

CROP MODEL REVIEW AND SWEET SORGHUM CROP MODEL PARAMETER DEVELOPMENT

by

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B.S., Wichita State University, 2007

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Department of Biological and Agricultural Engineering
College of Engineering

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2012

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Abstract

Opportunities for alternative biofuel feedstocks are widespread for a number of reasons: increased environmental and economic concerns over corn production and processing, limitations in the use of corn-based ethanol to 57 billion L (15 billion gal) by the Energy Independence and Security Act (US Congress, 2007), and target requirements of 136 billion L (36 billion gal) of renewable fuel production by 2022. The objective of this study was to select the most promising among currently available crop models that have the potential to model sweet sorghum biomass production in the central US, specifically Kansas, Oklahoma, and Texas, and to develop and test sweet sorghum crop parameters for this model.

Five crop models were selected (CropSyst, CERE-Sorghum, APSIM, ALMANAC, and SORKAM), and the models were compared based on ease of use, model support, and availability of inputs and outputs from sweet sorghum biomass data and literature. After reviewing the five models, ALMANAC was selected as the best suited for the development and testing of sweet sorghum crop parameters. The results of the model comparison show that more data are needed about sweet sorghum physiological development stages and specific growth/development factors before the other models reviewed in this study can be readily used for sweet sorghum crop modeling.

This study used a unique method to calibrate the sweet sorghum crop parameter development site. Ten years of crop performance data (Corn and Grain Sorghum) for Kansas Counties (Riley and Ellis) were used to select an optimum soil water (SW) estimation method (Saxton and Rawls, Ritchie et al., and a method that added 0.01 m m^{-1} to the minimum SW value given in the SSURGO soil database) and evapotranspiration (ET) method (Penman-Montieth, Priestley-Taylor, and Hargraeves and Samani) combination for use in the sweet sorghum parameter development. ALMANAC general parameters for corn and grain sorghum were used for the calibration/selection of the SW/ET combination. Variations in the harvest indexes were used to simulate variations in geo-climate region grain yield. A step through

comparison method was utilized to select the appropriate SW/ET combination. Once the SW/ET combination was selected the combination was used to develop the sweet sorghum crop parameters.

Two main conclusions can be drawn from the sweet sorghum crop parameter development study. First, the combination of Saxton and Rawls (2006) and Priestley-Taylor (1972) (SR-PT) methods has the potential for wide applicability in the US Central Plains for simulating grain yields using ALMANAC. Secondly, from the development of the sweet sorghum crop model parameters, ALMANAC modeled biomass yields with reasonable accuracy; differences from observed biomass values ranged from 0.89 to 1.76 Mg ha⁻¹ (2.8 to 9.8%) in Kansas (Riley County), Oklahoma (Texas County), and Texas (Hale County). Future research for sweet sorghum physiology, Radiation Use Efficiency/Vapor Pressure Deficit relationships, and weather data integration would be useful in improving sweet sorghum biomass modeling.

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Acknowledgements

I would like to thank my major professor Dr. Kyle Douglas-Mankin, and my co-advisor Dr. Richard Nelson. Their guidance and patience throughout this process has undoubtedly led to its success. With their support I have certainly found my voice in the field of modeling research. I would like to thank my committee members Dr. Scott Staggenborg, and Dr. Michael Langemeier, for their guidance and assistance with any questions I had.

I owe a special thanks to Vernon Schaffer and Mary Knapp for their assistance with acquisition of Kansas model variables and their commitment to answering questions I had. I owe special thanks Dr. Richard Vanderlip for his assistance with the SORKAM model.

I would like to thank Dr. Danielle Bellmer for her contributions to site information for the Oklahoma Counties used in this study, her input was for specific details for the sweet sorghum modeling and interpretation of results in Oklahoma. I grateful to Dr. Bill Rooney and Rebecca Corn for the data used for modeling sweet sorghum in Texas State.

I am especially thankful to Sumathy Sinnathamby for her friendship and encouragement throughout my research, which was important to the completion of this thesis. Additionally, I would like to thank Ben Kuestersteffen for his assistance with the development of a program that helped with the processing of the ALMANAC text files. I would also like to thank my family and friends for standing by me during my time as Kansas State University whose support and guidance was important for my success.

Finally I would like to thank my wife Erin Perkins for her love, faith, support, and motivation during the final year of my project, for without it this project would have been much more difficult.

Chapter 1- Literature Review

Ethanol Production in the US

High fuel prices in recent years have increased the need for alternative fuels (i.e., ethanol and biodiesel) to reduce the dependence on foreign oil supplies. Currently in the United States (US), ethanol production is dominated by first-generation (conventional) biofuels, specifically corn-based ethanol. In the US, 12.45 billion bushels of corn were produced in 2010, with production up 2.94 billion bushels from 2001 and 4.97 billion bushels from 1991 (USDA, 2010); with 4.7 billion bushels of corn used for ethanol production in 2010 (Abbot et al., 2011). The main area of corn production in the US is centered in the Corn Belt (Nebraska, South Dakota, Indiana, Illinois, Iowa, and Ohio), which accounts for > 80 percent of the corn produced in the US (Dhuyvetter, 2005). Figure 1.1 shows the corn production (bushels) and acres planted over the last twenty years in the US.

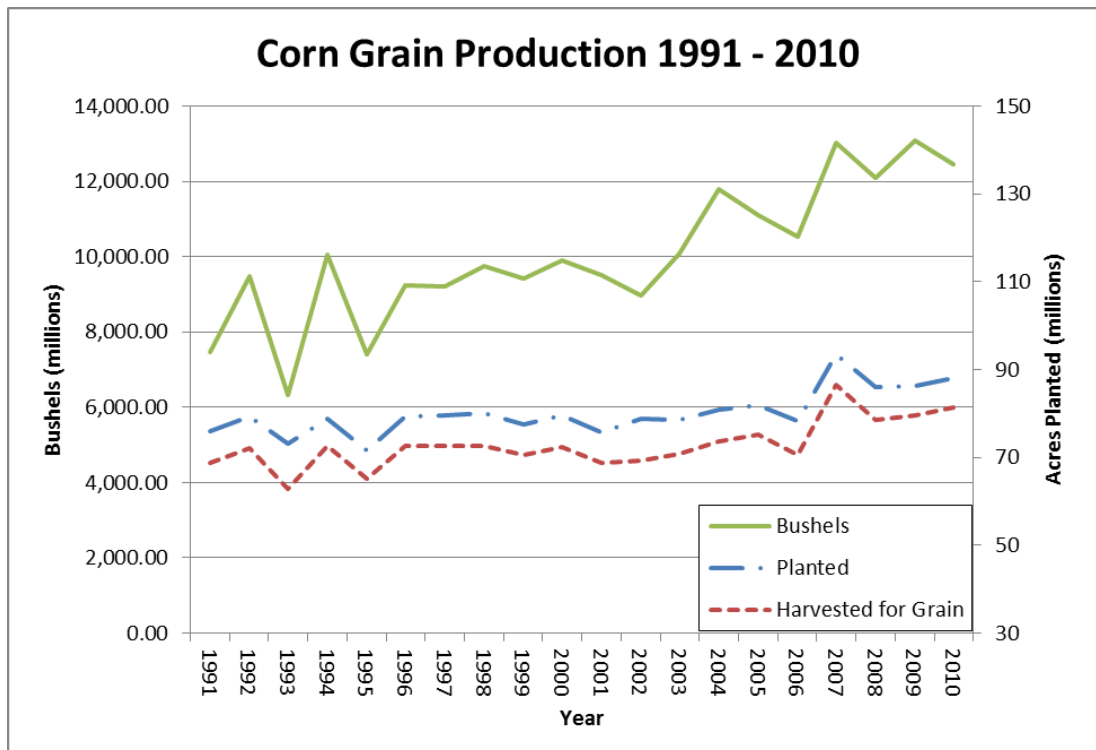


Figure 1.1 - Corn acres planted/harvested and bushels harvested. (Data Source: USDA, Economic Research Service Feed Grains Database, www.ers.usda.gov/data/feedgrains)

The main benefit for using corn grain as an ethanol feedstock is the existing production capacity and infrastructure (BRDI, 2008b). With this benefit there are many social, economic, and environmental problems that accompany the wide use of corn as a feedstock (Simpson et al., 2008; Shapouri et al., 2006; Rendleman and Shapouri, 2007). Some of the greatest economic and environmental problems with using corn occur during production and processing; coupled with these issues, a conflict over corn for fuel and food becomes apparent as a larger percent of the crop harvested is being used for ethanol production (Simpson et al., 2008; Wescott, 2007; Leibtag, 2008).

Economic and environmental problems increase with the need for the larger quantity of inputs. For example, nitrogen application rates increase per bushel of corn produced, depending on management, soil texture and expected yields, applied pounds of nitrogen per acre, and can range from 18 to 136 kg (40 to 300 lb) (KSU-AESCES, 2007), with closer to 136 kg (300 lb) in areas with higher yielding environments. The increase in the cost of fertilizer along with the increase in the cost of fuel has increased the overall production cost of corn and the price per bushel (Hoffman and Baker, 2009). The increased management intensity, by putting more acres into continuous corn, provides a higher probability for surface runoff, which can carry nutrients and pesticides into nearby water resources. Increasing surface runoff contributes to eutrophication/pollution of rivers, lakes, and oceans, contributing to the overall environmental concerns associated with high levels of corn production (Simpson et al., 2008; Malcolm and Aillery, 2009; Malcolm et al., 2009).

In addition to the field production costs, corn grain processing for ethanol is fairly energy intensive, though the energy ratio (ratio of the total energy in the fuel [output] to the total energy used to produce the fuel [input]) of the production process has increased from 1.34 to 2.29 with better processing techniques (Shapouri et al., 2002; Shapouri et al., 2010). The energy ratio for ethanol produced from corn starch is still well below that of projected ethanol yield from biofeedstocks, such as

cellulosic (varies with feedstock type) and sugar cane (8.0) (Vries et al., 2010). The low energy yield along with the low carbon credit for growing corn as a feedstock and the US cap on ethanol production from corn of 57 billion L (15 billion gal) (US Congress, 2007), are likely to discourage use of corn as an ethanol feedstock in the long term, opening up opportunities for alternative fuel development (Tyren, 2008).

Supplemental to the economic and social concerns in using corn for ethanol production, there are concerns over having a single feedstock, since there is a potential of price shocks due to unpredictable environmental factors (BRDI, 2008b). Opportunities for alternative biofeedstocks are widespread for a number of reasons: increased environmental and economic concerns over corn production and processing, limitations in the use of corn based ethanol to 57 billion L (15 billion gal) by the Energy Independence and Security Act (US Congress, 2007) and target requirements of 136 billion L (36 billion gal) of renewable fuel production by 2022 (US Congress, 2007; EPA, 2010) from a variety of biomass feedstocks, such as switchgrass, oilseeds, and short-rotation woody crops. Biofeedstocks such as sugar cane, agricultural residue, perennial grasses (specifically switchgrass), woody biomass, and sweet sorghum are being investigated for economic feasibility (BRDI, 2008a; BDRI, 2008b) and use on a commercial scale. In the following sections benefits and problems with each feedstock are presented.

Alternative Feedstocks

There are a variety of biofeedstocks available for ethanol production: sugar cane, agricultural residue, perennial grasses, woody residue, and sweet sorghum. In the following sections, a brief description of the alternative biofuels will be provided along with summarized overview of the benefits and problems of using these biofeedstocks for ethanol production in the US.

Sugar Cane

Sugar cane is a tropical perennial grass grown to produce raw sugar (Shapouri, 2006). Sugar cane is an effective crop at producing adequate amounts of feedstock substrate to be used in the production of ethanol to support the needs of a nation; this can be noted in the ethanol production from sugar cane in Brazil. Sugar cane can produce up to 49.28-73.25 Mg ha⁻¹ (22.0-32.7 tons acre⁻¹) in the US, which can yield approximately 81.4 L Mg⁻¹ (19.5 gal ton⁻¹) of sugar cane (Shapouri et al., 2006).

Though sugar cane has a high gallon per acre return for ethanol, the main problem with growing this crop in the US is the limited climate, which limits sugar canes production to the Gulf Coast, Florida, and Hawaii (Shapouri et al., 2006). The shorter growing season in northern states along with quick deterioration of the fermentable carbohydrates make it difficult to use this tropical perennial grass as a year round feedstock in the US, limiting its production for ethanol to the regions which it is well adapted.

Agricultural Residue

Agricultural residues are abundant and readily available. The top eight US crops produce approximately 450 tons of biomass per year (BRDIa, 2008; Perlack et al., 2005). Though these residues are available for cellulosic ethanol production, limitations due to economic and environmental concerns are preventing it from being widely used. Major economic concerns are logistics and processing costs (BRDIa, 2008; BRDIb, 2008).

Logistical concerns arise due to the limited infrastructure for the harvest and transport of the bulky substrate to a production facility. Pricing of corn residue has been estimated between 40 to 45 dollars per dry ton to make it feasible to use residue as a feedstock for ethanol production (Perlack et al., 2005; Malcom et al., 2009). Even with material coming into a facility, storing large quantities of biomass remains costly. Even with the probable price, cellulosic ethanol production facilities are not currently economically competitive with corn based ethanol production, and no commercial facilities

currently exist (Wescott, 2009), though a few companies have suggested within the next five years an economically competitive facility may be built and operational (Guzman, 2010).

Environmental concerns for residue feedstock focus specifically on soil health, nutrient loss, and soil erosion. Acceptable levels of residue removal are highly site-specific (Nelson et al., 2004), and removing too much crop residue for ethanol production increases the potential for erosion, nutrient loading in surface runoff, and inputs due to nutrients lost from the residue removal (Malcom et al., 2009; Simpson et al., 2008). Graham et al. (2007) studied the removal rates for corn stover and estimated that, under current conditions, with proper management only 30 percent of the total corn stover per year would be available for ethanol production, suggesting also more studies associated with residue removal need to be done to understand the impacts of biomass removal over the long term.

Perennial Grasses

Perennial grasses, specifically switchgrass, have gained interest in the field of biofuels. The interest comes from switchgrass's high biomass accumulation, low management requirements, and adaption to drier climates in the central US (BRDI, 2008a). These factors make switchgrass a probable feedstock for cellulosic ethanol production, especially on marginal lands not good for producing other crops, and its deep roots and low inputs, producing a high carbon credit, are making switchgrass even more appealing (BRDI, 2008a). Studies have estimated approximately 302.8 to 340.7 liters (80 to 90 gallons) of ethanol can be produced from 0.907 Mg (1 ton) of switchgrass biomass (Bain, 2007; Aden et al., 2002), allowing switchgrass to be a competitive feedstock for ethanol production in regions less adequate for corn production.

