy et al., 2001), cotton physiological, growth, and developmental processes as affected by abiotic stress factors were quantified. Based on data from these facilities, algorithms were developed to improve the model's functionality and accuracy of simulation results (Marani et al., 1985; Reddy et al., 1995; 2000; 1993; 1997a, 1997b; 2001; 2003). In 1984, GOSSYM was first implemented on commercial cotton farms as a decision support system (DSS). Based on user requests, the COMAX interface was developed to facilitate its delivery to over 70 cotton farms across the United States Midsouth. By 1990, GOSSYM-COMAX had been implemented on over 300 commercial farms (Ladewig and Taylor-Powell, 1989; Ladewig and Thomas, 1992). Extensive model validation efforts were conducted across the United States Cotton Belt (Boone et al., 1993; Fye et al., 1984; Reddy, 1994; Reddy and Baker, 1988; 1990; Reddy and Boone, 2002; Reddy et al., 1985; Reddy et al., 1995; Staggenborg et al., 1996) and overseas (Gertsis and Symeonakis, 1998; Gertsis and Whisler, 1998). Several modifications in the simulation procedures and model validation efforts using field data sets (Ali et al., 2004; Khorsandi and Whisler, 1996; Khorsandi et al., 1997) made the model applicable on many fronts, including farm management, economics, climate change, and policy issues (Doherty et al., 2003; Landivar et al., 1983a; 1983b; Liang et al., 2012a, 2012b; McKinion et al., 1989; 2001; Reddy et al., 2002b; Wanjura and McMichael, 1989; Watkins et al., 1998; Xu et al., 2005).

2.2.2. Cotton2K

The Cotton2K model was developed by Dr. Avishalom Marani at the School of Agriculture of the Hebrew University of Jerusalem. The source code of Cotton2K is written in C^{++} and is available for free download (Marani, 2004). Cotton2K uses the process-based equations of GOSSYM (Baker et al., 1972; 1983), and its history can be traced and linked to other cotton modeling efforts, including SIMCOTI (Baker et al., 1972), SIMCOTII (Jones et al., 1974), and CALGOS (Marani et al., 1992a; 1992b; 1992c). The main purpose of Cotton2K was to provide a more useful model for cotton production in arid, irrigated environments, such as the western United States and Israel.

A general description of the history, main characteristics, scientific principles, and input requirements for Cotton2K are given by Marani (2004). The fundamental difference between Cotton2K and GOSSYM is the weather data requirement. While GOSSYM uses daily weather data, Cotton2K uses either measured hourly values of air temperature and humidity, wind speed, and shortwave irradiance or calculates hourly values from daily data using the method of Ephrath et al. (1996). The hourly weather values are used to calculate corresponding hourly water and energy balances; this allows the model to more closely represent arid conditions and improves the model’s ability to more accurately calculate the water balance under irrigation (Marani, 2004). The main effect of these changes was to improve the accuracy in the calculation of ET, which also affected related variables. Further, the deviations created by using daily weather data time steps, rather than shorter time steps, was particularly important when hourly data followed non-linear diurnal patterns or where interactions of weather parameters were important in calculation of energy or water balances (i.e., non-linear diurnal wind speed patterns and/or interactions of wind speed and solar irradiance driving ET) (Ephrath et al., 1996). Other modifications in Cotton2K included a routine for sub-surface drip irrigation, updates to N mineralization and nitrification processes, calculation of N uptake using a Michaelis-Menten procedure, updates to plant growth and phenology functions, and energy balance equations to provide the temperatures of the soil surface and crop canopy (Marani, 2004). In summary, the addition of hourly weather input data allowed the calculation and the integration of differential equations on an hourly time-step for the processes of plant transpiration, soil water evaporation, soil water redistribution, heat and N fluxes, and the exchanges of energy and water at the soil-plant-atmosphere interfaces. These modifications greatly improved the utility and the applicability of Cotton2K for irrigation in arid environments.

The main processes calculated in Cotton2K are related to the exchanges of energy and water between the soil, plant, and the environment. Processes are based on the principles of mass and energy conservation, whereby inputs and outputs to the system are balanced and accounted for as a function of time. The Cotton2K model was designed for specific management of agronomic inputs, including irrigation, N fertilizer, defoliation, and application of a plant growth regulator. Plant growth and development are based on the 'stress' theory (Grime, 1977; Craine, 2005), which includes stresses related to air temperature, water, C, and N. In this context, stress is a condition that restricts potential production due to suboptimal air temperatures and shortages of water and nutrients (Grime, 1977). Plant growth rates are related to ambient temperature using the concept of heat units (Wang, 1960; Peng et al., 1989). Potential growth rates of all plant organs, including roots, stems, leaf blades and petioles, and fruiting sites (squares, bolls, and seed cotton), are related to source-sink relations of C and water via stress factors. The stress factors between source and sink vary numerically from 1 (no stress) to 0 (severe stress). The C stress is related to net C assimilation (i.e., gross photosynthesis minus photorespiration and growth and maintenance respiration). The water stress is related to transpiration and transport of water as a function of leaf water potential. The N stress is based on supply and demand of N. In the soil, Cotton2K calculates rates of available N from urea hydrolysis, mineralization of organic N, nitrification of ammonium, denitrification of nitrate, and movement of soluble N. The model also calculates the N in plant organs (roots, stems, leaves, and fruiting sites) and, if supply does not meet requirements, an N stress factor is calculated. All supply and demand functions related to temperature, water, C, and N are dynamic and thus their values change with time.

The boundary conditions that define the one dimensional soil-plant-atmosphere system in Cotton2K are 2 m above and 2 m below the soil surface. The height (2 m) above the soil surface represents the screen-height where input weather data are measured, and the soil depth of 2 m represents the lower boundary of the soil profile. Required input weather data include shortwave irradiance, air temperature and humidity, wind speed, and rainfall. Cotton2K uses hourly weather input values; however, if not available, daily values of radiation and wind run, and maximum and minimum values of air temperature and humidity are used to calculate hourly values (Ephrath et al., 1996). For each irrigation event, the application method (sprinkler, furrow, and drip), timing (start and end), and applied depth are specified. The user defines the geometry of the soil profile by specifying the number and the thickness of each soil layer. At the onset of simulation, (i.e., time = 0), the user specifies for each soil layer a value of temperature, water, organic matter, N, and soil salinity. In addition, the soil layers are grouped into horizons, each having unique soil hydraulic properties. These properties define the relationship of soil water content to water potential and to hydraulic conductivity and are used in Richards' equation to calculate water movement in the soil profile. The user specifies the water table depth and the date and depth of each cultivation event. Other fixed parameter input values are location (latitude, longitude, and elevation), start and end of simulation period, date of planting and/or emergence, and field data (planting density and row spacing, including skip rows). Parameters describing individual cultivars affect phenology, growth, and development and ultimately impact the calculation of cotton fiber yield as suggested by Marani (2004) and shown by Booker (2013). The current version of Cotton2K has been tested for six cotton cultivars: Acala SJ-2, GC-510, Maxxa, Deltapine 61, Deltapine 77, and Sivon.

The Cotton2K model can be used in a management mode for irrigation, N, defoliation, and application of a growth regulator. Under these options, Cotton2K is executed using predicted weather scenarios, and the user selects several options that include, for example, date of starting and ending irrigation, date of N fertilizer application, date of defoliation, and application of a plant growth regulator. Cotton2K outputs are recorded in text files, charts, and soil maps. The text files are a summary of all input and output values, detailed daily output, and plant maps. The charts plot the dynamics of key output variables with time, and the soil maps are two-dimensional plots of horizontal and vertical simulated values of soil water and nitrogen contents, temperature, and other variables, each as a function of time.

The Cotton2K model has been directly and indirectly used and tested by many researchers. Directly, Cotton2K has been used by Yang et al. (2008) where the effect of pruning and topping was tested under field conditions and by Yang et al. (2010) and Nair et al. (2013) to optimize irrigation allocation under limited water conditions. Recently, Booker (2013) incorporated Cotton2K into a landscape-scale model and applied it to cotton production across the major soil types of the Texas High Plains. Given the similarities of Cotton2K to GOSSYM and CALGOS models, indirectly some of the algorithms in Cotton2K have been evaluated for a wide range of soil and environmental conditions by Staggenborg et al. (1996), Clouse (2006), Baumhardt et al. (2009), and others.

2.2.3. COTCO2

The COTCO2 model simulates cotton physiology, growth, development, water use, biomass, and boll yield (Wall et al., 1994). Written in Fortran in a modular design, it is capable of simulating cotton crop responses to elevated [CO_2] and potential concomitant changing climate variables, particularly temperature. Explicit physiological mechanisms are used to minimize reliance on empirical relationships, which are data dependent. The morphogenetic template concept in the KUTUN model (Mutsaers, 1984) and the physiological detail in an alfalfa model, ALFALFA (Denison and Loomis, 1989), served as prototypes for the COTCO2 model.

Leaf physiology is central to simulating plant response to the environment in COTCO2 and consists of the following components, which are simulated hourly: 1) leaf energy balance to account for stomatal effects on leaf temperature, transpiration, and assimilation; 2) stomatal conductance coupled with leaf energy balance; 3) biochemical chloroplast CO_2 assimilation; 4) apparent dark respiration for each organ type based on basal coefficients for the quantitative biochemistry of biosynthesis of existing phytomass (maintenance respiration) and that linked to growth (growth respiration); and 5) carbohydrate pool dynamics.

Growth is simulated for individual meristem, stem segment, leaf blade, taproot, lateral root, and fruit (squares and bolls) organs. Potential growth is calculated, followed by the carbohydrate and N required to meet potential growth. Actual growth is based on potential growth, substrate availability, and water and temperature stress. Physiological age, which is the time-integrated value of developmental rate, places an upper limit on growth rate, and physiological age determines organ phenological state. The phenology of the simulated cotton plant does not develop based on calendar days. Rather, plant development and growth rates are based on a time-temperature running sum. The response of physiological time to temperature is based on an Arrhenius equation with both low and high temperature inhibition. At the reference temperature (e.g., 25°C), physiological time is equal to calendar days. Within the low and high temperature limits, physiological time proceeds faster and slower than calendar time at temperatures higher and lower than the reference temperature, respectively.

The COTCO2 model can simulate cotton production over a broad environmental range, while providing the means to predict the impact of change in [CO_2] and any associated potential climate change on global cotton production. Ultimately, it could aid in the development of strategies to mitigate the adverse effects of global climate change, while optimizing those that are beneficial.

2.2.4. OZCOT

The structure of the OZCOT model has been described in detail by Hearn (1994) and Hearn and Da Roza (1985). It was developed using a 'top down' approach, meaning processes were simulated with only sufficient detail to provide reliable estimation of the impact of management and environment on cotton growth, development, and fiber yield. Simulation approaches were broadly mechanistic at the crop and plant level. The OZCOT model, which advances on a daily time step, is principally driven by air temperature and intercepted radiation, and it was built by linking a model of fruiting dynamics with a water balance model and simple N uptake model. In addition to validation using research experiments (Hearn, 1994), OZCOT has also been validated in commercial fields for both irrigated (Richards et al., 2008) and rainfed cotton systems (Bange et al., 2005).