The main concern with switchgrass as a feedstock involves it not being completely domesticated and still has high levels of seed dormancy, which makes its emergence unpredictable (BRDI, 2008a; BRDI, 2008b). Switchgrass also takes time to establish, between 2 and 3 years, before is productive enough to be economical, and when established, will produce biomass for 10 years (BRDI, 2008a; BRDI,

2008b). These factors make it difficult to convince farmers to use as a dedicated energy crop. Though currently established Conservation Reserve Program (CRP) sites might provide existing opportunities for switchgrass, additional studies are needed to show how the increased management for feedstock may affect the CRP for its current function. The Biomass Research and Development Board (2008a) suggested larger test areas need to be established to test the viability of switchgrass as a bioenergy crop, and more research needs to be done to understand the effects of intense management on switchgrass as a dedicated energy crop. Lastly the logistics and commercialization of cellulosic ethanol production are still a major concern (Malcom et al., 2009; BRDI, 2008a; BRDI, 2008b).

Woody Biomass

Woody residue has the potential to be a great source of biofeedstock, with a relative abundance and variety of feedstock sources. These feedstock sources include : logging residue, thinning from timberland/other forest land, primary mill residue, urban wood waste, conventionally sources wood, short duration woody crops (willow and poplar), biorefining sugars, and spent pulping liquors (black liquors) (BDRI, 2008a).

The concerns with some of these feedstocks are that they may interfere with well-established infrastructure in the logging and paper industry, limiting the actual availability of some of these feedstocks, specifically primary mill residue, conventionally sourced wood, short duration woody crops (willow and poplar), and spent pulping liquors (BDRI, 2008a). The most promising source from woody biomass is the urban wood waste, which is not currently utilized in a captured market (BDRI, 2008a). As discussed before, the major limitation to utilizing cellulosic feedstocks are logistics and preprocessing, which are still in in the early stages of development (BDRI, 2008a).

Sweet Sorghum

Sweet sorghum, as an alternative to sugar cane and cellulosic biomass, is gaining attention as a potentially viable feedstock for the production of ethanol in the US. Sweet sorghum is similar to sugar

cane in that it produces a sugary juice in the stalk. This sugary juice can be harvested using current sugar cane processing methods and the extracted juice can then be immediately fermented into ethanol, which reduces the overall cost of processing feedstock for ethanol production. The high biomass potential, low management requirements (Smith and Buxton, 1993) and drought tolerance (Steduto et al., 1997; Dercas and Liakatas, 2006) make this crop attractive and inexpensive to grow in regions with climate limitations.

As with many other high biomass crops, concerns exist over logistics with growing this crop (BDRI, 2008a; Shapouri et al., 2006). Another factor, shared with sugar cane which differs from other biomass crops, is that the sugary juice tends to spoil quickly (Ferraris, 1981; Ekhauf et al., 1985; Schmidt et al., 1997) which may limit the use of this feedstock to the crop's growing season in many parts of the US.

As the renewable fuel standard states that the contribution of cellulosic ethanol production in the US need be around 56.8 billion liters (15 billion gallons) by 2015 (US Congress, 2007), research dollars are certainly available for the establishment of cellulosic ethanol in the next decade (Shapouri et al., 2006, BDRI, 2008a). As the development of cellulosic processing is being developed for commercial implementation, it is necessary to find a supplement to current corn ethanol production methods. Sweet sorghum could offer that supplement and a possible transition into cellulosic ethanol production.

In comparison to the current conventional and cellulosic feedstocks, sweet sorghum's juice gives it an advantage in that it can be incorporated into current ethanol production technology with less preprocessing than starch crops and cellulosic feedstocks. Additionally remaining biomass from juice extraction can possibly be burned for power at a processing facility or incorporated in the cellulosic processing as it becomes more economical. Also, as an advantage over switchgrass, which makes sweet sorghum more attractive as a feedstock, sweet sorghum has no significant issues related to seed dormancy, and stands can be established annually with no establishment period, with similar inputs or

fewer inputs. Also, sweet sorghum has a shorter maturity time than sugar cane and is adapted to a wider range of climates, adding to its viability. It is difficult to suggest the feasibility of sweet sorghum as a feedstock due to the limited published field data available on this feedstock and its production in the US (Belmer and Hunke, 2007). In recent years, research test plots have been planted in Kansas, Oklahoma, and Texas (Propheter, 2009, Belmer and Hunke, 2007; Belmer and Hunke, 2008; Belmer and Hunke, 2009; Corn, 2009). These test plots, along with sweet sorghum literature and preliminary economic reports (Morris, 2008; Bele, 2007; Bennet and Anex, 2008), offer opportunities to examine the feasibility of sweet sorghum as a feedstock which could be used to supplement the current ethanol production in the US. Modeling sweet sorghum biomass accumulation in a variety of environments can assist in economic and environmental decisions in determining the long and short term feasibility of sweet sorghum as a feedstock.

Objectives

The overall goal of this thesis was to develop the capacity to simulate sweet sorghum biomass yields. The objective of the first part of this study (Chapter 2) was to select, from among several crop models, the one with greatest potential to model sweet sorghum biomass production effectively in the central US, specifically Kansas, Oklahoma, and Texas. Selected crop models were compared based on ease of use, model support, and availability of inputs and outputs from sweet sorghum biomass data and literature. In the second part of this study (Chapter 3), the best suited crop model was applied to develop/calibrate a set of sweet sorghum crop parameters developed from available physiological literature. These calibrated sweet sorghum parameters were further validated across a variety of geo-climate regions.

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Chapter 2 – Model Review

Introduction

Modeling is an important part of research used to replicate real-time events normally too difficult and expensive to replicate on a large scale or multiple times. Models use empirically, physically, or theoretically based equations to estimate one or more outcomes of an event or multiple outcomes of the same event with variable input scenarios.

In agricultural applications, crop models can be used to make decisions that will affect the long term health, financial, and/or physical function of a farming operation. For example, MacCarthy (2009) applied the Agriculture Production Systems Simulator (APSIM) to understand the impacts of different nutrient and residue management practices on corn yields in Ghana. Models are also useful in estimating long term economic trends, such as quantity supply and demand as Mazraati and Shelbi (2011) did in a published report projecting the effect of alternative fuels and advanced technology vehicles on oil quantity demanded by the United States up to 2030. Finally, models can be useful in making environmental design decisions. An example is designing a sedimentation pond for a waste water treatment facility. Modeling interactions between factors such as particle size, particle density, fluid density, fluid velocity, and fluid shear stress play an important role in designing the necessary size and total volume of the sedimentation pond (Guetter and Jain, 1991). The application of modeling in these situations and many others opens up the opportunity for it to be used in a variety of other situations, including the development and impact assessment of alternative biofuel feedstocks.

The Energy Independence and Security Act (EISA) requires production of 36 billion gallons of renewable fuel by 2022 (EPA, 2010; US Congress, 2007) from a wide variety of biomass feedstocks such as switchgrass, oilseeds, and short-rotation woody crops. Crop models can assist with the search for regionally appropriate biofuel feedstocks, such as sweet sorghum (*Sorghum bicolor (L.) Moench*), which has good yield potential and may potentially qualify under the Renewable Fuel Standard-2 (RFS-2) (US

Congress, 2007). However, few crop models have incorporated specific crop parameters associated with estimating biomass production of sweet sorghum.

Shih et al. (1981) developed a model that utilized leaf area and leaf dry biomass to estimate sweet sorghum total fresh biomass produced during different plant growth stages. No other papers were found in continuation of this research. Ferraris and Vanderlip (1986) compared SORKE/SORK5 models in predicting sweet sorghum biomass and concluded more detailed physiology of sweet sorghum varieties are needed to improve the accuracy of these models. No literature was found that followed up the implementation of SORGF or SORG5 to model sweet sorghum.

The Biosystems and Agricultural Engineering (BAE) Department at Oklahoma State University (OSU) published a report predicting sweet sorghum yields by soil and climate regions using Soil Water Assessment Tool (SWAT) (BAE-OSU, 2006). Due to the limited availability of actual field scale sweet sorghum biomass data, the report recommended more sweet sorghum data is needed from known soils, either irrigated or dryland, in order to accurately predict sweet sorghum yields and to calibrate/validate current model parameters used for this study (BAE-OSU, 2006). This report did not have crop parameters specifically developed for sweet sorghum either through research or literature review; instead, parameters from corn, sorghum hay, and sugar cane were combined to make a sweet sorghum crop parameter set, which may not be representative of actual sweet sorghum physiology.

Morris (2008), in an economic study of sweet sorghum as a biofeedstock in Texas, used a Multi-Variate Empirical (MVE) probability distribution to estimate the annual stochastic yields from sweet sorghum. Sweet sorghum crop parameters did not appear to be used to estimate the MVE parameters; instead sweet sorghum yield data from Texas AgriLife Research field trials were used with MVE model parameters derived from corn, grain sorghum, and cotton yields, modeled from 47 years of weather data using output from CropMan crop model (Morris, 2008). This economic feasibility study concluded that a facility in Texas designated specifically for sweet sorghum would not be economically viable in

regions with a short growing season. The author suggested that sweet sorghum could be a supplement to the industry during part of the year in all the counties. Modeling was not described in detail in this study, and it appeared biomass yields from sweet sorghum were not directly estimated with the CroPMan model. No published literature was found describing CroPMan parameters or models being used to estimate the biomass accumulation of sweet sorghum.

In the modeling studies described above, a designated model and set of parameters developed from sweet sorghum literature were non-existent or not described in detail. The lack of specific literature-based modeling parameters and available biomass comparison data show a need for further sweet sorghum model development and viable field trials for model comparison. The versatility of models such as APSIM and SWAT show current models may be available to estimate sweet sorghum biomass by utilizing current crop models.

The objective of this chapter is to review and compare the inputs available related to published literature physiology data for a selected group of crop models. From the comparison, the model that best fits selected criteria will be chosen for detailed sweet sorghum crop parameter development and calibration.

Materials and Methods

The five models reviewed in this study were selected based a report published by Hydrological Systems Research (HSR) providing suggestions for sorghum crop modeling in Kansas (HSR, 2008). The top five models reviewed in the HSR report were Agricultural Land Management Alternatives with Numerical Assessment Criteria (ALMANAC), Agricultural Production Systems sIMulator (APSIM), Crop Environment Resource Synthesis Sorghum (CERE-Sorghum), Cropping Systems Simulation Model (CropSyst) and SORKAM. Each of the five models was downloaded or purchased and licensing, if needed, acquired. Websites that provide access for downloading/purchasing each model are located in

appendix A. ALMANAC was downloaded from the United States Department of Agriculture-Agricultural Research Service ALMANAC Simulation Model website. The CropSyst model was downloadable after completing and submitting a simple registration form. In order to download or attain the APSIM model, a registration and non-commercial licensing form had to be completed. The CERES model set was ordered from the International Consortium for Agricultural Systems Applications (ICASA) website under the Decision Support System for Agrotechnology Transfer (DSSAT) software link. SORKAM was the only model not available for direct download. A copy of the software and documentation for SORKAM was provided by Dr. Scott Staggenborg from Kansas State University Department of Agronomy. It should be noted that all of these systems have not been made compatible with the Windows 7 system, and should be run on either Windows XP or Windows Vista. Also, both Command Prompt based model's (ALMANAC and SORKAM) require an eight bit command prompt interface to operate, limiting their use to a Windows XP 32-bit operating system. Model Descriptions are as follows.

ALMANAC simulates daily biomass growth using a light interception model based on maximum intercepted biomass use efficiency (calculated from the Radiation Use Efficiency). Physiological growth stages are smoothed using S-shaped plant population and leaf area development curves, whose shapes are determined by two user input point values. Plant maturity is reached when total heat unit accumulation during the growing season attains the maximum heat unit value input by the user. Maximum leaf area and senescence initiation are also set by user-input fractions of the growing season. ALMANAC utilizes subroutines that inhibit growth when water, nitrogen, or phosphorus stresses occur.

SORKAM is a radiation interception crop growth model that partitions biomass and leaf area based on plant development stage. Development stages are set based on accumulation of heat units throughout the growing season. SORKAM assumes adequate nutrient concentrations for all simulated sorghum plants. SORKAM utilizes subroutines to calculate seed number and seed weight during seven days after growth differentiation and ten days after anthesis. Water stress during the plant development

before growth differentiation and anthesis has limited effect on overall grain yield, while water stresses during seed number determination have a greater effect on yields (Rosenthal et al., 1989).

CropSyst is a daily time step model that utilizes a transpiration-dependent biomass accumulation model except at low Vapor Pressure Deficits, for which biomass accumulation is simulated using a light interception model. Plant leaf area development and biomass accumulation within the model is dependent on plant physiological stage. Each of the physiological growth stages are reached based on the accumulation of thermal heat units during the growing season. CropSyst incorporates subroutines that govern leaf area development and limit biomass accumulation during nitrogen and water stress. CropSyst yields are determined by a Harvest Index (HI – harvested biomass to total above ground biomass) (Stockle and Nelson, 2004).

APSIM is a biomass model that utilizes a radiation interception efficiency to determine daily biomass accumulation. The leaf area development and daily accumulated biomass partitioning rates are dependent on plant growth development stage. Physiological development stages are achieved based on thermal time (degree days). Biomass accumulation is reduced if stresses associated with nitrogen, water, and vapor pressure deficit are present. The sorghum model in APSIM utilized a harvest index method to calculate the yields from the biomass accumulation. In an unstressed environment the harvest index increases throughout the growing seasons until it reaches a maximum (Hammer et al., 2011)

Ceres-Sorghum is a biomass model that utilizes a radiation interception efficiency to determine daily biomass accumulation. The leaf area development and daily accumulated biomass partitioning rates are dependent on plant growth development stage. Physiological development stages are achieved based on accumulation of growing degree days. Biomass accumulation is reduced if stresses associated with nitrogen, water, and vapor pressure deficit are present. Ceres-Sorghum utilizes a mass rate accumulation method for grain development (Hoogenboom et al., 2003; Jones et al., 2003).

After each model was acquired, a prescreening of the model's available documentation was done to determine the implementation time and model run requirements for model run development to ascertain if model run development fell beyond the scope of this study. If it was determined the model required a significant amount of background in programming and/or a modular development, the model was eliminated. If during the prescreening process a model was eliminated, further comparison was not needed, and a generalized description of the input parameters was produced.

Models that passed the prescreening were evaluated by using a process that reviewed each model based on a standard three-step method. Each model had to pass certain criteria in each step in order to move on to the next step. To assist with the review process, a generalized description of necessary model parameters was developed for CropSyst (Table 2.1), CERE-Sorghum (Table 2.2), ALMANAC (2.3), SORKAM (Table 2.4), and APSIM (Table 2.5). The generalized descriptions include crop parameters, weather variables, soil variables, evapotranspiration (ET) equations, and runoff estimation method. The review process had three main steps for comparison: input, output, and output yield comparison (Figure 2.1). The input section of the process was broken into two subsections: weather and crop parameters. A baseline set of available parameters was developed for both weather and the sweet sorghum crop to compare to parameters needed to run each model (Table 2.6). Available weather variables were taken from KSU Research Extension weather data library for Riley County, Kansas (Manhattan) weather station (KSRE, 2011). Soil parameters were not used as a comparison since most parameters were estimated, and no specific soil texture values were known for any sites with crop data.

Required weather variables were compared first to available weather data. Then crop parameters from each model were compared to the available sweet sorghum parameters. During the comparison, if two or more models shared a crop parameter, that variable was not counted toward total model variables needed for the crop model. This was done to magnify the differences and make it easier to define a cutoff value used to allow a model to move through the first step of the selection

process. A ratio of variables not available in literature to total variables needed to run was used to select the models that would pass the input step. If a model required more than fifty percent of crop parameters estimated by using model parameters from grain or forage sorghum (if available), the model was eliminated. Also, if less than two model variables were found in the literature, the model was eliminated.

Table 2.1- Generalized list of parameters for CropSyst after reviewing the model (Stockle et al., 2009) and documentation (Stockle and Nelson, 2009).

CropSyst	
<u>Crop Growth</u>	<u>Uptake</u>
Above Ground Biomass-Transpiration Coefficient	Maximum Uptake During Rapid Linear Growth
Unstressed Light Above Ground Biomass Conversion (RUE)	Residual N Not Available for Uptake
Optimum Mean Daily Temperature for Growth	Soil N Concentration at Which N Uptake Decreases
<u>LAI</u>	Plant Available Water at Which N Uptake Starts Decreasing.
Initial Green Leaf Area Index	<u>Weather</u>
Maximum Expected Leaf Area	Precipitation
Specific Leaf Area at Optimal Temperature	Maximum Temperature
Fraction of Maximum Leaf Area at Physiological Maturity	Minimum temperature
Stem Leaf Partition Coefficients	Solar radiation
<u>Root</u>	Maximum Relative Humidity
Maximum Rooting Depth	Minimum Relative Humidity
Root Length per Unit Root Mass	Maximum Dew Point Temperature
Maximum Surface Root Density at Full Rooting Depth	Minimum Dew Point Temperature
Curvature of Root Density Distribution	Average Dew Point Temperature
<u>Transpiration</u>	Average Wind Speed
Extinction Coefficient	<u>Soil</u>
Evaporation Crop Coefficient at Full Crop Canopy	Thickness
Maximum Water Uptake	Sand %
Leaf Water Potential at Onset of Stomatal Closure	Silt %
Wilting Leaf Potential	Clay%
<u>Phenology (Growing Degree Days)</u>	Permanent Wilting Point
Emergence	Field Capacity
Maximum Rooting Depth	Bulk Density
Begin Flowering	Saturated Hydraulic Conductivity
Begin Filling	Air Entry Potential
Physiological Maturity	Saturation
Adjustment factor for Phenological Response to Stress	Cation Exchange Capacity
<u>Crop Harvest</u>	pH
Unstressed Harvest Index	Albedo
Flowering Stress Sensitivity	Steepness
Grain Filling Stress Sensitivity	Slope Length
<u>Nitrogen Demand</u>	<u>ET¹</u>
Maximum N Concentration of Chaff and Stubble	Penman-Monteith
Standard Root N Concentration	Priestley-Taylor
	<u>Runoff</u>
	SCS Curve Number

1 – ET equation based on Penman-Monteith (Monteith, 1965) and Priestley and Taylor (1972).

Table 2.2- Generalized list of parameters for CERES-Sorghum after reviewing the model and documentation (Jones et al, 2003, Hoogenboom et al, 2003).

CERES-Sorghum	
Species Coefficients	Weather
	Rain
	Relative Humidity
	Solar Radiation
	Dew Point Temperature
	Maximum Temperature
	Minimum Temperature
FSLFW	Daily Fraction of Leaf Area Senesced Under 100% Water Stress
FSLFN	Daily Fraction of Leaf Area Senesced Under 100 % Nitrogen Stress
SDSZ	Maximum Potential Seed Size
RSGR	Relative Seed Growth Rate Below Which Plants May Mature Early Due to Water or Nitrogen Stress or Cool Temperature
RSGRT	Number of Consecutive Days Relative Seed Growth Rate is Below RSGR Before Early Maturity Occurs
DSGT	Maximum Days From Sowing to Germination Before Seed Dies
DGET	Growing Degree Days Between Germination and Emergence After Which Seed Dies Due to Drought
SWCG	Minimum Available Water for Seed Germination
STMWTE	Stem Weight at Emergence
RTWTE	Root Weight at Emergence
LFWTE	Leaf Weight at Emergence
SEEDRVE	Carbohydrate Reserve in Seed at Emergence
LEAFNOE	Leaf Number at Emergence
TMNCE	Plant Top Minimum Nitrogen
TANCE	Nitrogen in Above Ground Biomass at Emergence
RCNP	Root Critical Nitrogen Concentration
RANCE	Root N Content at Emergence
PORM	Minimum Volume Require for Supplying Oxygen to Roots for Optimal Growth
RWMX	Maximum Root Water Uptake Per Unit Length of Root
RLWR	Root Length to Weight Ratio
RWUEP1	Threshold Soil Water Content for Reducing Leaf Expansion
Ecotype File	Soil
Tbase	Base Temperature Below Which No Development Occurs
Topt	Temperature at Which Maximum Development Rate Occurs During Vegetative Growth Stages
ROPT	Temperature at Which Maximum Development Rate Occurs for Reproductive Development Stages
DJTI	Minimum Days From End of Juvenile Stage to Panicle Initiation if The Cultivar is Not Photoperiod Sensitive
GDDE	Growing Degree Days Per Centimeter Depth Required for Emergence
DSGFT	GDD From Flowering to Effective Grain Filling Period
RUE	Radiation Use Efficiency
KCAN	Extinction Coefficient
	Slope
	Drainage
	Runoff Potential
	Depth
	Clay Percent
	Silt Percent
	Organic Carbon Percent
	pH
	Cation Exchange Capacity
	Total Nitrogen
	Phosphorus Isotherm I
	Phosphorus Isotherm II
	Calcium Carbonate Content
	Potassium Exchangeable
	Nitrate Absorption Factor
	Lower Limit (Wilting Point)
	Drained Upper Limit
	Saturation
	Bulk Density
	Saturated Hydraulic Conductivity
	Root Growth Factors
	ET¹
	Penman-Montieth
	Penman FAO
	Priestley-Taylor
	Runoff Estimation Method
	SCS Curve Number

1 – ET equations from Montieth (1985), Doorenbos and Pruitt, (1977), and Priestley and Taylor (1972).

Table 2.3 - Generalized list of parameters for ALMANAC after reviewing the model and documentation (USDA-ARS, 2010).

ALMANAC	
Plant Growth Parameters	
WA	Biomass Energy Ratio (calculated from RUE)
HI	Harvest Index
TB	Optimal Temperature for Plant Growth
TG	Minimum Temperature for Plant Growth
DMLA	Maximum Potential Leaf Area Index
DLAI	Fraction of the Growing Season when Leaf Area Starts to Decline
DLAP 1	Leaf Area Development Curve First Point
DLAP 2	Leaf Area Development Curve Second Point
RLAD	Leaf Area Decline Rate Parameter
RBMD	Biomass-Energy Decline Rate Parameter
CAF	Critical Aeration Factor
HMX	Maximum Crop Height
RDMX	Maximum Rooting Depth
CNY	Fraction of Nitrogen in Yield
CNP	Fraction of Phosphorus in Yield
BN1	N fraction of Plant at Emergence
BN2	N fraction of Plant at 0.5 Maturity
BN3	N fraction of Plant at Maturity
BP1	P fraction of Plant at Emergence
BP2	P fraction of Plant at 0.5 Maturity
BP3	P fraction of Plant at Maturity
EXTINC	Extinction Coefficient
Weather	
Solar Radiation	
Precipitation	
Maximum Temperature	
Minimum Temperature	
Average Relative Humidity	
Average Wind Speed	
Soil	
Depth from the Surface to the Bottom of the Soil Layer	
Bulk Density of the Soil Layer	
Field Capacity	
Wilting Point	
Sand Content	
Silt Content	
Organic Content	
Soil pH	
Sum of Bases	
Calcium Carbonate	
Cation Exchange Capacity	
Coarse Fragments	
Nitrate Concentration	
Organic N Concentration	
Labile P Concentration	
ET¹	
Penman-Montieth	
Penman	
Priestley-Taylor	
Hargreaves and Samani	
Baier-Robertson	
Runoff Estimation	
SCS Curve Number	

1 – Kiniry (2012, personal communication) provided the references for the ET equations: Montieth (1977), Penman (1948), Priestley and Taylor (1972), Hargreaves and Samani (1985), Baier and Robertson (1965).

Table 2.4 - Generalized list of parameters for SORKAM after reviewing the model and documentation (Rosenthal et al, 1989).

SORKAM	
Plant Parameters	Soil Information
Leaf Number (Not Easily Editable)	Soil Type
Tiller Coefficients	Depth
Slope	Soil Albedo
Intercept	Field Slope
Seed Number Coefficients	Soil Water Evaporation Coefficients
Slope	- Stage 1
Seed Weight Coefficients	- Stage 2
Intercept	Thickness
Slope	Fraction Available Water
Duration of Grain Fill	Initial Fraction Available
Weather	Bulk Density
Rainfall	ET¹
Maximum Temperature	Priestley-Taylor
Minimum Temperature	Modified Penman
Maximum Relative Humidity	Runoff
Minimum Relative Humidity	SCS Curve Number
Irradiance (Solar Radiation)	
Average Wind Speed	
Average Vapor Pressure	

1 – ET equations used in the model were Priestley and Taylor (1972), and Doorenbos and Pruitt (1977).

Table 2.5 - Generalized list of parameters for APSIM after reviewing the model and documentation (APSIM, 2011).

APSIM	
Crop Factors	Soil
Radiation Use Efficiency	Soil Saturated Flow
Biomass Partitioning (Root, Shoot, Leaves, and Grain)	Bulk Density
Germination to Emergence	Air Dry Water Content
Emergence to End of Juvenile Stage	Lower Limit Water Content
End of Juvenile Stage to Floral Initiation	Drained Upper Limit
Floral Initiation to Appearance of Flag Leaf	Saturation Water Content
Appearance of Flag Leaf to Start of Grain Filling	Plant Lower Limit Water Content
Start of Grain Filling to End of Grain Filling	Plant KL
End of Grain Filling to Physiological Maturity	Organic Content
Physiological Maturity to Harvest Ripening.	- Fraction Biomass
Maximum LAI	- Fraction Inert
Maximum Tillering Rate	Rocks
Root Extension Parameters	Electrical Conductivity
Crop Lower Limit for Water Extraction (Each Soil Layer)	pH
Grain Filling Parameters	Chlorine Concentration
Nitrogen target concentration	Boron Concentration
Root	Cation Exchange Capacity
Flower	Calcium Concentration
Stem Nitrogen target	Manganese Concentration
Emergence	Aluminum Concentration
Flowering	Sand
Grain Fill Demand	Silt
Biomass growing degree days	Clay
Germination to Emergence	Nitrate Concentration
Emergence to End of Juvenile Stage	Ammonium Concentration
End of Juvenile Stage to Floral Initiation	ET
Floral Initiation to Appearance of Flag Leaf	Priestley-Taylor (1972)
Appearance of Flag Leaf to Start of Grain Filling	Runoff
Start of Grain Filling to End of Grain Filling	SCS Curve Number
End of Grain Filling to Physiological Maturity	
Physiological Maturity to Harvest Ripening.	
Leaf Area Development Parameters	
Leaf Appearance Rate for Different Phenological Stages	

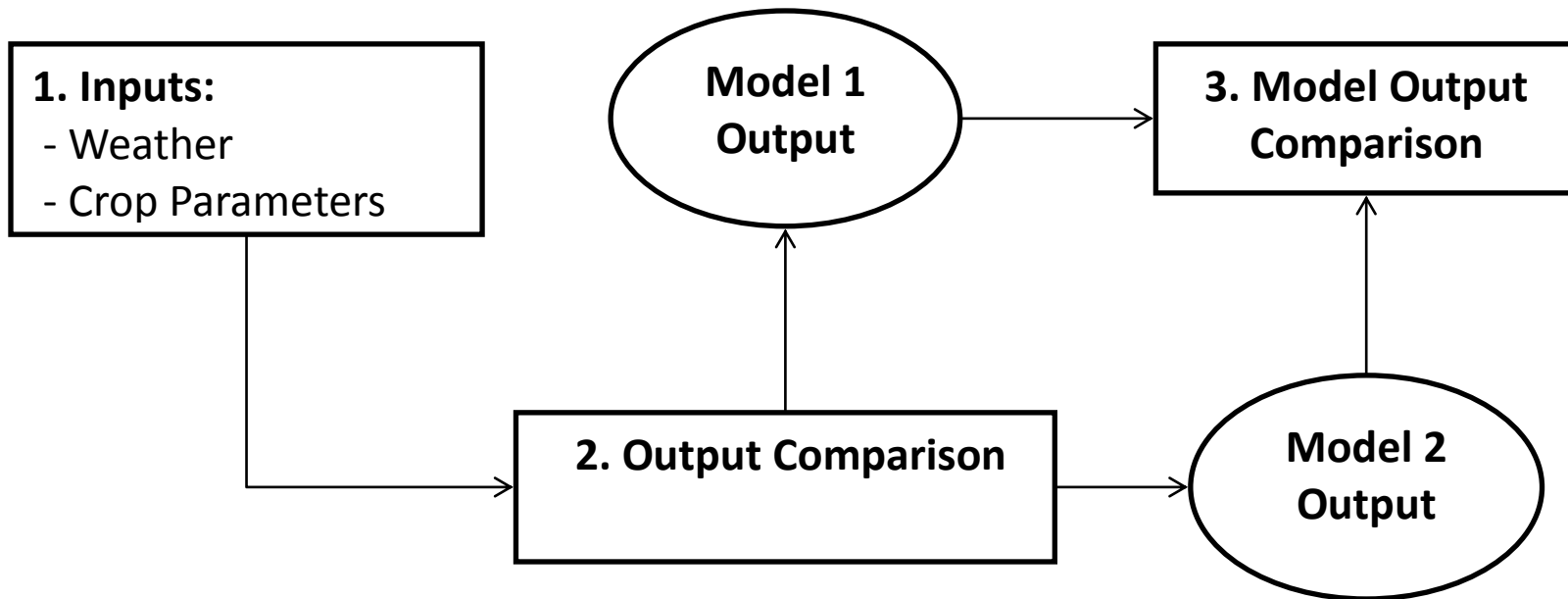


Figure 2.1 –Flow chart of the comparison process, which occurs in stages beginning with input comparisons, followed by output comparisons, and finishing with the Model output statistical comparisons.