The central component of OZCOT is the fruit production and survival subroutine (Hearn and Da Roza, 1985), which was used in the SIRATAC pest management DSS (Hearn and Bange, 2002). The rates of fruit production, fruit shedding, and growth of organs are governed by C supply. The OZCOT model tracks the total number of fruiting sites, squares, bolls, and open bolls by daily cohorts. A new cohort of squares is produced and subsequently developed through anthesis to maturity. Although OZCOT does not explicitly simulate the branching structure of the plant, aspects of morphology are implicit in the function that generates the number of squares (Hanan and Hearn, 2003).

Carbon supply for a given day is estimated from intercepted light and a canopy-level photosynthetic rate (Baker et al., 1983), with respiration calculated as an empirical function of fruiting site count and mean air temperature. Light interception is estimated using Beer’s law, and leaf area is simulated using an empirical correlation between fruiting site production and leaf area (Jackson et al., 1988). The rates of leaf expansion, photosynthesis, and fruiting are modulated by the supply of water and N and by waterlogging.

The water balance in OZCOT is calculated using the Ritchie (1972) approach with a calibrated soil water extraction routine based on increasing supply with increasing depth of extraction over time. The OZCOT model does not maintain a dynamic soil N balance analogous to water, but uses a N uptake model. At the start of the season, potential N uptake is estimated based on soil N and fertilizer inputs (Constable and Rochester, 1988) and is reviewed daily to calculate a stress index. The stress index scales the rate of a process and is based on the ratio either between supply and demand for a resource or between the current and maximum value of a state variable. In addition to N, there are also stress indices for shortages of water and C.

The OZCOT model can be principally used in two modes: a strategic mode that generates simulations over multiple seasons using pre-determined management rules and historical climate data or a tactical mode that simulates specific management practices for a particular season. In both modes, daily values of rainfall (mm), maximum and minimum air temperature (degrees C), and solar irradiation (MJ m^{-2}) are required. Relative humidity at 0900 h and wind run (km) can also be included for improved precision of daily ET estimates. Soil input information includes the number of soil layers and their depths, plant available water holding capacity, initial plant available water (in volumetric units), and average soil bulk density across layers.

Agronomic inputs include parameters for different cotton cultivars, including leaf type (okra or palmate), squaring rate, maximum boll size and development rate, fiber percentage, background fruit retention (transgenic or non-transgenic), row spacing, plants per m of row, initial available soil N, irrigation rates and application dates, N rates and application dates, and planting dates. If a specific planting date or days when irrigation occurs is not provided, management rules are used to estimate these times in the strategic mode.

The OZCOT model can simulate production in rainfed or limited irrigation cropping systems using ‘skip row’ configurations (Bange et al., 2005). These are row configurations that have entire rows missing from the planting configuration to increase the amount of soil water available to the crop at critical growth stages. The OZCOT model uses a modified soil water content stress index that accounts for the non-uniform distribution of the availability of soil water from the planted and non-planted rows (Milroy et al., 2004).

Key outputs generated by the OZCOT model include seasonal estimates of fiber yield, yield components, dates of phenological stages, maximum LAI, N use, and water balance metrics such as effective rainfall and crop water use efficiency (WUE). A separate output file is also generated that provides daily within-season calculations of crop progress, stress indices, and resource use.

The OZCOT model is the only supported cotton model in Australia that is used in decision support and research. Currently, the OZCOT model is the core component of the HydroLOGIC tactical and strategic cotton irrigation DSS (Richards et al., 2008). To refine simulations of in-season crop water use in HydroLOGIC, OZCOT was modified to accept additional measurements of soil water status and crop growth, such as LAI and fruit number. Other DSSs that have used OZCOT include CottBASE (http://cottassist.cottoncrc.org.au) for irrigated cotton systems and Whopper Cropper (Nelson et al. 2002) for rainfed cotton systems. Both are databases of pre-run OZCOT simulations based on historical climate data for various combinations of management options, soils, and regions.

The crop growth component of OZCOT is used as the cotton module of the Agricultural Production Systems sIMulator (APSIM) modeling framework (Keating et al., 2003), which is used to address farming systems issues (Carberry et al., 2009). Four main components form the basis of APSIM: a set of biophysical modules that simulate farming system processes; management modules allowing users to specify management rules; modules to facilitate handling of input and output data; and a simulation engine that drives the simulation process and passes messages between independent modules. Biophysical modules are available for a diverse range of crops, pastures, and trees within APSIM, and modules for soil water balances, N and P transformations, soil pH, erosion and a full range of management controls are also included.

Until recently, OZCOT was written in Fortran and compiled as a dynamic link library. Currently called 'mvOZCOT', the OZCOT model has been rewritten in C# and was reengineered using the common modeling protocol of the Commonwealth Scientific and Industrial Research Organisation (CSIRO) to allow more seamless integration with APSIM and other modeling frameworks (Moore et al., 2007). This has enabled OZCOT users to implement the model with other soil water and N modules. While OZCOT continues to be used as a research and management tool, current efforts to enhance its functionality include the addition of new algorithms to simulate fiber quality and climate change impacts.

2.2.5. CSM-CROPGRO-Cotton

The Cropping System Model (CSM)-CROPGRO-Cotton model (Jones et al., 2003; Pathak et al., 2007) is implemented in the Decision Support System for Agrotechnology Transfer (DSSAT; Hoogenboom et al., 2012). The DSSAT system has a long history originating with the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) Project that was funded by the United States Agency for International Development from 1982 through 1993 (Uehara and Tsuji, 1989). The initial crop simulation models of DSSAT included the CERES-Wheat, CERES-Maize, SOYGRO, and PNUTGRO models. The SOYGRO, PNUTGRO, and BEANGRO models were later combined into a generic grain legume model, CROPGRO (Hoogenboom et al., 1992). To address cropping systems and especially crop rotations, the CSM was developed (Jones et al., 2003). The CSM model uses a single set of computer code for dynamic simulation of the soil water, inorganic soil N, and organic C and N balances (Gijsman et al., 2002; Godwin and Singh, 1998; Ritchie, 1998, Ritchie et al., 2009). Recently a soil phosphorus module was also added to CSM (Dzotsi et al., 2010). For the simulation of growth, development and ultimately yield for individual crops, different crop modules are being used, such as the CERES-Maize module for maize (*Zea mays*), CERES-Rice for rice (*Oryza sativa*; Ritchie et al., 1998) or the CROPGRO module for grain legumes (Boote et al., 1998). This allows for the continuous simulation of crop rotations, such as a soybean (*Glycine max*) and wheat (*Triticum aestivum*) rotation or a wheat and rice rotation (Bowen et al., 1998; Tojo Soler et al., 2011).

The CROPGRO module uses a daily time step for integration, starting at planting and ending at crop maturity or on the final harvest date. The differences among the individual crops or species are handled through external genotype files, as opposed to values or specific equations that are embedded in the code. There are three genotype files: one each for cultivar, ecotype, and species coefficients (Hoogenboom and White, 2003). The latter includes a range of temperature functions for development, photosynthesis, partitioning, and various other physiological functions. It also includes detailed composition parameters with respect to proteins, lipids, fiber, carbohydrates, and other properties of different plant components, including leaves, stems, roots, and reproductive structures. This approach assumes that the underlying plant physiological processes of each crop are similar, but the interaction of genetics with environment and management is different.

The original DSSAT systems did not include a model for fiber crops. Because of the importance of cotton in the southeastern United States, especially as part of common rotations with peanut (*Arachis hypogaea*), there was a need for the development of a comprehensive cotton model. Rather than developing a new set of code, the decision was made to use the CROPGRO module as a template. The emphasis was to obtain detailed physiological information to define the functions and parameters for the species file and experimental data for initial model calibration and evaluation. The CSM-CROPGRO-Cotton model was developed through a collaborative effort among scientists at the University of Florida and the University of Georgia (Pathak et al., 2007). Because of the existing infrastructure of DSSAT, the cotton model could easily be added to DSSAT without creating different utilities for data input and application programs.

Similar to the other DSSAT crop simulation models, the CSM-CROPGRO-Cotton model requires environmental data, crop management, and genetic information as inputs (Hunt et al., 2001). Required environmental measurements include daily weather data for maximum and minimum air temperatures, solar irradiance, precipitation, and soil profile data. Required soil data include soil surface characteristics, such as slope, color, albedo, soil drainage, and descriptions of a one-dimensional profile, including lower limit of plant extractable water (LL), drained upper limit (DUL), saturated soil water content (SAT), bulk density, organic C, and total soil N. Recently, a new feature was added to the CSM models that allows input of [CO_2] from an external file, which is based on the CO_2 values measured at the long-term CO_2 monitoring site on Mauna Loa in Hawaii. Crop management practices include planting date; plant density and row spacing; planting depth; dates and amounts of irrigation application; dates, amounts and type of fertilizer application; and dates, types, and depths of tillage. Environmental modifications, including climate change modifications, can be entered in the environmental modification section of the crop management file.

As stated previously, the genetic information is provided in three data files. The species file is associated with a specific crop and is part of the core model development and calibration. Therefore, end users should not modify parameters in the species file. The cultivar parameter file specifies 18 cultivar-specific parameters for each cultivar. These include coefficients that describe the time from emergence to flowering, time from flowering to first boll and first seed, time from first seed to physiological maturity, maximum single leaf photosynthetic rate, single leaf size, specific leaf area, individual seed size, fraction of seed cotton weight over total green boll weight, and oil and protein composition of the seeds. The cultivar file that is distributed with DSSAT includes a few cultivars for which the cultivar parameters have already been defined, including those for the example experimental files that are distributed with DSSAT. In general, however, users must calibrate their cultivar parameters using a set of measured data from either experiments or variety trials (Pathak et al., 2012). The ecotype file includes 17 parameters that define the unique characteristics of a group of cultivars, such as a short season versus a long season cultivar, and they normally will not change among a group of similar cultivars.

In CSM-CROPGRO-Cotton, the overall integration of differential equations occurs on a daily time step. The CSM is written in Fortran (Thorp et al., 2012), and the software code includes different sections for model initialization, calculation of the rate variables, integration of the equations, and update of the state variables. Both daily and seasonal output routines are available (Jones et al., 2003). The model is initiated at the start of simulation, which can occur at or prior to planting. At this point, the initial or boundary conditions are set, especially with respect to initial soil water content, inorganic soil N, soil organic C, and residue remaining from the previous crop. If the model is started prior to planting, only the soil processes are simulated. When planting occurs, the crop growth module is initiated and vegetative development is simulated. Internally, both the vegetative and reproductive development processes are calculated on an hourly basis while integration occurs at a daily level. Hourly ambient temperature is calculated internally based on the maximum and minimum daily air temperature. In parallel to crop development, photosynthesis is simulated on an hourly basis based on light interception of a hedgerow canopy, and integration occurs on a daily basis (Boote and Pickering, 1994). The model accounts for maintenance respiration based on current total biomass, for growth respiration based on partitioning to the different plant organs, including roots, stems, leaves, bolls, and seed cotton, and for the composition of each organ.

During vegetative growth, partitioning to roots, leaves, and stems is a function of the development stage and is source-driven. However, once reproductive development has started, partitioning is sink-driven based on the requirements for carbohydrates for the reproductive structures, including the bolls. Any remaining carbohydrates that are not used for growth of the reproductive structures can be used for further growth of the vegetative structures. Once flowering has started, the model accounts for the number of flowers that are formed on a given day, called clusters. This system is maintained through the entire reproductive process, allowing for the abortion of flowers, squares, and bolls if insufficient carbohydrates are available for reproductive growth. The priority of the carbohydrate distribution is based on the status of the cohorts; the ones that were formed first have the highest priority for carbohydrates and the ones that were formed last have the lowest priority. During reproductive growth, remobilization of N from senesced leaves and petioles can also occur in order to support reproductive growth. Most of the growth, development, and partitioning processes have their own temperature response functions that are defined in the species file.

Drought stress is represented by two different stress factors: one that affects the turgor-based growth processes and another that affects photosynthesis and growth processes. Drought stress occurs when the potential demand for water lost through transpiration and soil water evaporation is higher than the amount of water that can be supplied by the soil through the root system (Anothai et al., 2013). Evaporative demand is calculated using the Priestley-Taylor equation, which requires daily solar irradiance and maximum and minimum air temperatures as input (Priestley and Taylor, 1972). An option is also available to use the Penman-Monteith equation for calculating potential ET. The soil water balance is based on the tipping bucket approach for a one-dimensional soil profile (Ritchie, 1972; 1998). Each soil horizon or computational soil layer is characterized by the LL, DUL, and SAT, which can be calculated based on soil texture and bulk density using utilities provided with DSSAT. The daily potential ET demand is calculated first, and the potential water supply for root uptake is based on the soil water content of each layer, the root distribution, and a root resistance factor. If the potential supply is greater than the potential demand, the supply is set equal to the demand, and the associated processes are updated. If the demand is greater than the supply, transpiration and soil water evaporation are reduced to the simulated supply, and drought stress factors are calculated based on the difference between potential demand and potential supply.

The CSM-CROPGRO-Cotton model includes a detailed soil and plant N balance. Although the original CROPGRO model included N fixation, the modular structure of CSM allows for individual modules to be turned on or off (Jones et al., 2003). A detailed description of the soil N balance is given by Godwin and Singh (1998), which is the same for all crop modules of the CSM. Soil N includes a myriad of processes that are calculated for each soil horizon or computational layer for the transformation of organic N to inorganic N in the form of nitrate and ammonium. For the calculation of the processes associated with soil organic C and N, there are two options. One is the original model developed by Godwin and Singh (1998), and the other is an advanced approach based on CENTURY (Gijsman et al., 2002). The latter approach is especially suitable for low-input systems or for determining the soil C balance associated with soil C sequestration.

Because of the generic structure of the CROPGRO model, the CROPGRO-Cotton module benefits from other model features that were previously added to CROPGRO. One such feature is the generic coupling points that emulate the potential impact of pests and diseases on crop growth and development (Boote et al., 2008; 2010; 1983). These coupling points allow for the removal of tissue of the various organs, a modification of leaf area, a reduction in the availability of carbohydrates, and various others that are specified in a crop specific pest input file. The actual removal or changes are provided through a time-series input file. Ortiz et al. (2009) used this option to study the impact of southern root-knot nematodes on biomass growth and seed cotton yield.

Most of the applications of the CSM-CROPGRO-Cotton model have been conducted in the southeastern United States, including the determination of irrigation water use in Georgia (Guerra et al., 2007), the impact of climate variability and El Niño/La Niña Southern Oscillation (ENSO) on seed cotton yield under different cotton management options (Garcia y Garcia et al., 2010; Paz et al., 2012), sensitivity to solar irradiance (Garcia y Garcia et al.; 2008) and other inputs (Pathak et al., 2007), and crop insurance (Cabrera et al., 2006). Applications beyond the United States have been limited, except for a climate change application in Cameroon (Gérardieux et al., 2013) and a study of irrigation strategies in Australia (Cammarano et al., 2012).

The CSM-CROPGRO-Cotton model is included in DSSAT (Hoogenboom et al., 2012). The most recent version of DSSAT can be requested from the DSSAT Foundation web site (www.DSSAT.net) at no cost. Utility programs are available within DSSAT for entering experimental and environmental data, as well as measured data, for model calibration and evaluation. DSSAT also includes special application programs for crop sequence or rotation analyses and for seasonal analyses that include economic components. The source code for the model is available upon request.

2.2.6. Generic crop models

Several generic crop models, which simplify crop growth routines for applicability to a variety of crops, have also been developed, and limited reports are available for the use of such models in cotton. The Environmental Policy Integrated Climate (EPIC) model, originally called the Erosion-Productivity Impact Calculator (Williams et al., 1984), simulates the impact of climate and management on soil erosion, water quality, and crop production. The generic crop model in EPIC (Williams et al., 1989) is currently parameterized for approximately 80 crops. Evaluations of the EPIC model have been conducted for cotton systems in Georgia (Guerra et al., 2004) and Texas (Ko et al., 2009a). The Simple and Universal CROp growth Simulator (SUCROS; Van Ittersum et al., 2003) models daily canopy CO_2 assimilation for potential production and includes a tipping bucket soil water balance routine with Penman ET. Zhang et al. (2008) modified SUCROS (SUCROS-Cotton) to simulate 'cut-out', fruit dynamics, fruit abscission, single boll weight, and fiber yield for cotton. The model was evaluated for a cotton system in China. Another Wageningen crop model, WOrld FOod STudies (WOFOST; Van Diepen et al., 1989; Van Ittersum et al., 2003), is used for generic crop growth simulations in the Soil-Water-Atmosphere-Plant model (SWAP; Kroes et al., 2008), which simulates vadose zone transport of water and solutes. Crop yield in SWAP can also be computed using a simplified crop growth algorithm (Doorenbos and Kassam, 1979). The GRAMI model (Maas, 1993a; b; c) was originally developed to estimate growth and yield of gramineous crops such as wheat, maize, and sorghum (*Sorghum bicolor*). The model was specifically designed to accept remote sensing data inputs for improving the accuracy of its crop growth simulation. Ko et al. (2005) modified the original GRAMI model to simulate growth and fiber yield of non-stressed cotton. The Root Zone Water Quality Model (RZWQM; Ma et al., 2012) originally incorporated a generic crop growth model but now includes the CSM crop modules (Jones et al., 2003), specifically the CROPGRO-Cotton model for cotton systems. CropSyst (Stöckle et al., 2003) is a daily time-step cropping system model that simulates water and N balances, crop growth and development, residue recycling, erosion by water, and salinity in response to climate, soils, and management. Sommer et al. (2008) recently evaluated CropSyst for cotton in Uzbekistan.

2.3 Historic applications of cotton models

In the previous century, cotton simulation models were used to assess irrigation and N fertilizer management strategies and to understand the effects of climate variability on cotton fiber yield. Many of these early efforts were based on the GOSSYM model (McKinion et al., 1989). Comparisons of GOSSYM-simulated crop water use with field measurements were an important step to evaluate the model for irrigation management purposes (Asare et al., 1992; Staggenborg et al., 1996). The Australian model, OZCOT, was used to make irrigation management decisions in relation to water supply (Dudley and Hearn, 1993a; Hearn, 1992). To characterize N impacts on cotton production, GOSSYM was used to manage N fertilization events for a field study in South Carolina (Hunt et al., 1998), to evaluate N fertilizer recovery and residual soil N for cotton systems in Mississippi (Stevens et al., 1996), and to assess the effect of N fertilization rate and timing on cotton fiber yield over a long-term weather record in west Texas (Wanjura and McMichael, 1989). Ramanarayanan et al. (1998) used the EPIC model to optimize N fertilization management in Oklahoma while considering N recovery in cotton fiber yield and N loss to the environment.

Using GOSSYM, Landivar et al. (1983a) examined effects of the 'okra-leaf' trait on cotton fruit abscission and fiber yield. Under favorable N conditions, it appeared that a slight yield advantage with the okra-leaf trait was the result of improved light interception. However, under less favorable conditions, okra-leaf restricted LAI, which reduced yields. In a second paper (Landivar et al., 1983b), photosynthetic rate, specific leaf weight, and leaf longevity were varied. Greater photosynthetic rate increased fiber yield, but if increased photosynthesis was achieved through greater specific leaf weight (thicker leaves), no yield benefit occurred. Extending leaf longevity appeared more promising for increasing yield, but the model did not deal with possible tradeoffs between leaf longevity and processes such as N remobilization.

Due to concerns of declining cotton fiber yield over several decades, GOSSYM was used to examine climate effects on cotton fiber yield at several locations across the United States Cotton Belt (Reddy and Baker, 1990; Reddy et al., 1990; Wanjura and Barker, 1988). Weather variables were shown not to be a driver of fiber yield declines, but increasing ozone level may have reduced fiber yields in Phoenix, AZ and Fresno, CA (Reddy et al., 1989). Small increases (10%) in fiber yield due to elevated CO_2 were found when soil N levels were sufficient. Dudley and Hearn (1993b) used OZCOT to evaluate El Niño effects on irrigated cotton systems in Namoi, Australia. Other early applications of the GOSSYM model included an economic evaluation of alternative desiccant application strategies (Watkins et al., 1998) and an assessment of N fertilizer recommendations in the context of precision agriculture (McCauley, 1999). Exploration of the link between crop simulation models and canopy spectral reflectance indices was also an early priority in cotton research (Wiegand et al., 1986). Within-season calibration of crop growth models using remote sensing data was originally described by Maas (1988a; 1988b) and later implemented in GRAMI. In this calibration procedure, within-season estimates of actual crop growth, such as LAI or ground cover, were obtained from remote sensing data. The model parameters and initial conditions were then iteratively adjusted to minimize the difference between simulated crop growth and the measured growth from remote sensing data (Maas, 1993a; b; c). Finally, Larson and Mapp (1997) used the COTTAM model (Jackson et al., 1988) to estimate cotton production responses and net revenue to various management inputs. The simulation results were then used to evaluate the performance of cotton cultivars and to assess planting, irrigation, and harvest decisions under risk. These studies laid the foundation for cotton modeling applications in the new century.

3. Present Directions: 2000-2013

3.1. Recent development of cotton models

Studies on the application of cotton simulation models after year 2000 vastly outnumbered the studies reporting new model developments. However, there are a few recent and notable accomplishments in the development of simulation models for cotton. The AquaCrop model, supported by the Food and Agriculture Organization (FAO) of the United Nations, is a new generic crop model for simulating yield response to water management (Raes et al., 2009; Steduto et al., 2009). This effort resulted in a simulation model, based on plant physiology and soil water balance, that replaced previous FAO publications for estimating crop productivity in relation to water supply. In a short time, the model has been used for a number of irrigation management studies in cotton, discussed in the next section, and in other crops. Pachepsky et al. (2009) developed and parameterized the new WALL model for cotton, which simulates individual leaf transpiration with emphasis on water movement within the leaf. Finally, Liang et al. (2012a) developed a GOSSYM-based, geographically distributed cotton growth model that has been coupled with the Climate-Weather Research Forecasting Model (Skamarock et al., 2005) for studying the effects of changing climate on cotton production.

The literature demonstrates a significant research thrust toward cotton simulation model development in China, the world's leading cotton producer. Ma et al. (2005) conducted field studies at four locations in China and developed a simulation model for cotton development and fruit formation. Zhu et al. (2007) designed a web-based DSS for crop management that included process-based simulation models for four crops, including cotton. Li et al. (2009) developed a model for simulating boll maturation, seed growth, and oil and protein content of cottonseed. The model was calibrated and evaluated using experimental data sets from two locations in China. Zhao et al. (2012) focused on cotton fiber production and developed a model for simulating cotton fiber length and strength based on air temperature, solar irradiance, and N effects.