Table 2.6 – Available variables for sweet sorghum crop parameter development. Including the units for the weather variables and the literature which values for sweet sorghum crop parameters are found.

Weather Variables	Units
Solar Radiation	(MJ m ⁻¹)
Total Precipitation	(mm)
Minimum Air Temperature	(°C)
Maximum Air Temperature	(°C)
Average Wind Speed	(m s ⁻¹)
Average Relative Humidity	(%)
Maximum Relative Humidity	(%)
Minimum Relative Humidity	(%)
Maximum Wind Speed	(m s ⁻¹)
Sweet Sorghum Parameters (Inputs)	Literature
Radiation Use Efficiency	(Mastrorilli, 1999; Mastrorilli, 1994; Dercas and Liakatas, 2006; Curt et al., 1998)
Water Use Efficiency	(Mastrorilli, 1999; Mastrorilli, 1994; Dercas and Liakatas, 2006; Steduto et al., 1997)
Maximum Plant Height	(Ferraris, 1981; Propheter, 2009)
N/P Concentration at Harvest	(Han et al., 2010; Propheter, 2009)
N/P Concentration at Anthesis	(Han et al., 2010)
Maximum Leaf Area Index	(Ferraris, 1981)
Extinction Coefficient	(Curt et al., 1998)
Days to	
Emergence	(Ferraris and Edwards, 1986)
Three Leaf	(Ferraris and Edwards, 1986)
Panicle Initiation	(Ferraris and Edwards, 1986)
Anthesis	(Ferraris and Edwards, 1986)
Milk Dough	(Ferraris, 1981)
Maturity	(Ferraris and Edwards, 1986)
Potential at Onset of Stomatal Closure	(Mastrorilli, 1999; Steduto et al., 1997)
Leaf Area Index Development	(Ferraris and Edwards, 1986; Dercas and Liakatas, 2006)
Carbon Partitioning	(Fernandez et al., 2003)
Sweet Sorghum Parameters (Outputs)	
Biomass Yield	(Propheter, 2009; Corn, 2009; Bellmer and Huhnke, 2007; Bellmer and Huhnke, 2008)
Grain Yield (Riley county, Kansas only)	(Propheter, 2009)
Juice Content	(Propheter, 2009; Corn, 2009; Bellmer and Huhnke, 2007; Bellmer and Huhnke, 2008)
Brix Value	(Propheter, 2009; Corn, 2009; Bellmer and Huhnke, 2007; Bellmer and Huhnke, 2008)

1 – Available weather variables were taken from the Manhattan weather station in Riley County, Kansas located on the Kansas State University North Agronomy Farm (KSRE, 2010).

The models that passed input comparison moved onto output review. The available output comparisons for sweet sorghum are listed in Table 2.6. If greater than three outputs related to biomass and grain yield were not available in literature and or available collected data, the model was eliminated. If more than one model passed the output review step, those models proceeded to the output yield comparison step.

The models that passed the output comparison step were used to estimate grain sorghum and corn yields, in Mg ha^{-1} , for a ten year period from yield data available from the KSU North Agronomy Farm located in Riley County and KSU experimental fields located in Ellis County. Each model used the same standardized crop rotation for the comparison; the results from each model were analyzed with two statistical methods: Pearson's Correlation Coefficient-squared (R^2) and a concordance correlation coefficient (P_c) (Lin, 1989). The model with the best overall statistical values was chosen as the best fit model.

Results

As a result of the prescreening process, the APSIM model was eliminated. CropSyst, CERES-Sorghum, SORKAM, and ALMANAC passed the prescreening process and moved into the step-through comparison process. The only model that passed input comparisons was ALMANAC, which had a calculated ratio of 0.21 (Table 2.7) of variables not available in literature over total variables needed for crop modeling. SORKAM and CERES-Sorghum both had a ratio of 1.0 (Table 2.8 and 2.9). CropSyst had a ratio of 0.67 (Table 2.10). Since ALMANAC was the only model to pass the input selection process, no further comparison was necessary, and ALMANAC was chosen as the best model for the task of development and testing of the sweet sorghum crop parameters.

Table 2.7 - Comparison of available literature values and variables needed for crop modeling parameters. Column A is the parameters needed to run the model with all sweet sorghum parameters, Column B is the available in literature. Zero values in column A are duplicate values shared by one or more models. Zero values in column B are either values shared by one or more models or values found in literature.

ALMANAC			
A	B	Plant Growth Parameters	
0	0	WA	Biomass Energy Ratio (Calculated from RUE)
0	0	HI	Harvest Index
0	0	TB	Optimal Temperature for Plant Growth
0	0	TG	Minimum Temperature for Plant Growth
0	0	DMLA	Maximum Potential Leaf Area Index
1	0	DLAI	Fraction of the Growing Season When Leaf Area Starts to Decline
1	0	DLAP 1	Leaf Area Development Curve First Point
1	0	DLAP 2	Leaf Area Development Curve Second Point
1	0	RLAD	Leaf Area Decline Rate Parameter
1	1	RBMD	Biomass-Energy Decline Rate Parameter
1	1	CAF	Critical Aeration Factor
1	0	HMX	Maximum Crop Height
0	0	RDMX	Maximum Rooting Depth
1	0	CNY	Fraction of Nitrogen in Yield
1	0	CNP	Fraction of Phosphorus in Yield
0	0	BN1	N Fraction of Plant at Emergence
1	0	BN2	N Fraction of Plant at 0.5 Maturity
1	0	BN3	N Fraction of Plant at Maturity
1	1	BP1	P Fraction of Plant at Emergence
1	0	BP2	P Fraction of Plant at 0.5 Maturity
1	0	BP3	P Fraction of Plant at Maturity
0	0	EXTINC	Extinction Coefficient
14	3		
	0.21	Ratio of Values Not Available in Literature to Total Variables needed ¹	

¹ – Ratio is B/A. Each ratio excluded common variables from 2 or more models. (i.e., RUE, etc.)

Table 2.8 - Comparison of available literature values and variables needed for crop modeling. Column A is the parameters needed to run the model with all sweet sorghum parameters, Column B is the available in literature. Zero values in column A are duplicate values shared by one or more models. Zero values in column B are either values shared by one or more models or values found in literature.

SORKAM		
A	B	Plant Parameters
1	1	Leaf Number (Not Easily Editable)
		<i>Tiller Coefficients</i>
1	1	Slope
1	1	Intercept
		<i>Seed Number Coefficients</i>
1	1	Slope
		<i>Seed Weight Coefficients</i>
1	1	Intercept
1	1	Slope
1	1	Duration of Grain Fill
7	7	
	1.0	Ratio of Values Not Available in Literature to Total Variables needed ¹

1 – Ratio is B/A. Each ratio excluded common variables from 2 or more models. (i.e., RUE, etc.)

Table 2.9 - Comparison of available literature values and variables needed for crop modeling. Column A is the parameters needed to run the model with all sweet sorghum parameters, Column B is the available in literature. Zero values in column A are duplicate values shared by one or more models. Zero values in column B are either values shared by one or more models or values found in literature.

CERES-Sorghum					
A	B	Species Coefficients			
			1	1	Carbohydrate Reserve in Seed at Emergence
0	0	Emergence	1	1	Leaf Number at Emergence
0	0	End of Juvenile	1	1	Plant Top Minimum Nitrogen
0	0	Floral Induction	0	0	Nitrogen in Above Ground Biomass at Emergence
0	0	75% Flowering	1	1	Root Critical Nitrogen Concentration
0	0	Maturity	1	1	Root N Content at Emergence
0	0	Harvest	1	1	Minimum Volume Required for Supplying Oxygen to Roots for Optimal Growth
1	1	Daily Fraction of Leaf Area Senesced Under 100% Water Stress	1	1	Maximum Root Water Uptake Per Unit Length of Root
1	1	Daily Fraction of Leaf Area Senesced Under 100% Nitrogen Stress	1	1	Root Length to Weight Ratio
1	1	Maximum Potential Seed Size	1	1	Threshold Soil Water Content for Reducing Leaf Expansion
1	1	Relative Seed Growth Rate Below Which Plants May Mature Early Due to Water or Nitrogen Stress or Cool Temperature	0	0	Base Temperature Below Which No Development Occurs
1	1	Number of consecutive days relative seed Growth Rate Below RSGR Before Early Maturity Occurs	0	0	Temperature at Which Maximum Development Rate Occurs During Vegetative Growth Stages
1	1	Maximum Days From Sowing to Germination Before Seed Dies	1	1	Temperature at Which Maximum Development Rate Occurs for Development Stages
1	1	Growing Degree Days Between Germination and Emergence After Which Seed Dies Due to Drought	0	0	Minimum Days from End of Juvenile Stage to Panicle Initiation if the Cultivar is Not Photoperiod Sensitive
1	1	Minimum Available Water for Seed Germination	1	1	Growing Degree Days Per Centimeter Depth Required for Emergence
1	1	Stem Weight at Emergence	0	0	GDD from Flowering to Effective Grain Filling Period
1	1	Root Weight at Emergence	0	0	Radiation Use Efficiency, g Plant Dry Matter/MJ PAR
1	1	Leaf Weight at Emergence	0	0	Canopy Light Extinction Coefficient
1	1		23	23	
1	1			1	Ratio of Values Not Available in Literature to Total Variables needed

1 – Ratio is B/A. Each ratio excluded common variables from 2 or more models. (i.e., RUE, etc.)

Table 2.10 – Comparison of available literature values and variables needed for crop modeling. Column A is the parameters needed to run the model with all sweet sorghum parameters, Column B is the available in literature. Zero values in column A are duplicate values shared by one or more models. Zero values in column B are either values shared by one or more models or values found in literature.

CropSyst				Phenology (Growing Degree Days)	
A	B	A	B	A	B
1	1	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
1	1	0	0	0	0
0	0	1	1	0	0
1	1	0	0	0	0
1	0	0	0	0	0
1	0	1	1	0	0
0	0	0	0	0	0
0	0	1	0	0	0
0	0	1	1	0	0
0	0	1	1	0	0
1	0	1	1	0	0
1	1	1	1	0	0
1	1	1	1	0	0
1	0	1	1	0	0
1	0	18	12	0	0
1	0	0.67	0.67	0	0

1 – Ratio is B/A. Each ratio excluded common variables from 2 or more models. (i.e., RUE, optimal temperature, etc.)

Discussion

The prescreening process eliminated the APSIM model since it required a modular XML format, along with an understanding of in C++, .NET, or FORTRAN programming languages, setting it outside the scope of this project. The remaining model comparison results were straight forward, partly because shared factors among the models were not used to calculate the ratios. Since all the input weather variables for most of models required similar, if not exactly the same, weather variables, the climate variables were not used to calculate the final ratios. Determining similar variables was difficult since most of the models did not word the variables in the same way. An example: the Biomass Energy Ratio (WA) for the ALMANAC model is determined from the Radiation Use Efficiency (RUE) given in literature, and the units for WA factor are ($\text{Mg ha}^{-1} \text{ MJ}^{-1}$); the units for RUE are ($\text{g m}^{-2} \text{ MJ}^{-1}$), which made a conversion necessary in order to create the WA value, which is essentially the RUE value.

Though the results focus specifically on somewhat minute differences between the models, it does appear to be fair in the selection, by making differences more apparent and allowing the reviewer to determine what areas of research would improve the suitability of each individual model. The results indicate that with more detailed understanding of sweet sorghum physiology, CropSyst would qualify with this method for sweet sorghum modeling development. It may be important to point out that three of the five models used in this review had functions that focused specifically on development of grain coupled with biomass production, which is why some of them did not pass the initial input step.

The later portion of this study was focused specifically on biomass development and not on seed development, for which data is limited for sweet sorghum. HSR (2008) listed the crop models in order of suitability: CERES-Sorghum, SORKAM, ALMANAC, CropSyst, and APSIM. As a result of this study for sweet sorghum modeling, the models were in this order: ALMANAC, CropSyst, CERES-Sorghum, SORKAM, and APSIM, with SORKAM and CERES-Sorghum models tied with a ratio of 1.0 (Table 2.8 and

2.9). The CropSyst ratio was 0.67 (Table 2.10) which was four variables away from reaching the 0.50 ratio cut-off.

Using borrowed values from another crop, such as grain sorghum, was deemed not appropriate since there are distinct differences in physiology that give sweet sorghum certain advantages, including but not limited to high biomass accumulation (Han et al., 2010; Propheter, 2009; Curt et al., 1998), high RUE (Mastrorilli et al., 1999; Mastrorilli et al., 1994; Dercas and Liakatas, 2006; Curt et al., 1998), high Water Use Efficiency (WUE) (Mastrorilli et al., 1999; Mastrorilli et al., 1994; Dercas and Liakatas, 2006; Steduto et al., 1997), and lower nitrogen requirement (Smith and Buxton, 1993). Therefore, a better understanding of sweet sorghum physiology is needed to make the other models in the review able to meet the criteria needed to be suited to model sweet sorghum under this screening process. The research needs to focus mainly on what stresses affect biomass accumulation/grain fill and how the sweet sorghum uptakes and partitions plant nitrogen and phosphorus throughout the development of the plant.

Appendix A

ALMANAC - <http://www.ars.usda.gov/Main/docs.htm?docid=16601>

APSIM - <http://www.apsim.info/ProductRegistration/Registration.aspx>

CropSyst - http://www.bsyse.wsu.edu/cs_suite/CropSyst/index.html

CERES-Sorghum - <http://dssat.net/>

SORKAM – Not Available Online

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Chapter 3- Sweet Sorghum Parameter Development

Introduction

High fuel prices in recent years have increased the need for alternative fuels (i.e., ethanol and biodiesel) to reduce the dependence on foreign oil supplies (Shapouri et al., 2006). Currently in the United States, ethanol production is dominated by first-generation (conventional) biofuels, specifically corn-based ethanol. In 1995, corn ethanol made up 97% of the 3.9 billion gallons of ethanol produced for fuel in the United States (Shapouri et al., 2006) with one bushel of corn producing between 2.60 to 2.75 gallons of ethanol (Dhuyvetter et al., 2005). The current dominant alternative biofuel feedstock, corn, has both environmental and sociological problems associated with its increased production and use as a biofuel (Simpson et al., 2008; Shapouri et al., 2006; Rendleman and Shapouri, 2007). These concerns, along with requirements imposed by the Energy Independence and Security Act (EISA), which requires the production of 36 billion gallons of renewable fuel by 2022 (EPA, 2008), show a growing need for the development and implementation of alternatives to corn grain ethanol. Crop models can be an effective tool for screening regionally appropriate biofuel feedstocks and evaluating their agro-ecological and socio-economic impacts. Sweet sorghum (*Sorghum bicolor (L.) Moench*), with its low management and input requirements, is one crop with biofuel feedstock potential in the Midwest.