Another noteworthy direction of research is the recent development of higher-dimensional models that simulate cotton canopy and root architecture. Coelho et al. (2003) used principles from GOSSYM and DSSAT-CSM to develop a model for simulation of horizontal and vertical distributions of cotton root growth at the field scale. Similarly, simulation of three-dimensional cotton root growth was investigated by Zhang and Li (2006) in China. Hanan and Hearn (2003) linked a model of cotton plant morphogenesis and architecture with OZCOT. The combined models allocated flower buds to assigned positions on the plant, and water, N, and C stresses controlled fruit growth and abortion. Jallas et al. (2009) combined a mechanistic model of crop growth and development with a three-dimensional model of plant architecture. Together, the two models produced an animated visualization of cotton growth for one or several cotton plants. Alarcon and Sassenrath (2011) analyzed digital images of cotton canopies and developed a dynamic model to simulate changes in cotton leaf number and leaf size during the growing season. These studies evidence a move toward simulation models that consider the influence of plant architecture on cotton growth, a characteristic that is not considered in most existing cotton models.

3.2. Recent applications of cotton models

3.2.1. Crop water use and irrigation management

3.2.1.1. North American cotton production

Several cotton simulation models, including Cotton2K, CSM-CROPGRO-Cotton, EPIC, GOSSYM, and GRAMI, were implemented for water-related research in North America since 2000.

Researchers have used these models to assess crop water demand and as a tool for cotton irrigation scheduling. The models were sometimes integrated with other models and software to increase their utility and effectiveness.

Baumhardt et al. (2009) simulated fiber yield using GOSSYM for a 40-year period at Amarillo, Texas and used these data to analyze the impact of irrigation depth, irrigation duration, and initial soil water content on WUE and fiber yield of cotton. At lower initial moisture content, fiber yield and WUE increased with increasing irrigation depth, while at higher initial soil water content, WUE was lower for the higher irrigation depth although fiber yield was higher. They also reported that, with low irrigation water availability, concentrating the irrigation water to a subset of the field area could increase cotton fiber yield.

The CSM-CROPGRO-Cotton model was evaluated for simulating cotton growth and development under different irrigation regimes in Georgia and was found to be a promising tool for irrigation scheduling (Suleiman et al., 2007). Simulations of ET were compared with field experimental data from Griffin, Georgia to evaluate the FAO-56 crop coefficient procedure for irrigation management in deficit irrigated cotton production. Root mean squared errors between measured and simulated ET ranged from 2.5 to 3.5 mm d^{-1}, and model efficiency statistics were less than 0.28. These results indicate potential for further refinement of the model's ET simulation.

Guerra et al. (2004) evaluated the EPIC model to simulate cotton fiber yield and irrigation demand in Georgia. The model simulated cotton fiber yield and irrigation requirements with root mean squared deviations of 0.29 t ha^{-1} and 75 mm, respectively. The model performance for cotton was better than for soybean and peanut. The EPIC model was also used to compare simulated crop water requirements for cotton, peanut, and corn with the actual irrigation amounts applied by farmers in Georgia (Guerra et al., 2005). This study revealed that EPIC was useful for assessing on-farm irrigation water demand. Guerra et al. (2007) used the CSM-CROPGRO-Cotton model to simulate irrigation applications for individual fields and then used kriging to estimate the spatial distribution of the irrigation water use for cotton in Georgia. The technique enabled estimation of water use at spatial scales more suitable to inform policy makers.

Nair et al. (2013) evaluated Cotton2K for the Texas High Plains by simulating cotton fiber yield for a 110-year period at Plainview, Texas. Sixty-eight different irrigation treatments were simulated to analyze the production and profitability impacts of partitioning a center pivot irrigated cotton field into irrigated and dryland areas. By irrigating only a subset of the field area, cotton fiber yield and profitability were increased. The benefit was higher when available irrigation water was low and in low rainfall years.

Ko et al. (2006) used a modified version of GRAMI, capable of within-season calibration using remotely sensed crop reflectance data, to model water-stressed cotton growth at Lubbock, Texas. Even though the model adequately simulated cotton growth under deficit irrigation, its performance was unsatisfactory at higher irrigation regimes. Ko et al. (2009b) used data from field trials conducted in Uvalde, Texas to calibrate the radiation use efficiency and the light interception coefficient of the EPIC crop model. The calibrated model simulated field conditions with more accuracy and hence could be a better tool to manage irrigation water resources.

Evett and Tolk (2009) reviewed nine papers that used cropping system simulation models to simulate yield and WUE of four crops, including cotton. All the models in these studies simulated WUE with considerable accuracy under well-watered conditions, but performed poorly under water stress. Crop growth models are important components of web-based DSSs, which can be used by crop managers for irrigation scheduling decisions (Fernandez and Trolinger, 2007).

3.2.1.2. Australian cotton production

The Australian cotton model, OZCOT (Hearn, 1994), is commonly used for irrigation water management research and decision support in Australia. It was used extensively to assess potential and risk of productivity and value of improvements in WUE across all Australian cotton production regions at the field scale (e.g., Hearn, 1992). The need for these assessments was associated with considerable reductions in water allocations and climate variability, including severe droughts. These investigations have also included assessments of seasonal climate forecasts to improve risk quantification (e.g., Bange et al., 1999). Today much of this information is delivered in databases of pre-run OZCOT simulations, based on historical climate data for various combinations of management options, soils, regions, and seasonal forecasts (CottBASE; http://cottassist.cottoncrc.org.au/). Cammarano et al. (2012) used a calibrated CSM-CROPGRO-Cotton model to undertake similar assessments for research purposes.

In parallel to the use of OZCOT for research, a DSS named ‘HydroLOGIC’ was developed to calibrate the OZCOT model using available weather, soil water, fruit load and leaf area data for irrigation scheduling (Hearn and Bange, 2002; Richards et al., 2008). Irrigation timing was assessed by varying target soil water deficits for triggering irrigations and then by simple user optimization of fiber yield and water use estimates generated by OZCOT outputs. Simulations of fiber yield and water use were based on potential growth determined by OZCOT and historical climate records for the remainder of the season. HydroLOGIC can also be used in a strategic mode which enables users to explore the fiber yield and water productivity of irrigation management practices (pre- and post-season) under different weather patterns using long-term climate data. In this mode, schedules are user-defined and can irrigate the crop when the soil-water deficit reaches a set level, where the first and final irrigation dates are determined by square and boll development.

Recent advances in irrigation management have included the development of a framework 'VARIwise' that develops and simulates site-specific irrigation control strategies (McCarthy et al., 2010). VARIwise divides fields into spatial subunits based on databases for weather, soil, and plant parameters to better account for field variability. The OZCOT model is used in two capacities in VARIwise: 1) to simulate the performance of the control strategies and 2) to calculate the irrigation application that achieves a desired performance objective (e.g., maximized bale yield or water productivity). In the first option, industry standard irrigation management strategies are tested, which apply irrigation to fill the soil profile. In the second option, VARIwise executes the calibrated crop model with different irrigation volumes over a finite horizon (e.g., five days) to determine which irrigation volumes and timing achieves the desired performance objective (e.g., maximize bale yield or water productivity) as calculated by the model. The optimal combination is implemented and this procedure is repeated daily to determine the timing of the next irrigation event and the site-specific irrigation volumes. An automatic model calibration procedure for soil water, vegetation, and fruit load was developed to minimize the error between the measured and simulated soil and plant responses (McCarthy et al., 2011). A genetic algorithm was used to refine the soil and plant parameters that characterized cotton development.

Evaluation of VARIwise has shown improvements in irrigation WUE for center pivot irrigated cotton (McCarthy et al., 2010) and surface irrigation. The field implementation of VARIwise for surface irrigation includes irrigation hydraulics to determine the control actions (inflow rate and cut-off time) required to achieve the appropriate irrigation distribution along the furrow as determined by the control strategies. This further improves irrigation efficiencies. McCarthy et al. (2013) reviewed the use of crop models for advanced process control of irrigation and argued that process-based simulation models perform better than crop production functions. Significant opportunity remains to further enhance the VARIwise system by linking the predictive functionalities of HydroLOGIC, which is focused on crop growth performance, with the improved irrigation practice recommendations generated by VARIwise.

On-farm water storage and distribution are limiting factors of the irrigation decision making process for cotton production. The APSIM framework incorporates water storage and has enabled the exploration of irrigation management options that rely on effluent water or opportunistic capture of overland flow as water sources (Carberry et al., 2002a). To provide probabilistic forecasts of on-allocation and off-allocation water, catchment models and seasonal climate forecasts have been implemented, and the simulated water supply was used with a cotton simulation model to determine seasonal water requirements and cotton bale yield (Power et al., 2011a; 2011b). The gross margins, water requirements, and subsequent bale yields were then used to evaluate different cropping areas with different water availability and management paradigms. Alternatively, the irrigation events were scheduled when the OZCOT-simulated soil water deficit reached a set limit or when OZCOT maximized bale yield (Ritchie et al., 2004). Then, a gross margin model was developed using the seasonal climate forecasts, estimated bale yield, and water application for the given water supply. The resulting bale yield, water and crop production costs, and crop price were provided for each year of the simulation.

With current water reform actions in the Australian states of Queensland and New South Wales, water supply was calculated using seasonal stream flow forecasts from the Australian Bureau of Meteorology (Power et al., 2011b) and the Integrated Quantity Quality Model (IQQM), a river flow and water use hydrological model (Ritchie et al., 2004). The calculations can be used to estimate water availability for input into crop models. In these applications, OZCOT was used to determine the optimal planting area and water requirements for different planting areas according to the calculated volume of water at sowing (Power et al., 2011b).

3.2.1.3. Asian cotton production

Asia is home to several major cotton producing countries in the world, including China, India, Pakistan, Kazakhstan, and Uzbekistan. Irrigated cotton production in these countries relies mostly on traditional water management using surface irrigation practices. Nevertheless, several studies applied cotton simulation models for improving water management strategies in these Asian countries. Yang et al. (2010) used the Cotton2K model for estimating the irrigation water requirements for cotton in the North China Plain using 20 years of agronomic, hydrologic, and climate data. On average, irrigated cotton production accounted for 8% of the total water requirements in that region. Singh et al. (2006) evaluated water management strategies at various spatial and temporal scales using the SWAP model in an agricultural district in Northern India. The simulation results indicated that seed cotton yield and water productivity could be improved by ensuring an adequate water supply during the *kharif* (summer) season. The SWAP model was also used by Qureshi et al. (2011) to determine irrigation amounts for cotton grown in the Syrdarya province of Uzbekistan. Results demonstrated that an irrigation application of 2500 m^3 ha^{-1} produced an optimal seed cotton yield of 3000 kg ha^{-1} under the current climatic conditions with a water table depth of 2 m. Buttar et al. (2012) used a calibrated CropSyst model for studying the impact of global warming on seed cotton yield and water productivity of Bt cotton grown under semi-arid conditions in North India. Their results showed that total ET and crop water productivity decreased with an increase in air temperature from 28° to 32° C.

3.2.1.4. Mediterranean cotton production

Irrigation water management simulation studies in the Mediterranean region have mostly used the AquaCrop, CropWat, and SWAP models. While using the SWAP model to evaluate the performance of the Menemen Left Bank irrigation system, located at the tail end of the River Gediz in western Turkey, Droogers et al. (2000) determined that the cotton irrigation requirement was about 1000 mm, and water productivity, expressed in terms of seed cotton yield per amount of water depleted from the soil, was maximized at an irrigation amount of 600 mm. Ismail and Depeweg (2005) also studied water productivity and cotton production in relation to water supply under continuous flow and surge flow irrigation methods in short fields of clay and sandy soils in Egypt using the CropWat model (FAO, 2013). Their analysis indicated that surge flow irrigation is an efficient tool either to produce the same yield with less water than in continuous flow or to produce higher yields than continuous flow when using the same gross irrigation supply.

Garcia-Vila et al. (2009) determined the optimum level of applied irrigation water for cotton production in southern Spain under several climatic and agricultural policy scenarios using AquaCrop. After calibrating the model with data from four experiments in the Cordoba Province, functions of seed cotton yield versus applied irrigation were developed for different scenarios, and an economic optimization procedure was applied. Maximum profits occurred when irrigation amounts were between 540 and 740 mm for the conditions at the study area, depending on the climatic scenario. However, profits remained close to the maximum (above 95%) for applied irrigation water levels exceeding 350 mm.

Accurate simulation of crop yield under various irrigation regimes (full and deficit irrigation) is important to optimize irrigation under limited availability of water resources. Farahani et al. (2009) evaluated AquaCrop for cotton under full (100%) and deficit (40%, 60%, and 80% of full) irrigation regimes in the hot, dry, and windy Mediterranean environment of northern Syria. AquaCrop simulated seed cotton yields within 10% of the measured yields for the 40% and 100% irrigation regimes, while the errors increased to 32% for the 60% and 80% irrigation regimes. Simulations of ET, biomass, and soil water for the four irrigation regimes were particularly promising given the simplicity of the AquaCrop model and its limited parameterization. AquaCrop was also used to study seed cotton yield responses to deficit irrigation for a three-year (2007-2009) field experiment conducted in the southeast of Damascus, Syria (Hussein et al., 2011). Drip irrigation was used for cotton management under full and deficit irrigation (80%, 65%, and 50% of full irrigation). Simulations of seed cotton yields were within 6% of the measurements. However, the model overestimated WUE under water-deficit conditions.

3.2.2. Nitrogen dynamics and fertilizer management

Over application of N and other fertilizers on farmlands not only increases input costs but also causes excessive vegetative growth and delayed maturity in cotton. Excess N fertilizer can also contaminate surface water and groundwater and can increase nitrous oxide emissions from the soil. Cotton simulation models that include soil processes help assess impacts of fertilizer management, including application rates, method, and timing, on nutrient dynamics and water quality. Reddy et al.

(2002b) reviewed the use of GOSSYM to assess the impact of fertilization on cotton productivity, evaluate N dynamics as influenced by fertilizer application rates, and investigate the effect of N fertilizer application timing on cotton fiber yield. In general, GOSSYM overestimated fertilizer N recovery by plants, which was attributed to the inability of the model to simulate mineralization and immobilization processes or ammonia volatilization losses from the soil or the plants (Boone et al., 1993).

Braunack et al. (2012) examined the effect of cotton planting date and cultivar selection on N use efficiency in cotton farming systems in Australia through field experiments and OZCOT model simulations. From the field experiments conducted over two years at Narrabri in New South Wales, they found that there was no difference in N use efficiency between two cotton cultivars: CSX6270BRF and Sicot 70BRF. They also found that the N use efficiency was not statistically decreased if planting occurred within 30 days from the normal target planting date of 15 October. The OZCOT simulations using 53 seasons (1957 to 2010) of climate data for long, medium, and short cotton growing regions in New South Wales and Queensland indicated that the N use efficiency was relatively constant over planting dates from 30 September to 30 October in the medium and short season areas and from 30 September to 30 November in the long season areas, and decreased steeply thereafter.

The soil N dynamics and seed cotton yields under varying N rates for cotton in the Khorezm region in Uzbekistan were simulated by Kienzler (2010) using the generic cotton routine within the CropSyst model. The simulated plant N uptake was higher than the applied fertilizer for all treatments up to the N fertilizer rate of 160 kg ha^{-1} and increased with higher N fertilizer amounts to a maximum of 214 kg N ha^{-1} for a fertilizer rate of 250 kg N ha^{-1}. Simulated crop production under farmers' practice was not N-limited when more than 80 kg N ha^{-1} was applied. Hence, while maintaining the total amount of N fertilizer within 120 to 250 kg N ha^{-1}, changing the timing or number of applications did not improve seed cotton yields. The simulations also indicated that increasing seed cotton yields without increasing N losses was possible when water supply better matched demand.

The EPIC model was used by Kuhn et al. (2010) to estimate cotton fiber yields as a function of fertilizer application rates (ranging from 0 to 300 kg N ha^{-1}) at the regional scale, by dividing the Upper Oueme basin in Benin, West Africa into 2550 crop response units, which were quasi-homogenous with respect to land use, soil, and climate. The outputs of the crop simulations for different N application rates were then used to establish yield response functions, which were finally integrated to an economic model to simulate the effects of tax exemptions on fertilizer use, crop yields, food balances, and use of land resources for the most important crops of the region, including cotton.

Chamberlain et al. (2011) used DAYCENT, a C and N cycling model, to simulate N dynamics under cotton production and then employed the simulation results to assess the environmental impacts of land conversion from cotton to switchgrass in the southern United States. Long-term simulations showed a reduction of N in runoff (up to 95%) for conversion from cotton to switchgrass at N application rates of 0–135 kg N ha^{-1}. They concluded that the model could more accurately simulate 'relative differences' rather than 'absolute values' for each cropping system. Using RZWQM, Abrahamson et al. (2006) simulated nitrate leaching from tile drains under conventional and no-tillage management practices in cotton production and rye (*Secale cereale*) cover cropping practices in a Cecil soil (kaolinitic, thermic, Typic Kanhapludult) in Georgia. However, the model was unable to simulate the pattern of nitrate transport in these soils, which led to large differences between simulated and measured values of leached nitrate (62 and 73 kg ha^{-1} for conventional tillage and no-till, respectively). The authors stated that the ion exchange equations in the RZWQM were included only for the major cations and not for anions adsorbed onto soil, and this might have resulted in the poor simulation of nitrate leachate losses.

Recently, Shumway et al. (2012) tested the new Nitrogen Loss and Environmental Assessment Package (NLEAP) for its ability to simulate N dynamics for different cropping systems, including cotton, in three different locations in the Arkansas Delta. Simulations by the NLEAP showed that the model simulated the effects of management on residual soil nitrate, and it could be used as a tool to quickly evaluate management practices and their effects on potential N losses from cropped lands.

3.2.3. Genetics and crop improvement

The ability of crop models to simulate the interactive effects of plant traits, environment, and management makes such models attractive tools for crop improvement (White, 1998). Models find application both in simulating how specific traits impact yield and in analyzing how variability in production environments impact yield. While models are often proposed as tools for analyzing genotype by environment responses in support of breeding (e.g., Chapman et al., 2003; White, 1998), no examples were found where a cotton model was used to characterize the target population of environments or to analyze the environmental effects in breeding nurseries or varietal tests. One constraint may be that cotton simulation models lack sufficient genetic and physiological detail to describe cultivar differences in traits such as canopy temperature. Gene-based modeling is one avenue to strengthen the genetics and physiology of models, but it requires understanding of the genetic control of traits of interest (Bertin et al., 2010; White and Hoogenboom, 2003). Until gene-based modeling goals are realized, model inversion techniques may be useful to estimate crop traits of varieties in large field trials, where crop sensors are deployed for field-based high-throughput phenotyping (White et al., 2012).

3.2.4. Climatology

Since crop development is driven by weather, an important application of cotton models is to analyze the impact of climatological patterns on production. Fernandez and Trolinger (2007) described a web-based DSS that provides easy access to weather network data and numerical tools that simulate cotton responses to environmental conditions in south Texas. A heat unit approach was used for crop development, while crop height, LAI, and canopy cover were simulated using empirical equations. To use models for large-scale spatially distributed simulations, reliable weather data is often unavailable, particularly for solar radiation and precipitation. Therefore, researchers have sought alternative ways to derive such data. Richardson and Reddy (2004) used seven solar radiation models and four temporal averaging schemes to estimate solar irradiance, and cotton production simulations were evaluated at ten locations across the United States using the solar irradiance data in GOSSYM. Cotton fiber yield estimation accuracy depended on solar irradiance estimation accuracy, but location and management practice (irrigated versus rainfed) also impacted the simulation results. Although the radiation models estimated solar irradiance and fiber yield well, the combination of minimum and maximum air temperatures, rainfall, and wind speed performed best for simulation of solar irradiance and fiber yield at all locations. Garcia y Garcia et al. (2008) compared the effects of measured and generated solar irradiance on simulations of cotton, maize, and peanut crops in Georgia using the CSM. Simulations of total ET, aboveground biomass, and seed cotton yield were similar for generated and measured solar radiation. They concluded that generated solar radiation data could be reliably used as input to cotton simulation models in locations where measured data were not available.

Cotton simulation models have also been used to study the effect of cyclical climate variations on cotton production, particularly the ENSO. Garcia y Garcia et al. (2010) studied the spatial variability of seed cotton yield and WUE of cotton grown in the southeastern United States as related to ENSO phases. Seed cotton yield and WUE of rainfed cotton were differentially affected by ENSO, and seed cotton yield was differentially affected by rainfall, air temperature, and solar irradiance within ENSO phase. Simulated seed cotton yield for rainfed cotton was higher during La Niña than during El Niño and neutral years, ranging from 3044 to 3304 kg ha^{-1} during El Niño years, from 2950 to 3267 kg ha^{-1} during neutral years, and from 2891 to 3383 kg ha^{-1} during La Niña years. Also, simulated seed cotton yield of rainfed cotton showed a stronger spatial dependence during El Niño and neutral years than during La Niña years. Paz et al. (2012) examined the ENSO effect on cotton fiber yields in Georgia for various planting dates at three spatial levels: county, crop reporting district, and region. Using CROPGRO-Cotton, fiber yields were simulated for 97 counties and 38 to 107 years, depending on county, each with nine planting dates within the planting window of 10 April through 6 June. Fiber yields were separated by ENSO phase, and analyses showed different results regarding the ENSO effect. According to county level analyses, ENSO had little and spatially less consistent effects, but the effect became more evident at larger spatial scales. According to regional level analysis, the fiber yield difference among ENSO phases was minimal for average planting dates, but substantial if planting date deviated from the average. In the northern Murray

Darling Basin, Australia, the impacts of ENSO phases on precipitation patterns were used to develop seasonal climate forecasts for the region (Ritchie et al., 2004). To test the outcome of irrigators using climate forecasts to schedule irrigations, OZCOT simulations provided cotton bale yield responses to climate-based irrigation management over a long-term weather record.

Liang et al. (2012b) implemented a geographically distributed GOSSYM model to simulate United States cotton fiber yield responses over a long-term climate record from 1979 to 2005. The model simulated long-term mean cotton fiber yield within 10% of measurements at a scale of 30 km across the United States Cotton Belt, and the model responded appropriately to regional climate variation. The study was an important precursor to using the geographically distributed GOSSYM model for study of cotton responses to future climate scenarios. However, to use cotton models for future climate change scenarios, the weather inputs for air temperature, radiation, wind speed, and precipitation must be obtained from future climate models. These climate models, for now, provide monthly data, rather than the daily inputs required by most models. Reddy et al. (2002a) developed a method to create daily future weather files by modifying daily current weather assuming that changes in daily weather parameters remain constant for each month. The monthly mean maximum and minimum air temperature changes were added to current daily measurements and the change fractions for precipitation, solar irradiance, and wind speed were multiplied by current daily measurements to generate a 30-year record of daily future weather. This methodology retained the existing natural variability in the historic weather for those years. A similar methodology was used by Doherty et al. (2003) to simulate cotton fiber yields spatially across the southeastern United States.