Sweet sorghum has potential as an alternative/supplement biofuel feedstock to corn since it has a high biomass accumulation (Propheter, 2009: 32.2 Mg ha⁻¹; Mastrorilli et al., 1995: 32 Mg ha⁻¹), radiation use efficiency (RUE) (Curt et al., 1998: 4.96 g MJ⁻¹; Dercas and Liakatas, 2006: 3.55 g MJ; Mastrorilli et al., 1995: 3.71 g MJ⁻¹), and water use efficiency (WUE) (Dercas and Liakatas, 2006; Mastrorilli et al., 1999; Steduto et al., 1997) along with a low nitrogen requirement (Smith and Buxton, 1993).

Though all of these factors are impressive, a study by Morris (2009) concluded sweet sorghum alone might not be economically viable to support a stand-alone ethanol production facility in Texas, or

at higher latitudes, due to the limited growing season and difficulty in storage and logistics, but that it could serve to supplement other crops in the production of ethanol during the year. Bele (2007) concluded that in Oklahoma, with the development of effective harvesting machinery, on-farm production of ethanol using sweet sorghum could be economically viable and recommended further large scale field trials or modeling of sweet sorghum biomass to improve feasibility studies. These studies were based on assumptions of available feedstock or utilized statistical methods to determine available feedstock for the economic aspects of the studies, and no specific modeling parameters or real-time yield results were discussed in detail or found in companion publications. In addition to these studies, modeling can be employed to examine in more detail costs associated with sweet sorghum production as a biomass feedstock, allowing the feasibility to be determined with lower monetary input.

Only a few studies have addressed modeling of sweet sorghum biomass. Shih et al. (1986) developed a model that related overall moist biomass based on fractions of leaf area and leaf dry mass accumulation; no further literature was found to follow up on this study. Ferraris and Vanderlip (1986) compared SorgF and Sorg5, which were used to model sweet sorghum biomass accumulation, and concluded that more detail of the sweet sorghum physiology and growth stages would make the model more accurate in modeling sweet sorghum biomass; no further studies were found to follow up the research done with SorgF and Sorg5. In 2006, the Biosystems and Agricultural Engineering (BAE) Department at Oklahoma State University (OSU) utilized crop growth factors from corn, sorghum hay, and sugar cane to model sweet sorghum biomass potentials across a variety of climate regions using the Soil Water Assessment Tool (SWAT) (BAE-OSU, 2006). Limited biomass data prevented validation of the parameters and any formal conclusions from being made. Morris (2009) used a multi-variate empirical (MVE) probability distribution to estimate average yields for sweet sorghum in four counties in Texas. With the exception of the BAE-OSU publication in 2006, which used a combination of crop parameters

from corn, sorghum hay, and sugar cane, no parameter sets that are model specific have been developed specifically for sweet sorghum.

A need for model parameter development for sweet sorghum is apparent in the non-existence of specific crop parameters. Morris (2009) and Bele (2007) expressed how vital accurate sweet sorghum yield data are in order to substantiate the conclusions in their feasibility studies; Bele (2007) also suggested that accurate sweet sorghum yields were needed for better feasibility analysis. Therefore having viable sweet sorghum crop parameters to use for modeling would allow for reliable economic feasibility studies to be done in areas where real-world yield data are absent. The availability of a variety of crop models opens up opportunities for sweet sorghum model parameter development from either research or literature review. Developing a set of model parameters would enable researchers to better understand the dynamics of sweet sorghum in a variety of environments, and yield results from modeling with sweet sorghum crop parameters can show the impact of different management factors along with the climate and soil conditions on biomass accumulation, which will help determine the overall feasibility of sweet sorghum as a biofuel crop. Results from crop modeling would help with more accurate estimations of sweet sorghum biomass and management on both state and local scales, improving economic analyses. Along with biomass estimates improving accuracy in economic viability, an energy analysis from the production of sweet sorghum could be compared to other crops, and further validate or discount the potential of the sweet sorghum crop as a supplemental feedstock through an environmental impact analysis.

The objective of this study was to develop sweet sorghum crop parameters from literature, and to use a crop model to calibrate and validate model results for a variety of geo-climatic regions across three states. From a previous analysis (Chapter 2), ALMANAC was chosen as the model best suited for this task. ALMANAC will be used to develop the parameter set, and the parameters will be calibrated

and validated with sweet sorghum data available from select geographic locations in Texas, Oklahoma, and Kansas.

Materials and Methods

This study used data from five counties (Hale County, Texas; Texas and Caddo Counties, Oklahoma; and Riley and Ellis Counties, Kansas) to develop and test crop parameters for the ALMANAC model (Figure 3.1). Four counties (Riley, Texas, Caddo, and Hale; Figure 3.1) had sweet sorghum data available to help calibrate and validate the sweet sorghum model parameters. Riley County was used to develop/calibrate the sweet sorghum parameters, while Texas, Caddo, and Hale Counties were used to validate the parameters. The corn and grain sorghum grain data from Riley and Ellis Counties in Kansas were used to select the most appropriate combination of soil water (SW) and evapotranspiration (ET) equations. The selection was further affirmed using corn (grain and silage) and grain sorghum (grain) yield data from Texas County, Oklahoma.

Site Data Input Preparation

The five locations were chosen for this study because of the quality of the available data and proximity to marginal cropping areas, which might show potential for future expanded sweet sorghum production. Though Ellis did not have sweet sorghum crop data, it was used because of the available corn and grain sorghum grain yield data, which was useful in determining the SW and ET equations used in the development of the sweet sorghum parameters. To determine the baseline conditions for SW and which ET equation would be best suited for the development of the sweet sorghum parameters, 10 years (1999-2008) of corn and grain sorghum grain yield data from Ellis and Riley County Kansas were used (Table 3.1). Of the sites with corn and grain sorghum grain data, Riley County was the only one with readily accessible detailed records of tillage and fertilizer application data (specifically tillage and fertilizer application dates). Management scenarios for Riley County were developed from these tillage

and fertilizer records. In Ellis County, management scenarios were developed by utilizing planting dates, plant population rates, fertilizer amounts and previous crops found in crop performance reports for corn and grain sorghum (KSU-AESCES, 1999-2008a; KSU-AESCES, 1999-2008b). Since Ellis County did not have tillage practices nor dates of fertilizer application readily available, tillage practices were assumed to be in no-till management for the 10 years used in this study. Any other crop data collection sites with no available tillage information were assumed to use no-till management.

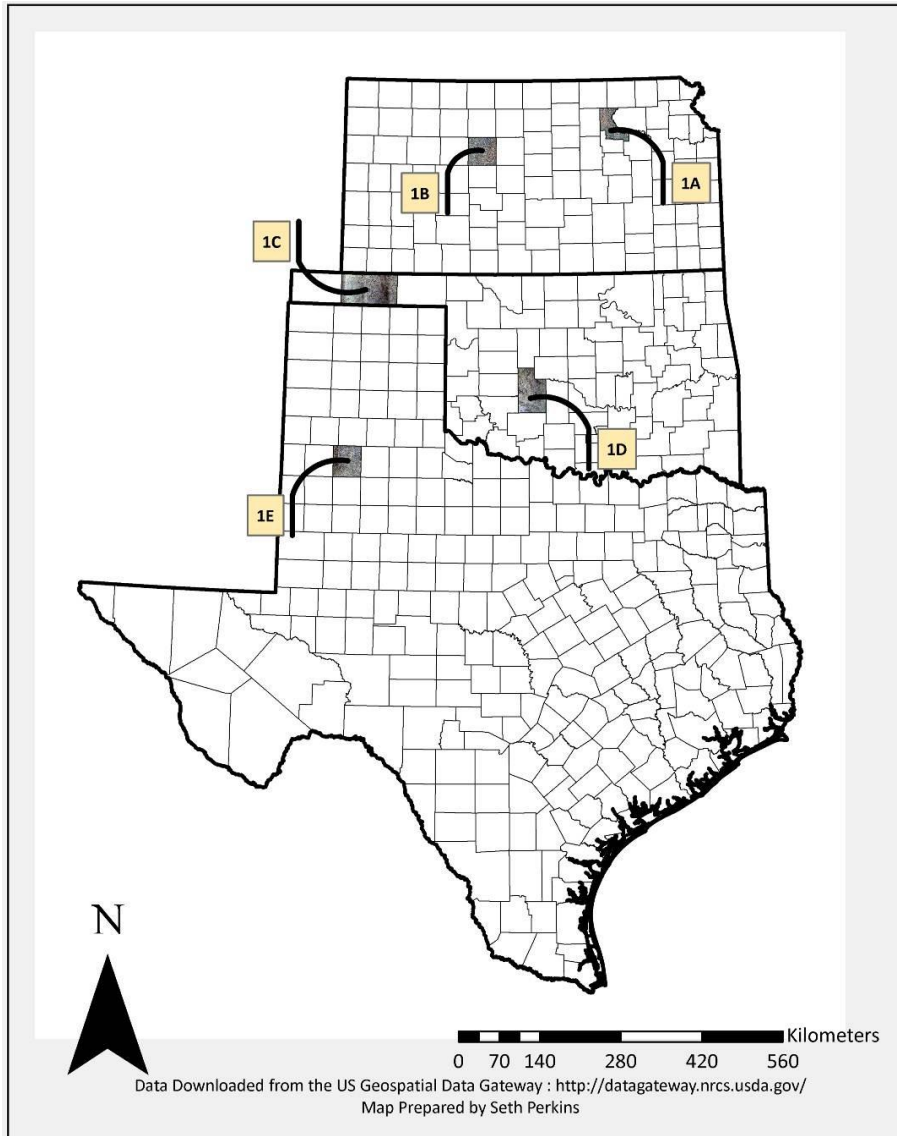


Figure 3.1 – The states and counties used in the crop parameter development. 1A – Riley County, 1B – Ellis County, 1C – Texas County, 1D – Caddo County, 1E – Hale County. 1A, 1B, and 1C had corn and grain sorghum grain yield data available to help with the soil water and ET determination. 1A, 1C, 1D, and 1E had sweet sorghum biomass data available for development, calibration and validation.

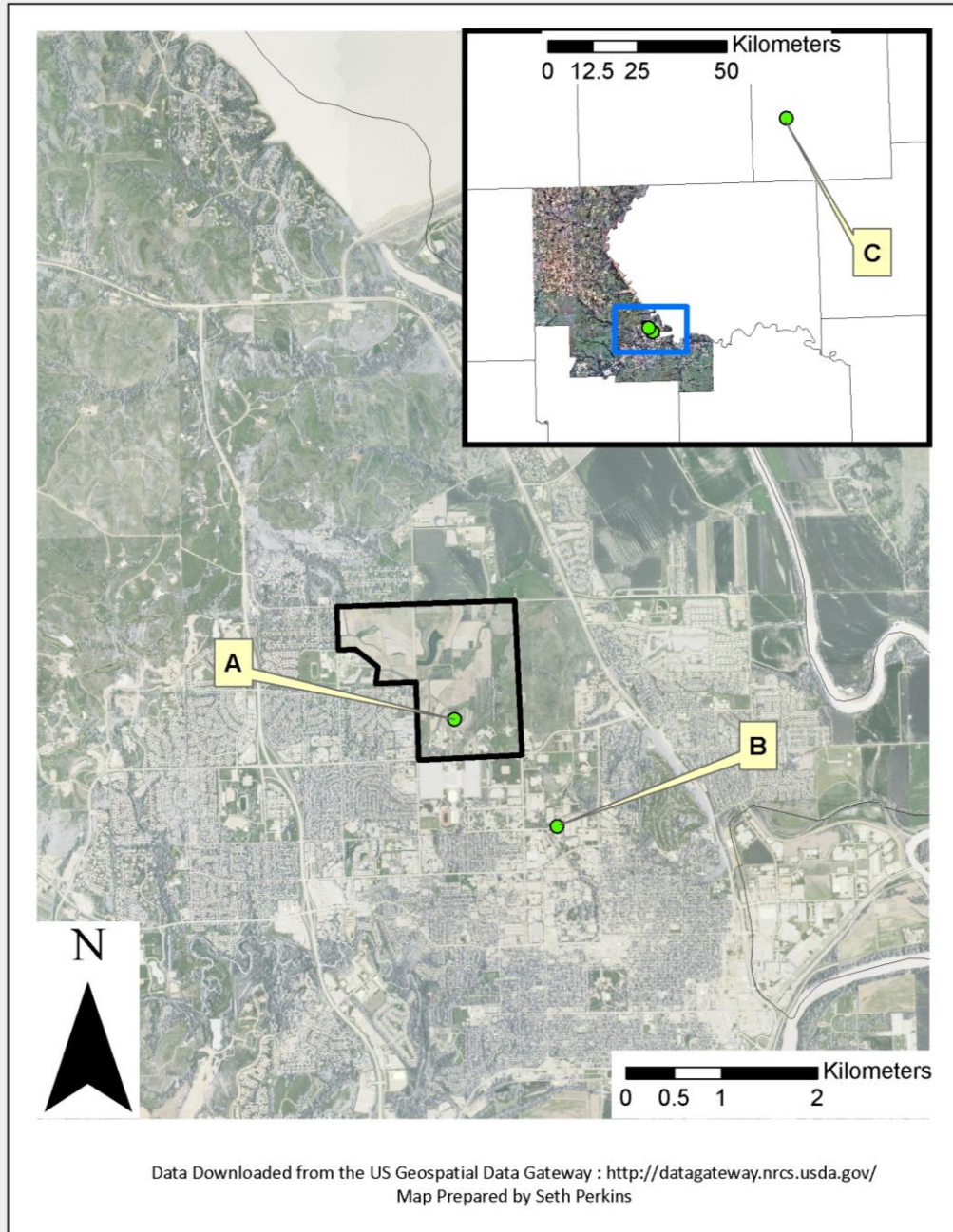


Figure 3.1A – The location of the Riley County, Kansas field research site is boxed in. No specific locations were given on where within the site the corn and grain sorghum crops were grown. Weather stations are as follows A: Manhattan Agronomy Farm, B: Manhattan (COOP ID 144972), C: Centralia (WID 17327)