3.2.5. Global climate change

Simulation models are widely used to assess the potential impacts of climate change on cropping systems (White et al., 2011) and to quantify greenhouse gas fluxes from agricultural systems. In both applications, the models are valued for their ability to quantify potential complex interactions of cultivars, weather, soils, and management. However, skeptics question the accuracy of simulation models relative to statistical models from historical analyses of yield and climate trends (Schlenker and Roberts, 2009; Lobell et al., 2011).

In impact assessment, the usual approach is to compare yield or other traits for a baseline situation (e.g., 30 years of historical weather and [CO_2]) with one or more scenarios where future climatic and [CO_2] conditions are input to the model for one or more reference periods or for an assumed generic change (e.g., by increasing daily air temperatures 2° C). Among methodological concerns in this process are how to realistically alter cultivar characteristics and management to account for likely adaptive changes in cropping seasons.

Modifications to the GOSSYM model were required to facilitate simulations of cotton responses under future climate scenarios. Model improvements have focused on the canopy photosynthesis response to elevated CO_2 (Reddy et al., 2008), pollen and fruit production efficiency responses to higher air temperatures (Reddy et al., 1997c), and growth and developmental responses to ultraviolet-B radiation effects (Reddy et al., 2003). Using GOSSYM, Reddy et al. (2002a) simulated cotton response to climate change, including an increase of [CO_2] from 360 to 540 ppm, for a 30-year period (1964 to 1993 as the baseline) at Stoneville, Mississippi. Considering only effects of [CO_2], fiber yield increased by 10% from 1560 to 1710 kg ha^{-1}, but when all projected climatic changes were included, fiber yield decreased by 9% to 1430 kg ha^{-1}. The adverse effect of warming was more pronounced in hot and dry years. With climate change, most days with average air temperatures above 32° C primarily occurred during the reproductive phase. As a result, the authors emphasized that irrigation will be needed to satisfy the high water demand, thus reducing boll abscission by lowering canopy temperatures. Also, if global warming occurs as projected, fiber production in the future environment will be reduced, and breeding cultivars tolerant to heat and cold will be necessary to sustain cotton production in the United States Midsouth. Cultural practices such as earlier planting may be used to avoid flowering in mid to late summer, when high air temperatures occur. Doherty et al. (2003) simulated cotton response to climate change for the southeastern United States using the GOSSYM model integrated with general circulation models. Baseline weather from 1960 to 1995 and a reference [CO_2] of 330 ppm were considered. Climate scenarios corresponded to a [CO_2] of 540 ppm. In the absence of [CO_2] effects and ignoring adaptation for planting date (i.e., changing the planting date from 1 May to 1 April), fiber yields decreased by 4% for a coarse-scale climate grid and by 16% for a fine-scale grid. Allowing for [CO_2] and adaptation, fiber yields increased 30% with the coarse grid and 18% with the fine grid. While confirming that increased [CO_2] and adaptation have the potential to offset likely adverse effects of warming, the large effects of spatial scale emphasize the uncertainties inherent in simulation of climate change.

Using the Cotton2K model for irrigated cotton in Israel, Haim et al. (2008) reported that adaptation by planting two weeks earlier and increasing irrigation could offset the negative effects of warming under two climate change scenarios. Using CropSyst to model irrigated cotton in India's Punjab region, Buttar et al. (2012) confirmed that warming could reduce seed cotton yield through accelerated development and hence shorter growth duration.

Independent of potential impacts of climate change on cotton production, researchers have also used simulation models to quantify greenhouse gas fluxes from cotton systems and to simulate long term changes in soil C where cotton is grown. The EPIC model was used to simulate changes in soil organic C under different management scenarios (Causarano et al., 2007). Differences due to landscape position were correctly simulated, but the model needed refinement before the simulations were accurate enough to direct management practices at that scale. The EPIC model was also used to evaluate the ability of a soil conditioning index to estimate the impact of different cotton tillage systems and other variables on soil C content (Abrahamson et al., 2007; 2009). In general, the index provided the same directional change in C as EPIC (increase or decrease); however, the relationship was not linear. Del Grosso et al. (2006) used the DAYCENT model to estimate nitrous oxide emissions across the United States and included cotton systems (typically a cotton-corn rotation) but only reported net emissions. Similarly, DAYCENT was used to quantify changes in greenhouse gas fluxes due to conversion from conventional to alternative cropping systems (Chamberlain et al., 2011; De Gryze et al., 2010).

3.2.6. Precision agriculture

The goal of precision agriculture is to optimize field-level management based on several factors, such as soil physical properties, yield history, and economic benefit. Since the initial pioneering efforts in the late 1990's (McCauley, 1999; Paz et al., 1998; 1999), various strategies to analyze spatial and temporal yield variability and develop precision crop management plans using cropping system simulation models have been proposed (Batchelor et al., 2002; Booltink et al., 2001; Sadler et al., 2002; Thorp et al., 2008). These studies highlighted the importance of using models to account for soil heterogeneity across the field. McKinion et al. (2001) integrated the GOSSYM-COMAX DSS with a geographic information system (GIS) to determine N fertilization and irrigation management strategies that optimized cotton fiber yield spatially. Variation in soil properties was specified in the model using soil sample data at 88 locations across the study area on a 1 ha grid. They opined that this system has the potential to be used in automatic calculation of optimal irrigation rates considering within-field spatial variability. Using data from a cotton study in Arizona, Jones and Barnes (2000) conceptually demonstrated the integration of GIS, remote sensing images, cropping systems simulation, and a decision model to provide decision support for precision crop management while considering competing economic and environmental objectives. Basso et al. (2001) showed that, with a combination of crop modeling and remote sensing methods, management zones and causes for yield variability could be identified, which is a prerequisite for zone-specific management prescriptions. Clouse (2006) used simulated annealing optimization to spatially calibrate the soil parameters of Cotton2K for sites in west Texas, and the calibrated model was used to compare site-specific and uniform irrigation management strategies. Simulated cotton fiber yields were higher with site-specific irrigation management, but the yield increases did not make site-specific irrigation more profitable. In China, Guo et al. (2008) developed a web-based DSS for cotton production systems, which integrated a crop simulation model into a GIS. McCarthy et al. (2011) reported the development of VARIwise, which incorporated the OZCOT model for evaluation of agronomic factors and engineering control strategies for variable-rate irrigation in cotton. Recently, Thorp and Bronson (2013) developed an open-source GIS tool that could manage spatial simulations for any point-based crop model. They demonstrated the tool using both the AquaCrop and CROPGRO-Cotton models to simulate site-specific seed cotton yield in response to irrigation management, N management, and soil texture variability for a 14 ha study area near Lamesa, Texas.

Although not directly applied to cotton production, several other studies have demonstrated important simulation methodologies that would also have relevance for precision cotton management. For example, Paz et al. (2002) examined site-specific soybean water stress by adjusting root growth factors and tile drainage parameters in CROPGRO-Soybean to minimize error between measured and simulated spatial soybean yield. Also, Paz et al. (2003) used CROPGRO-Soybean to analyze options for soybean variety selection and to develop prescription maps to achieve economic goals while considering weather history and soil variability. Thorp et al. (2006) developed a simulation methodology to determine precision N fertilization recommendations while considering the trade-off between maize production and loss of N to the environment. Thorp et al. (2007) also demonstrated a cross validation approach to evaluate site-specific maize yield simulations with the CERES-Maize model and to identify causes for spatial yield variability. Oliver et al. (2010) described the integration of farmer knowledge with several precision agriculture tools, including a crop simulation model, to devise practical and effective management plans for historically poor performing areas in the field. All of these simulation strategies would likely have similar applicability for cotton production systems.

3.2.7. Integration of sensor data with models

Despite the many potential uses for cotton simulation models described above, a potential drawback is the need to adequately specify the values of numerous model parameters to produce consistently accurate simulation results. Building on the pioneering work of Maas (1988a; b; 1993a; b; c), efforts in the new century have improved the accuracy of crop simulation models by incorporating reflectance measurements of the crop canopy during the growing season. A primary source of information for within-season crop model calibration is airborne and satellite remote sensing imagery and ground-based proximal sensors. For example, using medium-resolution satellite imagery, Maas and Rajan (2008) estimated ground cover for a variety of field crops. To demonstrate the utility of ground cover information for cotton growth model calibration, Ko et al. (2005) modified the GRAMI model for cotton and used a within-season calibration procedure to adjust model simulations using relatively simple input data derived from proximal sensing. Ko et al. (2006) revised and tested GRAMI to simulate cotton growth and fiber yield of water-stressed cotton. The model simulated cotton fiber yield with root mean squared errors ranging from 28 to 100 kg ha^{-1}, suggesting that the within-season calibration method could be used to model cotton growth under various water-limiting conditions. Rajan et al. (2010) described how GRAMI could be used with infrequent satellite input data for simulating daily crop ground cover and estimating crop water use for irrigation scheduling. Sommer et al. (2008) calibrated the CropSyst model using within-season satellite-derived LAI of cotton grown in the Khorezm region of Uzbekistan. The high temporal resolution of the satellite imagery was useful for improving above ground biomass and LAI simulations with the model.

Remote sensing images have also been useful in efforts to use crop models for crop yield forecasting. Bastiaanssen and Ali (2003) used data from the Advanced Very High Resolution Radiometer (AVHRR) with Monteith's biomass simulation model and the Surface Energy Balance Algorithm for Land (SEBAL) model to estimate regional crop yield for multiple crops, including cotton, in the Indus Basin in Pakistan. A limitation of the study was the spatial resolution of the images, which did not permit field-scale forecasts. Shi et al. (2007) used multi-temporal images from the Moderate Resolution Imaging Spectroradiometer (MODIS) with an agro-meteorological model, based on Monteith's biomass simulation model, to estimate seed cotton yield in the Khorezm region of Uzbekistan. The use of remote sensing data inputs reduced the need for field data input in their study. The difference between modeled seed cotton yield estimations and published government data was within 10%. Hebbar et al. (2008) used the Infocrop-cotton model along with data from the Indian Remote Sensing program's Linear Imaging Self-Scanning (LISS-III) satellite for simulating seed cotton yield in major cotton growing states in India. The model accurately simulated water and N stress, total biomass, and seed cotton yield. The ready availability of multispectral imagery at little or no cost, such as that from the Landsat series of satellites, ensures that remote sensing data will continue to be a viable source of information to guide crop model simulations and potentially improve model performance.

3.2.8. Economics

Economists use cotton simulation models to determine economically optimal resource use, analyze the risk associated with agricultural production, and assess the socio-economic implications of agricultural policies. Process-based crop simulation models are now regarded by economists as a better alternative to the traditional regression based models, because the former simulates the biological and physical process related to the plant growth with better precision (Bontemps et al., 2001). For example, Cammarano et al. (2012) used CROPGRO-Cotton to determine profit-maximizing strategies for cotton under deficit irrigation in Australia, and the long-term temporal seed cotton yield distribution generated by the model was used to determine the economic feasibility of deficit irrigation practices. Nair (2011) used cotton fiber yield simulations generated using Cotton2K and an economic model to determine the economically optimal strategies to allocate irrigation water among different growth stages of cotton at different sub-optimal levels of irrigation water availability. Cotton2K was also used to assess the profitability of partitioning a cotton field, irrigated by center pivot, into irrigated and rainfed portions (Nair et al., 2013). This study showed that the field partitioning increased both fiber yield and profitability of deficit irrigated cotton. Reddy et al. (2002b) reviewed applications of the GOSSYM model for economic and policy decisions.

From an economist’s point of view, the year-to-year variability in profit, which indicates production risk, plays an important role in a producer’s decision making. Bontemps et al. (2001) linked the data generated by EPIC to an economic model and showed that when irrigation water availability is too low to have risk-reducing impact, but high enough for normal crop growth, the farmers are very responsive to changes in water price. Ritchie et al. (2004) used OZCOT to assess risk management strategies using seasonal climatic forecasting for cotton in Murray-Darling Basin in Australia. Although adjusting planted area in response to seasonal climatic forecasts led to significant increases in returns, farmer responses to the forecasts depended on their attitude toward risk. The crop growth simulation model, APSIM, coupled with an economic model was used to analyze the benefits and risks of investing in recycled water in Australia (Brennan et al., 2008), and a case study was used to illustrate the combination of biological and economic models. The Cotton2K model was used along with an econometric model to assess the impact of a cotton producer’s attitude towards risk on optimal irrigation water allocation decisions for center pivot irrigated cotton in the Texas High Plains (Nair, 2011). The results indicated that optimal irrigation water allocation has both profit increasing and risk reducing effects.

Cotton simulation models are also used to analyze the impact of agricultural policies and to assist in making whole-farm management decisions. A windows-based application of the EPIC model, CROPMAN, was used to assess the effectiveness of water conservation policies for the Ogallala Aquifer in the Texas High Plains (Das et al., 2010; Johnson et al., 2009). These studies compared the water saving potential and local economic impacts of water conservation policies, such as imposing pumping restrictions and charging a water tax. A multi-field configuration of APSIM named 'APSFarm' was used to explore management alternatives and develop whole-farm management decisions in Australia (Power et al., 2011a). Kuhn et al. (2010) used EPIC along with an economic model to evaluate the effect of tax exemptions on fertilizer use in Benin and reported that tax exemption on fertilizers increased crop productivity and decreased excessive expansion of cropped area. Wang and Nair (2013) developed a theoretical framework for determining economically optimal irrigation water allocations for cotton under deficit irrigation and used this economic model along with the fiber yield data generated using Cotton2K to analyze the water saving potential of the cost-share program aimed at improving adoption of high efficiency irrigation systems. They concluded that this program did not provide any incentive for the producers to conserve water.

3.2.9. Classroom instruction

Cropping system simulation models have been used by instructors to teach principles of life sciences and environmental management (Boote et al., 1996; Graves et al., 2002; Reddy et al., 2002b). However, most models are not classroom-friendly and are not easily portable from one instructor or institution to another. Therefore, models as instructional aides are limited even though the potential benefits to students, instructors, and institutions exist (Graves et al., 2002).

Many graduate students and postgraduate researchers at Mississippi State University and other institutions have contributed to various aspects of GOSSYM model development (Reddy et al., 2002b). Researchers in agricultural engineering, agronomy, climate change, computer science, economics, entomology, extension education, meteorology, and soil and biological sciences have engaged in this effort. The GOSSYM model has been used as an instructional tool to teach students the basic principles of botany, climate impacts, and management options in cotton production, to enhance problem solving skills in the life sciences, and to provide a holistic understanding of cropping system processes. Two instructional methodologies have been used: one in which students improve the functionality of the models by adding new knowledge to the existing model code and another in which the model is used for classroom instruction. One approach for classroom instruction teaches a given cropping system concept by demonstrating how it is modeled. For example, students learn how cotton growth and development is affected by multiple stress factors and how these factors are summarized using the environmental productivity index to reduce photosynthesis (Reddy et al., 2008; www.spar.msstate.edu/classes.html). Another approach for classroom instruction demonstrates how a model can be used to study management options and to understand crop development and yield responses to environmental variables, such as climate change. Students learn to implement cropping system simulation models to study the effects of alternate planting dates, future climate change, and alternate fertility or irrigation schedules on crop development and yield. Without a process-based model such as GOSSYM, it would be difficult to teach crop and climate interactions in a traditional setting. Students appreciate the utility of simulation models for understanding cropping system concepts and how management affects cotton production in real-world scenarios.

Instruction on the use of the DSSAT crop models has been provided during annual short-term training workshops. These training programs have attracted between 50 to 100 attendees internationally from private businesses, universities, and government agencies, demonstrating the interest in the models among a variety of people. Such workshops are currently the primary source of formal training for post-graduate agricultural professionals aiming to use crop models in their work.

3.2.10. Other agronomic considerations

To assist research in cotton management issues, OZCOT has been used to investigate opportunities for using high fruit retention transgenic cotton with changes in planting time to improve crop WUE (Braunack et al., 2012) and to assess the risk of alternative management strategies for early crop maturity (Richards et al., 2001). As part of the FARMSCAPE initiative, which was a participatory action research approach used to encourage the use of cropping system models in Australian commercial cotton production (Carberry et al., 2002b), OZCOT was implemented to assist dryland cotton growers in choosing summer crops (sorghum or cotton) and cotton row configurations (solid planted versus skipped rows) to reduce risk of crop failure (Bange et al., 2005). Extending this effort by using the APSIM simulation framework (Keating et al., 2003) has enabled assessments of the production, economic, and environmental consequences of different dryland crop rotation sequences involving cotton (Carberry et al., 2002b).

To estimate changes in soil organic C for different cropping systems in West Africa, Tojo Soler et al. (2011) used CROPGRO-Cotton with other DSSAT crop modules to simulate eight crop rotations that included cotton, sorghum, peanut, maize, and fallow. In agroforestry research, Zamora et al. (2009) used the CROPGRO-Cotton model to investigate light availability to cotton under a pecan alley cropping system. Finally, Ortiz et al. (2009) used CROPGRO-Cotton to assess the impacts of root-knot nematode parasitism on biomass and seed cotton yield in Georgia.

4. Future Directions and Opportunities

In the last century, research efforts resulted in the development of several cropping system simulation models for cotton, including GOSSYM, Cotton2K, COTCO2, OZCOT, and CROPGRO-Cotton. At that time, research funding was available specifically for model development and testing. For example, GOSSYM development was initially funded within the USDA Agricultural Research Service (Baker et al., 1983), and CROPGRO development originated with the IBSNAT Project (Uehara and Tsuji, 1998) funded by the United States Agency for International Development (USAID). Sources of funding for model development have largely disappeared. The Agricultural Model Intercomparison and Improvement Project (AgMIP) is a recent noteworthy effort to improve existing crop simulation models, although model developers are expected to provide their own resources for this effort. AgMIP is an international effort to link climate, crop, and economic models to address climate change impacts on world food security in both developed and developing countries (www.agmip.org). Two major themes of AgMIP that will advance the use of cropping systems simulation models in the new century are 1) the intercomparison and improvement of existing crop models to identify simulation approaches that best estimate cropping system processes and 2) the development of multidisciplinary teams that unite researchers in the areas of climate science, crop science, computer science, and economics. Multidisciplinary teamwork and efforts to compare cotton models, such as that exemplified in AgMIP, will increase the utility of these models for addressing cotton production issues in the new century.

A notable accomplishment reported herein is the development of the spatially-distributed GOSSYM model (Liang et al., 2012b), because large-scale applications of cropping system models are becoming increasingly important to address the imminent challenge of global climate change. Policy makers, economists, and climate scientists are more interested in simulation results at regional scale, such as county-level, state-level, or the 30 km grid used by Liang et al. (2012b). However, because existing cotton simulation models were developed from decades of experiments at the scale of individual agronomic plots, plants, or plant leaves, the implementation of the models at regional scale offers several challenges. Foremost is the challenge of collecting model input data over large areas with spatial resolution high enough to satisfy the original model scaling assumptions. Since current data collection methods are unable to provide such detailed information, the only option has been to conduct simulations at reduced spatial resolutions with knowledge that landscape heterogeneity can largely invalidate the original scaling assumptions of the model. The degree to which system processes measured and simulated at the point-scale is relevant at broader scales remains an open question. One solution lies in the development of better data collection methodologies, so model input requirements can be satisfied at an appropriate spatial scale. Until that goal is realized, generalization and simplification of existing models is necessary to provide appropriate simulation tools for large-scale analyses that are not focused within the borders of a given agronomic unit.

Satellite remote sensing has been proposed as a source of spatial data for model parameterization and calibration; however, remaining challenges are how to appropriately interface remotely sensed measurements with the simulation models and whether remote sensing offers enough information to effectively guide a given model. This issue is also likely related to the issue of model complexity versus generality. With the notable exception of GRAMI, most cropping system simulation models were developed independently from advancements in remote sensing, which complicates their union. Further development and perhaps generalization of existing models, while considering the types of information that can be obtained from remote and proximal sensing, will promote the union of the models with these sensing technologies. Conversely, model parameterization requirements can advise the development of novel sensors that provide better estimates of model input parameters. For example, sensors that measure leaf orientation or boll development may assist model parameterization efforts. Improving the union of models and sensor data will facilitate the regional-scale modeling endeavors described above as well as precision agriculture applications at the field scale.

While large-scale applications of cotton simulation models are becoming increasingly important, the main utility of the models remains as a tool for guiding management decisions. In the last decade, the literature has demonstrated substantial efforts to use cotton simulation models for irrigation water management in all major cotton-producing regions across the globe. The models were also used to address N fertilization issues and to make crop management decisions in response to near-term climatological predictions or water supply constraints. Lascano and Booker (2013) discussed several factors that have contributed to the surge in use of mechanistic crop models as management tools. Factors included advances in computer hardware and software, electronics, variable-rate application, and proliferation and availability of the input data required by the models. For example, soil data provided by the United States Department of Agriculture, elevation data provided by the United States Geological Survey, and weather data from weather networks provide the necessary inputs for model implementation throughout most of the United States Cotton Belt. Despite these positive developments, a substantial gap persists between the use of cotton simulation models for research and for on-farm decision making (McCown, 2002b; McCown et al., 2002). Scientists have theorized (McCown, 2002a) and developed (McCown et al., 2002) many agricultural DSSs to deliver scientific knowledge to farm managers. Unfortunately, many such DSSs remain unused (McCown, 2002b). Also, McCown et al. (2012) documented farmers' tendency to reduce model simulation results to a set of intuitive management rules, thereby foregoing model use as an on-going decision aid. Lessons for successful on-farm implementation of scientific DSSs include 1) treatment of the DSS as a tool to assist the decision process rather than to by-pass it, 2) the importance of positive social interaction between the DSS developer and the farmer, and 3) the potential for co-creation of DSSs that incorporate both practical and scientific knowledge (McCown, 2002b). Notable examples of successful interactions between scientists and farmers include the early efforts to use GOSSYM-COMAX for on-farm cotton management (McKinion et al., 1989); the use of APSIM in the FARMSCAPE initiative to examine the benefits of science-based soil sampling, climate forecasting, and simulation modeling applied to on-farm decision support (Carberry et al., 2002b); and an application of OZCOT within the HydroLOGIC irrigation management software for eleven on-farm experiments in Australia (Richards et al., 2008). Continued interaction between cotton growers and research scientists is warranted to facilitate the use of cotton models for on-farm decisions and to develop appropriate decision tools that implement the models to answer pertinent questions.