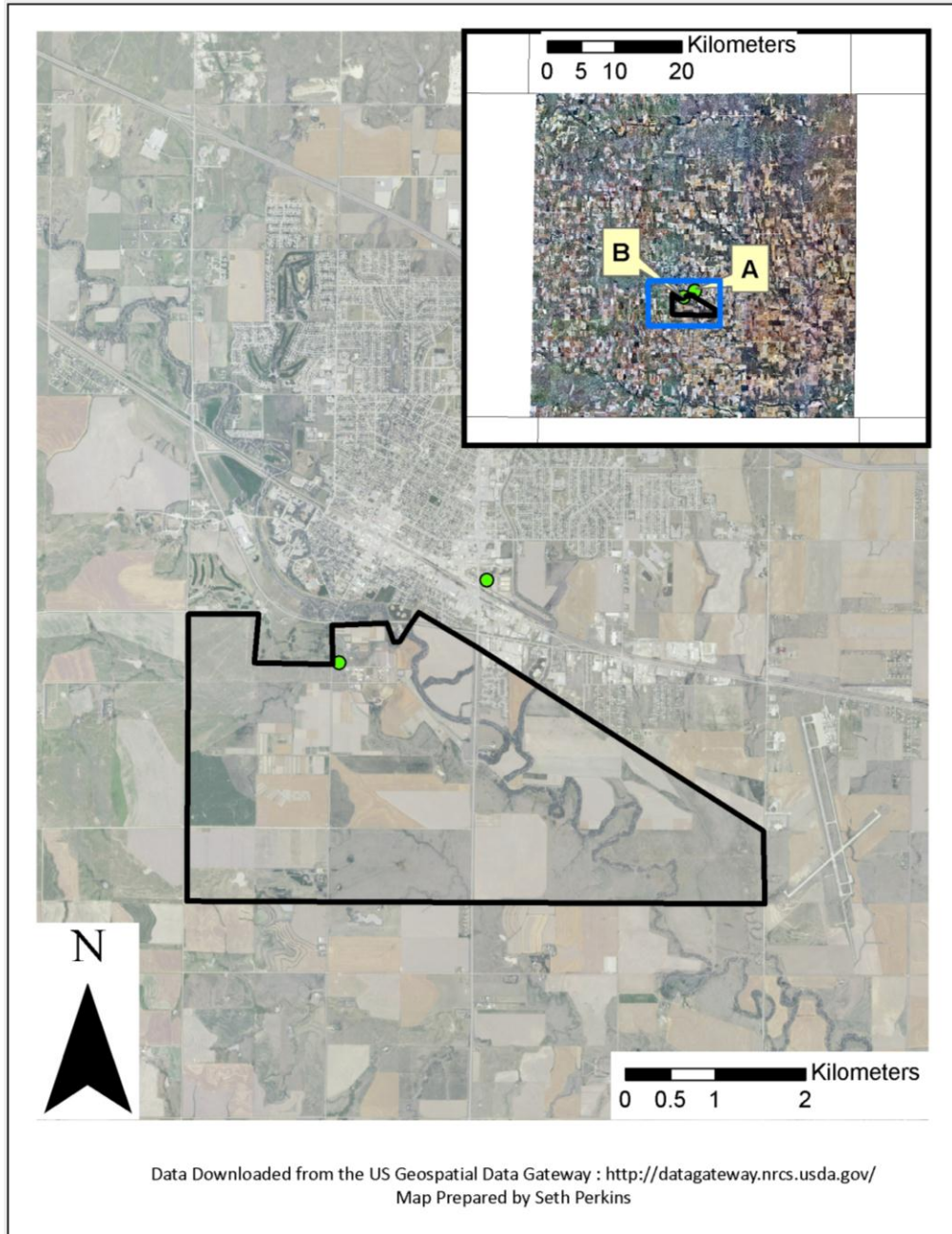


Figure 3.1B – The location of the Ellis County, Kansas field research site is boxed in. No specific locations were given on where within the site the corn and grain sorghum crops were grown. Weather stations are as follows A: Hays, B: Hays 1S (COOP ID 143527; WID 17333).

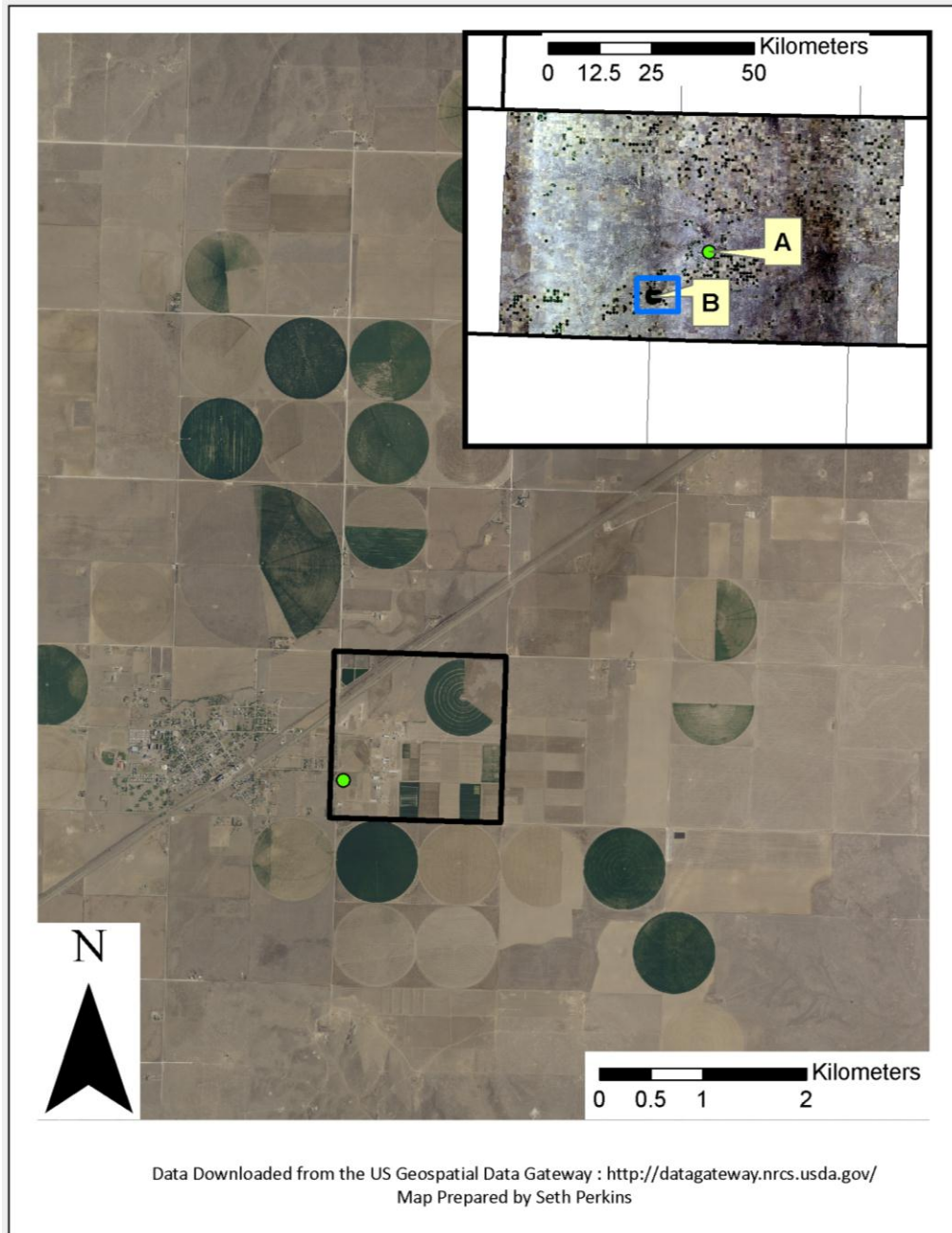


Figure 3.1C – The location of the Texas County, Oklahoma field research site is boxed in. No specific locations were given on where within the site the corn and grain sorghum crops were grown. The weather stations are as follows A: Guymon (COOP ID 343835), B: GOODWELL

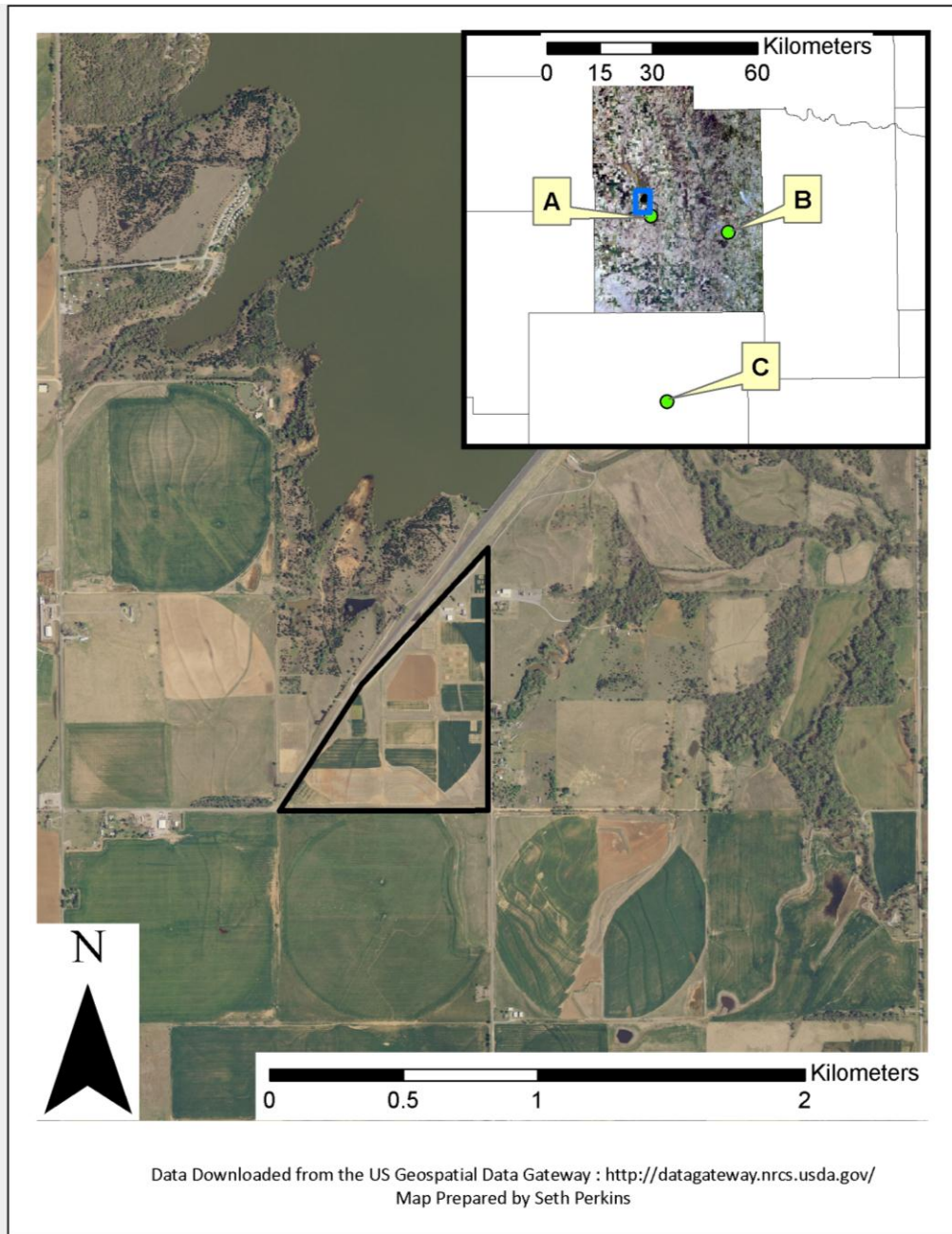


Figure 3.1D – The location of the Caddo County, Oklahoma field research site is boxed in. No specific locations were given on where within the site the corn and grain sorghum crops were grown. Weather stations are as follows A: FT. COBB, B: Andarko (COOP ID 340224), C: LAWTON (WID 17747)

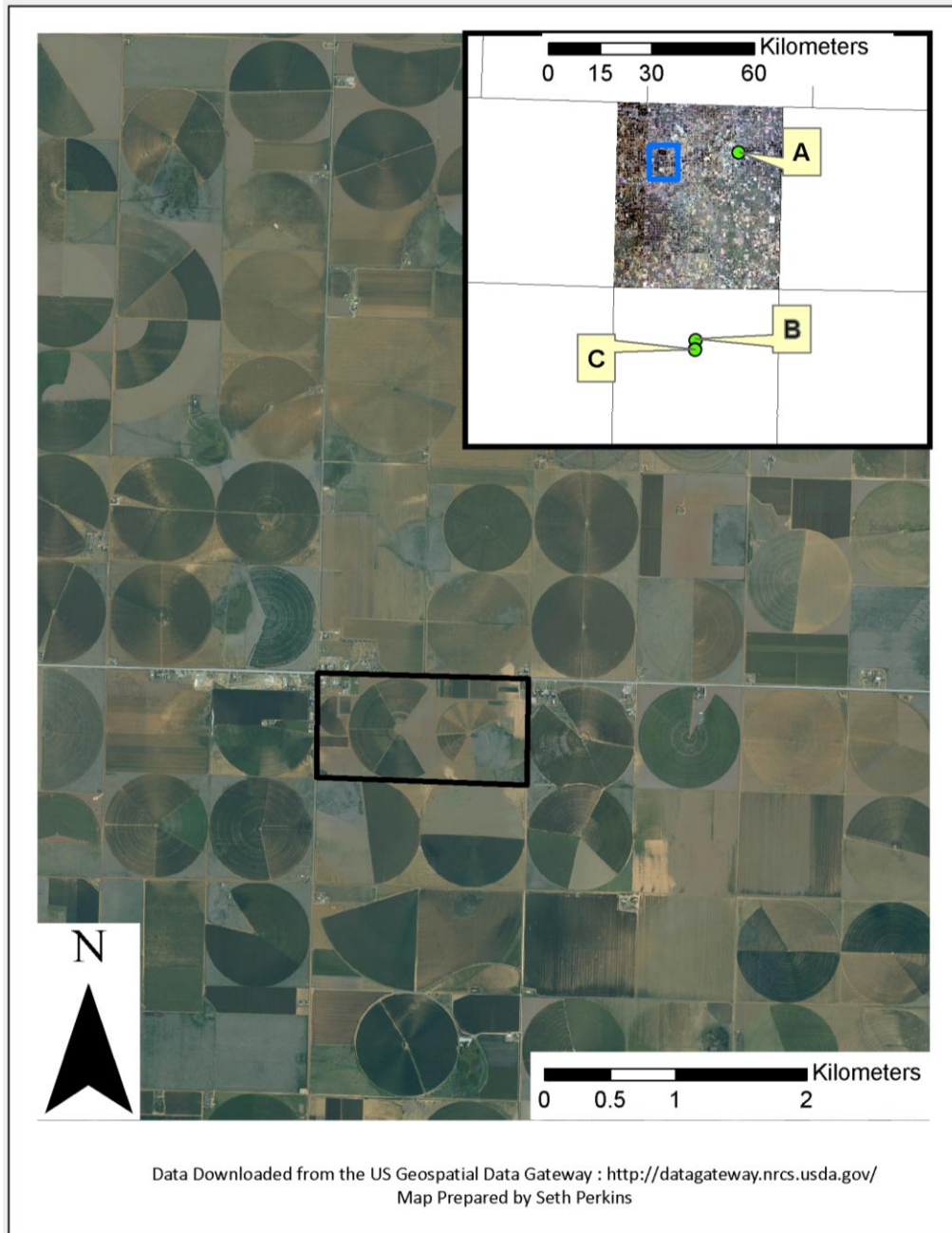


Figure 3.1E – The location of the Hale County, Texas field research site is boxed in. No specific locations were given on where within the site the corn and grain sorghum crops were grown. Weather Stations are as follows A: Plainview (COOP ID 417079), B: Lubbock 9N (COOP ID 415410), C: LUBBOCK WB AP (WID 17895)

¹**Table 3.1** - Shows the crop type, years that crop yield and ancillary data were available, source, and heat units used.

State	County	Crop	Best Years Available	Source	² Heat Units
³ Kansas					
	<u>Riley</u>	CO	1999 - 2008	KSU Agron. Crop Performance Reports	2000 - 2400
		GS	1999 - 2008	KSU Agron. Crop Performance Reports	1900 - 2300
		SS	2007 - 2008	Propheter, 2009	2300
	<u>Ellis</u>	CO	1999 - 2008	KSU Agron. Crop Performance Reports	2000 - 2400
		GS	1999 - 2008	KSU Agron. Crop Performance Reports	1900 - 2300
⁴ Oklahoma					
	<u>Caddo</u>	⁵ SS	2006 - 2007	SS Trials Oklahoma	2300
	<u>Texas</u>	CO	2006 - 2008	OSU Agron. Crop Performance Reports	2000 - 2400
		CS	2006 - 2008	OSU Agron. Crop Performance Reports	2000 - 2400
		GS (Limited Irrigation)	2006 - 2008	OSU Agron. Crop Performance Reports	1900 - 2300
		GS (Dry)	2006 - 2008	OSU Agron. Crop Performance Reports	1900 - 2300
		SS	2006 - 2007	SS Trials Oklahoma	2300
Texas					
	<u>Hale</u>	SS	2007 - 2008	Corn, 2009	2300

1 – CO - Corn; CS – Corn Silage; GS - Grain Sorghum; SS - Sweet Sorghum; Agron. – Agronomy

2 – Range of heat units were modeling GS, CS, CO to capture the variety differences of early, mid, and late maturing crops.

2 - Kansas crop performance data is available at: <http://www.ksre.ksu.edu/library/p.aspx?tabid=16&topic=Crops>

3 - Oklahoma crop performance data available at :<http://croptrials.okstate.edu/>

4 - Data was provided by Danielle Bellmer. She can be contacted at danielle.bellmer@okstate.edu. All other crop performance data, if not cited by a specific source, is available online.

For consistency, and because of the difficulty getting the ALMANAC model to run appropriately when two fertilizer application dates were added in the same season, all fertilizer applications were done at the beginning of the growing season in the top centimeter of soil.

NRCS curve number tables were used to select curve numbers for each study area based on site soil drainage class with fields planted as row crops with residue and good field condition (Table 3.2) (USDA-NRCS, 1999). The surface roughness factor (Manning’s n) was set to 0.090 for all sites in the study. The Manning’s n value was taken from Engman (1983) and chosen to maintain consistency across all modeling areas. The Manning’s n value falls within the roughness value ranges for conventional tillage and no-till management practices with approximately one ton per acre of residue, given in Engman (1983).

Monthly weather statistics for each modeling site were taken from the nearest station for these values available in the AutoALMANAC (USDA-ARS, 2010) initial processing tool (Table 3.3). All values for wind erosion factors were set to zero to eliminate wind erosions for this study, since no wind erosion data were available for comparison. Corn and grain sorghum crop factors were those from the original ALMANAC 2009 model; the only crop growth factor that varied within the corn and grain sorghum crop parameters, which varied with location, was the Harvest Index (HI) (Table 3.4).

Table 3.2 – Soil Name, Map Symbol, Drainage Class, and Curve Number used in the development and testing of the sweet sorghum parameters.

State	County	Soil Name	¹Map Symbol	Drainage Class	²Curve Number
Kansas	Ellis	Harney Clay Loam	2613	B	75
	Riley	Ivan-Kennebec	4050	B	75
		Reading Silt Loam	7170	B	75
Oklahoma	Caddo	Pond Creek	PcB	B	75
	Texas	Gruver	Rc	C	82
Texas	Hale	Pullman	PuA	B	75

1 – Soil Name, Map Symbol, Drainage Class were taken from the SSURGO dataset (USDA-NRCS, 2005)

2 – Curve Number was determined from the SCS curve number tables (USDA-NRCS,1999)

Table 3.3 - This figure lists the stations used to fill missing dates from those stations from table 3.5 and the stations that were used to filled the average weather variables inside the ALMANAC main input file. The distance from the modeling site, and location latitude and longitude are listed.

State	Station Name	Station ID ¹	Station Type	Distance From Modeling Site ²	Station Location			
				<i>km</i>	<i>LAT.</i>	<i>LONG.</i>		
Kansas	<i>Riley</i>	Manhattan	COOP ID 144972	Fill Station	< 2.0	39.2	96.58	
		CENTRALIA	WID 17327	Mon. Statistics	< 72.0	39.72	96.13	
	<i>Ellis</i>	Hays 1 S	COOP ID 143527	Fill Station	< 2.0	38.87	99.33	
		HAYS 1 S	WID 17333	Mon. Statistics	<2.0	38.87	99.33	
	Oklahoma	<i>Caddo</i>	Andarko	COOP ID 340224	Fill Station	< 28	35.67	98.2
			LAWTON	WID 17747	Mon. Statistics	< 36	34.6	98.4
<i>Texas</i>		Guymon	COOP ID 343835	Fill Station	< 17.0	36.7	101.48	
		GOODWELL	WID 17745	Mon. Statistics	< 2.0	36.6	101.62	
Texas	<i>Hale</i>	Lubbock 9 N	COOP ID 415410	Fill Station	< 56.0	33.68	101.82	
		LUBBOCK WB AP	WID 17895	Mon. Statistics	< 60.0	33.65	101.83	

1 – The Coop ID is given by the Nation Climate Data Center (NCDC, 2011). The WID is the identification number given by the AutoALMANAC model (USDA-ARS, 2011).

2 – Distance was approximated using the lat. and Long. coordinates. Actual values were difficult to determine due to conflicts between the geographic coordinate systems of the map layers used in the creating the figures and not knowing the exact location of the field used for all crop trials. Less than implies that the estimated distances were all rounded up.

Table 3.4 – Harvest Index¹ (HI) used in the development of the sweet sorghum parameters.

State	County	Crop²	HI Range
Kansas	<i>Ellis</i>	CO	0.30 - 0.50
		GS	0.45 - 0.50
	<i>Riley</i>	CO	0.30 - 0.52
		GS ³	0.30 - 0.50
		SS ⁴	0.98
	Oklahoma	<i>Caddo</i>	SS
<i>Texas</i>		CO ⁵	0.45 - 0.52
		CS	0.45 - 0.52
		GS	0.45 - 0.50
Texas	<i>Hale</i>	SS	0.98

1 - Harvest index is a ratio of the harvested biomass to the total above ground biomass produced during the growing season.

2 - CO – Corn; GS – Grain Sorghum; SS – Sweet sorghum; CS – Corn Silage.

3 - Grain sorghum HI's range was widened in Riley County to account for higher precipitation amounts and higher biomass accumulation.

4 - SS HI was 0.98 in all study areas, since values crop was hand harvested, and yields given as total above ground biomass.

5 - Irrigated Corn/Silage had a Higher HI than dryland Corn to account for competent irrigation methods.

To utilize the entire 10-year rotation for model output, for both Ellis and Riley Counties, the initial soil water values were estimated using hand calculations to determine the SW contributions from just after the harvest of the previous crop and the end of the previous year (calculations not shown). To maintain consistency, this was done for all of the sites used in the study, even if the rotations were two or three years. Each sweet sorghum data collection site had some form of management information available. Caddo County, Oklahoma sweet sorghum trials had irrigation and fertilizer application amounts for the 1996 trials (Bellmer and Huhnke, 2007), while in the 1997 trials no irrigation amounts were given and 112 kg ha⁻¹ of nitrogen fertilizer was applied (Bellmer, 2011, personal communication). The Texas County, Oklahoma sweet sorghum trials in Goodwell had irrigation (whole season) and fertilizer application amounts given for the 1996 trials, while in the 2007 trials no irrigation or fertilizer

application information was given (Bellmer and Huhnke, 2007-2008). Irrigation details for Goodwell and Ft. Cobb are discussed in detail later. Missing fertilizer application information for Goodwell was taken from the previous year's value given in the sweet sorghum performance reports. No specific tillage practices, soil data, or irrigation application dates were available for any other sites in Oklahoma, or Texas (Bellmer and Huhnke, 2007-2008; Corn, 2009). The most complete sweet sorghum management information was in Riley County (Propheter, 2009), which was selected as the sweet sorghum crop parameter development (calibration) site.

Climate data for each of the counties were downloaded from the National Climate Data Center (NCDC) (NCDC, 2011), Kansas State University (KSU) weather data library (KSRE-WDL, 2011), or Oklahoma Mesonet Website (Mesonet, 2011). The weather station from each county was selected based on its proximity to the crop data collection sites (Table 3.3 and 3.5). Table 3.5 lists the approximate latitude and longitude of the crop data sites and closest weather stations, and lists available weather variables from each weather station with the distance from the data collection site. Weather data were easily accessible online for all three states, and each data site had unique challenges in dealing with missing data.

Table 3.5 – Crop data and weather station locations and available weather data types.

State	County	⁵ Crop Data Location		Weather Station	Station Location		Elevation (m)	Available Data	⁶ Distance From Modeling Site
		Lat.	Long.		Lat.	Long.			
¹ Kansas	<u>Riley</u>	39.20	-96.583	Manhattan	39.20	-96.583	336.8	Rain, Temp, Radiation, Windspeed, Relative Humidity	< 1.0
	<u>Ellis</u>	38.87	-99.333	Hays	38.87	-99.333	612.65	Rain, Temp, Radiation, Windspeed, Relative Humidity	< 1.0
^{2,3} Oklahoma	<u>Caddo</u>	35.08	-98.27	FTCB - Fort Cobb	35.08	-98.27	421.84	Rain, Temp, Radiation, Windspeed, Relative Humidity	< 1.0
	<u>Texas</u>	36.60	-101.37	GOOD - Goodwell	36.60	-101.37	1008.6	Rain, Temp, Radiation, Windspeed, Relative Humidity	< 7.0
^{3,4} Texas	<u>Hale</u>	34.19	-101.95	NCDC ST.# 417079	34.20	-101.7	1027.2	Rain, Temp	< 23.0

1 - Kansas State Research and Extensions weather data available at : <http://wdl.agron.ksu.edu/>

2 - Oklahoma Mesonet weather data available at : http://www.mesonet.org/index.php/weather/daily_data_retrieval

3- Crop Data locations were not given with the data, and were assumed to be near weather station sties. Halfway, Texas was described in Corn (2009), no location information was given, and so regional value was given by <http://texas.hometownlocator.com/tx/hale/halfway.cfm>.

4 - Hale County data available at : <http://www.ncdc.noaa.gov/oa/climate/stationlocator.html>

6 - Locations are approximated; specific coordinate locations are not given in any of the publications.

5 - Distance was approximated using the Lat. and Long. coordinates. Actual values were difficult to determine due to conflicts between the geographic coordinate systems of the map layers used in the creating the figures and not knowing the exact location of the field used for all crop trials. Less than implies that the estimated distances were all rounded up.

To ensure weather data fidelity to the actual sites data sites, total monthly rainfall and average temperature, if available (OSU-CES, 2006-2008a; OSU-CES, 2006-2008b; KSU-AESCES, 1999-2008a; KSU-AESCES, 1999-2008b; Corn, 2009), were compared to downloaded weather data for each site used for modeling in this study (Table 3.5). If the monthly rainfall data from the crop data collection site did not equal the summed monthly (+/- 50 mm) values for the downloaded weather data used for the ALMANAC model, and had no missing data values, adjustments were made by adding irrigation or leaving irrigation out to represent field conditions more closely. Irrigation, if needed, would be added after one week with no rainfall. If variations in the average monthly temperature were greater than 0.5 °C then another weather station's temperature data were compared to the monthly average temperature from the research site. To remain consistent to real time events, any additional irrigation, aside from the necessary modifications previously describe, used in this study to simulate crop growth had to come from actual irrigation data amounts from the region of modeling and had to occur in the same year.

None of the sites in the study had differences in the monthly average temperature to warrant modifications or removal from the study (calculations not shown). Since no sites in Kansas and Oklahoma deviated from the monthly rainfall values given by the data collection sites, no irrigation modifications were needed to equate the downloaded weather rainfall monthly sums to that of the given monthly rainfall (OSU-CES, 2006-2008a; OSU-CES, 2006-2008b; KSU-AESCES, 1999-2008a; KSU-AESCES, 1999-2008b; Corn, 2009). In Hale County, Texas the sum of the monthly downloaded rainfall values (May-September) exceeded those given by Corn (2009). Corn (2009) showed rainfall for the study site (May-September) was 340.4 mm (13.40 inches) in 2007 and 262.6 mm (10.34 inches) in 2008. The excess rainfall calculated from the downloaded rainfall was 69.8 mm (2.75 inches) in 2007 and 94.3 mm (3.73 inches) in 2008. Therefore, the amount of addition rainfall given from the calculations using the

downloaded weather data would be subtracted from the total irrigation requirements in Hale, County Texas.

Irrigation added for modeling sweet sorghum in Caddo County, Oklahoma in 2006 was 25.4 mm (1 inch) per week of irrigation during the growing season, while the 2007 irrigated sweet sorghum was not modeled due to lack of irrigation information, and no alternative crop irrigation (i.e., irrigation for grain sorghum) values were available. In Texas County, Oklahoma 76.2 mm (3 inches) of irrigation was added during the growing season in 2006 (Bellmer and Huhnke, 2007), since the irrigation value for 2007 was not available (Bellmer and Huhnke, 2008) the irrigation value of 177.8 mm (7 inches) was taken from the limited irrigation grain sorghum trials and used (OSU-CES, 2007b). The irrigation amount added to the Hale County, Texas sweet sorghum modeling scenarios was the absolute value of the difference of the downloaded weather data monthly sums (May-September) and the total sum of the rainfall and irrigation amounts given in Corn (2009). The total sums of the rainfall and irrigation given by Corn (2009) were 459.9 mm (17.87 inches) in 2007 and 529.3 mm (20.84 inches) in 2008. The absolute values of the difference were 43.8 mm (1.72 Inches) in 2006 and 172.0 mm (6.77 inches) in 2007. The differences were rounded up to 50.8 mm (2 inches) of irrigation in 2007, and 177.8 mm (7 inches) of irrigation in 2008.