Applications of cotton simulation models in the broader assessment of environmental impacts are also increasing in importance. This review provides many examples of model use for analyzing losses of N fertilizer and other production inputs to the environment, quantifying greenhouse gas emissions from agricultural soils, and assessing the potential for soil C sequestration. However, there is currently a movement toward life-cycle assessment or cradle-to-grave analysis for many consumer products, including textiles and food. These efforts originate both from policy mandates such as those in the European Union (Wolf et al., 2012) and from industry initiatives such as The Sustainability Consortium (www.sustainabilityconsortium.org). Cropping system simulation models are the only tool that can account for complex cropping system processes and estimate the impacts of crop management practices over a wide range of environmental conditions and geographic locations.

In the early days of cropping system simulation model development, the models were commonly regarded as stand-alone tools for crop growth simulation, and computing technology at that time did not permit much more. Increasingly, the models are now implemented as a single component within broader software and hardware systems. For example, the use of cotton simulation models with optimization algorithms and advanced process control for irrigation management (McCarthy et al., 2013), within GIS software for spatial simulation analyses (Thorp et al., 2013), or with other process models that simulate water availability (Ritchie et al., 2004), irrigation hydraulics (Bautista et al., 2009), or climate forecasts (Liang et al., 2012b) will be increasingly important for optimizing management practices while more broadly considering the desired management outcomes. Hence, it is expected that the greatest benefit of cotton simulation models will be realized by integrating the models with the other software and hardware components, as required for whole system optimization. For example, cotton simulation models could be integrated with equipment control systems (e.g., irrigation consoles and tract sprayer controllers), which use real-time telemetry data that describe environmental conditions and crop status to automatically adjust crop inputs both spatially and temporally for optimum crop production. Simultaneously, models integrated with geospatial technologies on a large server could calculate cropping system responses regionally and provide field-scale control systems with information on crop input limitations or restrictions, considering potential environmental impacts, resource restraints, and climate predictions at the regional scale.

This broad vision for model implementation requires the models to be succinct, well-structured, and flexible enough for seamless integration into diverse software and hardware systems. It also necessitates improvements in model documentation, training courses, and educational materials, because the next generation of cotton modelers will likely come from diverse disciplines and may have limited knowledge of the ecophysiology represented in the models. Efforts are needed to design models that are more foolproof, quickly learned, and easily implemented. This will increase confidence in the models, attract more users who find value in modeling endeavors, and insure that future generations benefit from the model development efforts undertaken in the past decades.

5. Conclusions

Prior to conducting this review of literature, the consensus among several of the authors was that the development and application of cotton simulation models had somewhat languished since the early successes with the GOSSYM model in the last century. With regard to model development, this assessment appears accurate. No sustained advancements in the development of simulation models specific to cotton were noted in the new century. However, there has been a substantial increase in the application of cotton models since 2000. In fact, the main topics of early reports on cotton simulation modeling applications, including irrigation and fertilizer management, climate assessment, and model integration with remote sensing, have all been expounded to full sections herein, each describing several reports of new progress since the turn of the century. These contributions have been largely disconnected however, an issue that this review aimed to remedy.

An encouraging finding is the increased interest and use of cotton simulation models by non-agronomists and non-traditional crop modelers. Researchers in economics, engineering control, and climate forecasting recognize the utility of process-based cropping system simulation models for applications within their areas of expertise. Increasingly, cotton simulation models are being implemented beyond simple evaluations of agronomic experiments. As a result, a challenge for model developers is to address complexity issues with the models and to insure that models of appropriate complexity are available for a given application. A related issue is to improve the ease of model implementation for non-traditional crop modelers.

While improving model versatility for non-agronomists is an important goal, a main thrust for cotton simulation modeling research and application continues to be in the area of on-farm management decisions, including both strategic planning for allocation of limited resources and routine management of production inputs by growers. Thus, further efforts to develop and evaluate existing cotton simulation models are warranted to improve their ability to respond adequately to environmental conditions and simulate cotton growth, development, and yield at the field scale. No efforts to compare existing cotton simulation models were found in literature, so this would be advisable as a first effort to evaluate methodologies among existing cotton simulation models.

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List of Abbreviations

Advanced Very High Resolution Radiometer	AVHRR
Agricultural Model Intercomparison and Improvement Project	AgMIP
Agricultural Production Systems sIMulator	APSIM
Atmospheric Carbon Dioxide Concentration	$[CO_2]$
Carbon	C
Carbon DiOxide	CO_2
Commonwealth Scientific and Industrial Research Organization	CSIRO
CrOp MAnagement EXpert	COMAX
Cropping System Model	CSM
Decision Support System for Agrotechnology Transfer	DSSAT
Decision Support System	DSS
Drained Upper Limit	DUL
El Niño/La Niña Southern Oscillation	ENSO
Environmental Policy Integrated Climate	EPIC
EvapoTranspiration	ET
Food and Agriculture Organization	FAO
Genetics by Environment by Management	GEM
Geographic Information System	GIS
International Benchmark Sites Network for Agrotechnology Transfer	IBSNAT
Integrated Quantity Quality Model	IQQM
Leaf Area Index	LAI
Linear Imaging Self-Scanning	LISS
Lower Limit of plant extractable water	LL
MODerate Resolution Imaging Spectroradiometer	MODIS
Nitrogen	N
Nitrogen Loss and Environmental Assessment Package	NLEAP
Root Zone Water Quality Model	RZWQM
SATurated soil water content	SAT
Simple and Universal CROp growth Simulator	SUCROS
Soil-Water-Atmosphere-Plant	SWAP
Surface Energy Balance Algorithm for Land	SEBAL
United States Agency for International Development	USAID
United States Department of Agriculture-Agricultural Research Service	USDA-ARS
Water Use Efficiency	WUE
WOrld FOod STudies	WOFOST

Table 1. General information on existing cotton simulation models.

Model	Predecessor Models	Programming Language	Time Step	Key References	Decision Support Tools
GOSSYM	SIMCOTI SIMCOTII	Fortran	Daily	Baker et al. (1983) Reddy et al. (2002b)	COMAX
Cotton2K	GOSSYM CALGOS	C++, formerly Fortran	Hourly	Marani (2004)	None
COTCO2	KUTUN ALFALFA	Fortran	Hourly	Wall et al. (1994)	None
OZCOT	SIRATAC	C#, formerly Fortran	Daily	Hearn and Da Roza (1985) Hearn (1994)	APSIM CottBASE HydroLOGIC VARIwise Whopper Cropper
CSM-CROPGRO-Cotton	CROPGRO-Soybean	Fortran	Daily	Hoogenboom et al. (1992) Jones et al. (2003)	DSSAT

Table 2. Crop growth and development processes simulated by existing cotton simulation models.

	GOSSYM	**Cotton2K**	**COTCO2**	**OZCOT**	**CROPGRO-Cotton**
Phenology	Develops vegetative and fruiting branches and nodes based on thermal time Calculates the number of branches, squares, bolls, open bolls, fruiting sites, and aborted fruits	Develops vegetative and fruiting branches and nodes based on thermal time Calculates the number of branches, squares, bolls, open bolls, fruiting sites, and aborted fruits	Develops meristem tissue, leaf primordia, petioles, growing and mature leaves, stem segments between nodes, squares, bolls, and open bolls based on thermal time	Develops the number of fruiting sites based on thermal time Calculates the number of squares, bolls, open bolls, and aborted fruits based on crop carrying capacity	Development proceeds through growth stages based on photothermal time: emergence, first leaf, first flower, first seed, first cracked boll, and 90% open boll. Calculates boll number and aborted fruits
Plant maps	Yes	Yes	Yes	No	No
Potential carbon assimilation	Canopy-level radiation interception	Canopy-level radiation interception	Organ-level biochemistry (Farquhar et al., 1980)	Canopy-level radiation interception	Leaf-level biochemistry (Farquhar et al., 1980)
Respiration	Uses an empirical function of respiration based on biomass and air temperature	Calculates growth and maintenance respiration and photorespiration	Calculates organ-level growth and maintenance respiration and photorespiration	Uses empirical functions of respiration based on fruiting site count and air temperature	Calculates growth and maintenance respiration
Partitioning	Allocates carbon to individual growing organs	Allocates carbon to individual growing organs	Allocates carbon to individual growing organs	Allocates carbon to cohort pools for developing bolls	Allocates carbon to single pools for leaves, stems, roots, and bolls
Canopy size	Calculates plant height	Calculates plant height	Calculates stem segment lengths	None	Calculates hedgerow-based canopy height and width
Yield components	Calculates fiber mass as a fraction of boll mass and boll size	Calculates burr mass and seed cotton mass	Calculates boll mass	Calculates fiber mass as a fraction of boll mass and boll size	Calculates boll mass, seed cotton mass, seed number, and unit seed weight
Stress	Calculates stress due to water, nitrogen, and air temperature	Calculates stress due to water, nitrogen, and air temperature	Calculates stress due to water and air temperature	Calculates stress due to water, nitrogen, and air temperature	Calculates stress due to water, nitrogen, and air temperature

Table 3. Atmospheric and soil processes simulated by existing cotton simulation models.

	GOSSYM	**Cotton2K**	**COTCO2**	**OZCOT**	**CROPGRO-Cotton**
[CO_2] effect on photosynthesis	Yes	Yes	Yes	No	Yes
[CO_2] effect on transpiration	No	No	Yes	No	Yes
ET	Ritchie (1972)	Modified Penman equation from CA Irrigation Management Information System	Leaf-level energy balance coupled with stomatal conductance	Richie (1972)	Priestley and Taylor (1972) and FAO-56 (Allen et al., 1998)
Soil water	2D RHIZOS model (Lambert et al., 1976)	2D RHIZOS model (Lambert et al., 1976)	2D model	Ritchie (1972)	Ritchie (1998) and Ritchie et al. (2009)
Soil nitrogen	Dynamic simulation of soil and plant nitrogen balances	Dynamic simulation of soil and plant nitrogen balances	No	Static, empirical approach that predicts potential N uptake	Godwin and Singh (1998) or Gijsman et al. (2002)
Soil phosphorus	No	No	No	No	Yes
Soil salinity	No	Yes	No	No	No
Waterlogging	No	No	No	Yes	Yes
Flooding	No	No	No	No	Yes

Table 4. Management practices simulated by existing cotton simulation models and other applications.

	GOSSYM	**Cotton2K**	**COTCO2**	**OZCOT**	**CROPGRO-Cotton**
Sowing date	X	X	X	X	X
Cultivar selection	X	X	X	X	X
Row spacing	X	X	X	X	X
Skip rows	X	X		X	
Planting density	X	X	X	X	X
Irrigation	X	X	X	X	X
Fertilizer	X	X		X	X
Crop residue					X
Tillage		X			X
Growth regulators	X	X			
Defoliation	X	X		X	X
Insect damage	X	X	X	X	X
Disease impact		X			X
Climate change	X		X		X
Cropping sequences				X	X
Geospatial analysis		X		X	X