Missing weather data from each weather station were filled in using several methods (Table 3.6). Rainfall and temperature data gaps greater than three days per month were filled in using weather data from nearby stations. Stations missing three non-consecutive days (or less) of rainfall and temperature data per month were filled by averaging the previous and next day values. Though averaging the previous and next day values may exclude possible precipitation events, it did not appear that any precipitation events occurred on the dates with missing precipitation values (data not shown). Missing solar radiation data were either left blank, estimated, or averaged from the previous and following day values. Weather Stations that provided solar radiation data (Table 3.5) that had missing

solar radiation data during the non-growing season, November to March, were left blank in the weather file to allow for ALMANAC to estimate the solar radiation values. Missing solar radiation data for these stations during the growing season were estimated using a solar radiation estimation method FAO 056 (Allen et al., 2006). Weather stations missing solar radiation data less than three non-consecutive days per month were filled by averaging the previous and next day's solar radiation data values. For sites that did not provide any solar radiation data, the FAO 056 spreadsheet was used to estimate all solar radiation data. If data values did not get filled by a nearby station and were not filled any other way, they were left blank for solar data values or set to 999 for the precipitation and temperature data, so they could be estimated within the ALMANAC model's weather generator.

Weather data for Ellis and Riley Counties had no missing weather data until 2006. The missing weather data, from 2006 to 2008, was intermittent with no consecutive missing dates. A total of six daily data values were missing for Riley and seven for Ellis (Table 3.6).

The weather station for the Texas County crop data site in Oklahoma had substantially more missing weather data values. Guymon (NCDC, 2012: Coop # 343835) (Table 3.3) was used to fill the missing weather values (Table 3.6) for the Goodwell weather station in Texas County. Andarko (NCDC, 2012: Coop # 340224) (Table 3.3) was used to fill the missing values (Table 3.6) for the Ft. Cobb weather station in Caddo County.

Table 3.6 – Missing weather variables with the dates.

State	County	Weather Data Type	Missing Weather Dates
Kansas	Riley	Solar Radiation	9/13/07; 12/11/07; 6/23/08; 8/15/08; 8/20/08; 11/10/08
		Precipitation	9/13/07; 12/11/07; 6/23/08; 8/15/08; 8/20/08; 11/10/08
		Maximum Temperature	9/13/07; 12/11/07; 6/23/08; 8/15/08; 8/20/08; 11/10/08
		Minimum Temperature	9/13/07; 12/11/07; 6/23/08; 8/15/08; 8/20/08; 11/10/08
	Ellis	Solar Radiation	8/12/06; 9/13/07; 12/11/07; 6/23/08; 8/15/08; 8/20/08;11/10/208
		Precipitation	8/12/06; 9/13/07; 12/11/07; 6/23/08; 8/15/08; 8/20/08;11/10/208
		Maximum Temperature	8/12/06; 9/13/07; 12/11/07; 6/23/08; 8/15/08; 8/20/08;11/10/208
		Minimum Temperature	8/12/06; 9/13/07; 12/11/07; 6/23/08; 8/15/08; 8/20/08;11/10/208
Oklahoma	Texas	Solar Radiation	9/12/06
		Precipitation	9/12/06
		Maximum Temperature	3/20/06; 9/12/06; 12/19/06 - 12/21/06; 12/29/06 - 12/31/06; 1/1/07; 12/8/07 - 12/12/07; 2/5/08; 12/22/08 - 12/24/08
		Minimum Temperature	9/12/06; 12/10/07; 12/11/07
	Caddo	Solar Radiation	2/3/06
		Precipitation	1/1/00
		Maximum Temperature	2/3/06
		Minimum Temperature	2/3/06
Texas	Hale	Solar Radiation	7/1/08-7/31/08
		Precipitation	2/20/06; 7/1/08-7/31/08
		Maximum Temperature	7/1/08-7/31/08
		Minimum Temperature	7/1/08-7/31/08

The closest weather station to the crop data collection site in Hale County was located directly east of the Halfway research site, in Plainview, Texas (Table 3.5). The NCDC weather station did not have a record of the solar radiation data for Hale County. The Hale County, Texas weather station was the only station having substantial differences in the total rainfall. The differences in total rainfall were discussed along with the irrigation above.

Soil composition variables (Table 3.7) for each county were collected from the Soil Survey Geographic (SSURGO) dataset (USDA-NRCS, 2005).

Table 3.7 - Soil Variables imported from the SSURGO dataset into the ALMANAC .DAT soil section. Values that were not available were left blank in the file.¹

SALB	Soil Albedo	--
Z	Depth From the Surface to the Bottom of the Soil Layer	m
BD	Bulk Density of the Soil Layer (33 kPa)	Mg/m ³
U	Wilting Point (1500 kPa for many soils)	m/m
FC	Field Capacity (33 kPa for many soils)	m/m
SAN	Sand Content	%
SIL	Silt Content	%
WN	Organic N Concentration	g/Mg
PH	Soil pH	--
SMB	Sum of Bases	cmol/kg
CNB	Organic Carbon	%
CAC	Calcium Carbonate	%
CEC	Cation Exchange Capacity	cmol/kg
ROK	Coarse Fragment Content	%
WNO3	Nitrate Content	g/Mg
AP	Labile P Concentration	g/t
BDD	Bulk Density (oven dry)	Mg/m ³
PSP	Phosphorus Sorption Ratio	--
SC	Saturated Conductivity	mm/h
WP	Organic P Concentration	g/Mg

1- Table adapted from Tables.pdf (table 5.1 section 7) from the USDA-ARS ALMANAC Simulation model website: <http://www.ars.usda.gov/Main/docs.htm?docid=16601>

Three methods of SW estimation were tested: Saxton and Rawls (2006), Ritchie et al. (1999), and a method that added 0.01 mm⁻¹ to the minimum available SW value listed in the SSURGO Dataset. Table 3.8 shows an example of the SW values for Reading silt loam in Riley County. To simplify importing

to soils for the sweet sorghum crop parameter development and testing, the import tool for AutoALMANAC (USDA-ARS, 2010) was used.

Table 3.8 – Wilting Point, Field Capacity, and Soil Water (m m^{-1}) totals for Reading Silt Loam.

Reading Silt Loam					
¹Saxton and Rawls					
<i>Layer</i>	<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	<u>5</u>
<i>Wilting Point</i>	0.133	0.133	0.188	0.223	0.202
<i>Field Capacity</i>	0.331	0.331	0.365	0.385	0.374
<i>Soil Water</i>	0.198	0.198	0.177	0.162	0.172
²Ratliff					
<i>Layer</i>	<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	<u>5</u>
<i>Wilting Point</i>	0.165	0.165	0.205	0.233	0.203
<i>Field Capacity</i>	0.307	0.307	0.332	0.347	0.331
<i>Soil Water</i>	0.142	0.142	0.127	0.114	0.128
³SSURGO					
<i>Layer</i>	<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	<u>5</u>
<i>Wilting Point</i>	0.121	0.121	0.174	0.217	0.147
<i>Field Capacity</i>	0.351	0.351	0.364	0.357	0.337
<i>Soil Water</i>	0.230	0.230	0.190	0.140	0.190

1 - Saxton and Rawls (2006)

2 - Ritchie et al. (1999)

3 - Values are the method 0.01 plus the minimum soil water value given by the physical soil properties in SSURGO.

The soil water estimation method inherent in the AutoALMANAC soil processing tool was Ritchie et al. (1999) (Kiniry, 2011, personal communication). The processing tool's soil texture output was used to estimate the soil water contributions using equations from Saxton and Rawls (2006) to maintain a consistency in the soil water estimations. Since field capacity and wilting point were not directly given in the SSURGO dataset, the original soil water output's field capacity and wilting point values estimated by Ritchie et al. (1999) were used as the base for the SSURGO soil water field capacity and wilting point. The soil water values were expanded to match the minimum soil water value + 0.01 m m^{-1} in the SSURGO database by dividing the soil water value by two, and adding one half to the field capacity and subtracting the second half from the wilting point.

Three methods of evapotranspiration (ET) estimation were tested within the ALMANAC model: Hargreaves and Samani (1985), Penman-Montieth (Montieth, 1977), and Priestley and Taylor (1972). All

combinations of baseline SW conditions (Table 3.8) and ET methods were used to model 10 years of corn and grain sorghum rotations in Riley and Ellis Counties, Kansas. In order to encompass the varietal maturity range of the average yield data from Riley and Ellis Counties, a range of heat units (in increments of 100) were tested for corn and grain sorghum crops (Table 3.4).

Site Data Analysis and Sweet Sorghum Crop Parameter Development

Before the statistical analysis of corn and grain sorghum modeled data were performed, yield data collected from both Ellis and Riley Counties were evaluated to see if there were any instances that were not able to be adequately modeled in ALMANAC, either from missing data or extreme weather events. There were two years in Ellis County in which corn yields could not be compared to measured data: 2002 and 2006. In both years the crop performance reports showed that these sites were abandoned due to drought, and no yield or biomass data were given for this site (KSU-AESCES, 2002a; KSU-AESCES, 2006a). These years were left out of the calculations of the final statistical values. In Riley County, 2001 and 2005 were excluded from the statistical calculations for the corn modeling. In 2001, hail damage during the growing season shredded the leaves of the corn crop, which lowered overall potential yields (KSU-AESCES, 2001a). Also, two days of frost damaged the emerging corn crop by burning off the top three inches of the leaves in 2005, potentially lowering yields (KSU-AESCES, 2005). The ALMANAC frost-damage subroutine did not adequately model damage to the leaves during that year, and in all cases the yields were grossly overestimated (data not shown). The grain sorghum modeled crop yields in Riley County 2001 were excluded due to the hail storm that damaged the crop during the growing season (KSU-AESCES, 2001b). No significant events or missing data required the exclusion of any years from the grain sorghum in Ellis County.

The yields were compared using a Concordance Correlation Coefficient (C_c) (Lin, 1989), Pearson's Product-Moment Correlation Coefficient-squared (P_c^2), and a slope of a first-order linear regression of observed vs. predicted yields with the origin at (0, 0). Both C_c and the regression slope

provided measures of accuracy and precision along the 1:1 (observed: predicted) line with origin at (0, 0). To minimize bias in selection of the best combination of soil water and ET equations, a simple filter method was employed. First the six highest C_c values were selected. From the six highest C_c values, the three highest P_c^2 values were compared, and the slope of the regression line of the three highest P_c^2 with the value closest to 1 (i.e., observed data perfectly matched simulated data) was selected. If more than one combination was selected as the best combination (different combinations were selected for each scenario), the occurrence of the three selected soil water and ET combinations in the P_c^2 stage of the comparison were used to determine the resultant combination. This did not require the combination to be selected for the best fit for any of the scenarios modeled in the study. Occurrence is defined in this instance as a ratio the number of times (0-4) any combination occurs to the total scenarios (4). The combination with the highest occurrence within all four scenarios was chosen. The resultant combination was then used to validate grain sorghum and corn model results in Texas County, Oklahoma. Results from grain sorghum and corn models were compared using box and whisker plots. Oklahoma State University Cooperative Extensions Service crop performance reports (OSU-CES) (2006-2008) reported grain yields for grain sorghum and corn were given in $Mg\ ha^{-1}$ with moisture contents of 14.0% and 15.5% and Corn Silage was reported in $Mg\ ha^{-1}$ with a moisture content of 68% percent. Modeled results were compared at the same moisture content.

The selected and validated soil water estimation method and ET equations were then used to develop the sweet sorghum parameters using data from Riley County. Model parameters used in the development are shown in Table 3.9. The focus of the sweet sorghum crop parameter development was around three main parameters which were adjusted to attain optimal model performance for sweet sorghum; the parameters were optimized sequentially in the following order: Biomass Energy Ratio (WA), LAI Development Curve (DLAP1, DLAP2), and Plant Population Density Curve (PPL1, PPL2). Any other adjustments to the other crop parameter set were around these three main crop parameters.

Table 3.9 – Final sweet sorghum crop parameters. Definitions of variables are in Table 3.12.

Crop Parameters : sweet sorghum					
Parameter (Units)	Value	Citation³	Parameter (Units)	Value	Citation³
WA ² (Mg ha ⁻¹ MJ ⁻¹)	55.0		WSYF	0.98	
HI (kg kg ⁻¹)	0.98		WCY ⁷ (kg kg ⁻¹)	0.00	
TB (°C)	30.0		BN1 ⁸ (kg kg ⁻¹)	0.0180	
TG (°C)	8.0		BN2 ⁸ (kg kg ⁻¹)	0.0093	Han et al. (2010)
DMLA ³	6.0	Ferraris et al. (1986)	BN3 ⁸ (kg kg ⁻¹)	0.0057	Propheter (2009)
DLAI	0.65		BP1 ⁸ (kg kg ⁻¹)	0.0020	
DLAP1 (%)	15.05	Ferraris and Edwards (1986);	BP2 ⁸ (kg kg ⁻¹)	0.0010	Han et al. (2010)
DLAP2 (%)	42.95	Mastrorilli (1999)	BP3 ⁸ (kg kg ⁻¹)	0.0070	Propheter (2009)
RLAD ⁵	0.02	Ferraris and Edwards (1986)	VPTH (kPa)	1.0	
RBMD ⁵	0.02		VPD2 ⁹ (kg ha ⁻¹ MJ ⁻¹)	-5.4	
PPL1 ⁶	10.38	Propheter (2009)	GSI (m s ⁻¹)	0.0074	
CAF	0.85		EXTINC	0.59	Curt et al. (1998)
HMX (m)	3.5				
RDMX (m)	2.0				
PPL2 ⁶	15.84	Propheter (2009)			
CNY (kg kg ⁻¹)	0.017	Propheter (2009)			
CPY (kg kg ⁻¹)	0.0046	Propheter (2009)			

1 - Values with no given units are unit-less in ALMANAC. Parameters not listed used common or default parameters for crops in ALMANAC. More information on these parameters is listed in the tables section at: <http://www.ars.usda.gov/Main/docs.htm?docid=16601>

2 – Biomass Energy Ratio is 20% higher than that given in literature to account for root growth in the ALMANAC model (Kiniry, 2011, personal com.)

3 - This value is greater than the value from the literature to compensate for root biomass accumulation in the ALMANAC model.

4 - Parameter values with no citation were taken from ALMANAC grain sorghum crop parameters.

5 - Values were kept to a minimum or removed to ensure adequate biomass production throughout the growing season, and to reflect minimal lost to overall biomass since HI was not reflective of just grain yields.

6 - Value was correlated to match closely with the plant populations in Propheter (2009).

7 - Value was set to zero to give total above ground dry biomass as yield (Seed + Above ground biomass). Harvested biomass ranges from 69 to 83% moisture in most of the data/publications reviewed in this study. (This did not reflect the moisture content of the seed.)

8 – Values were lower than the given literature values, this was to ensure that nitrogen stress on the plant was limited or non-existent in the development area as the data suggested (Propheter, 2009). It was assumed that the reduction was necessary since the roots may contain a lower fraction of nutrients, lowering the overall concentration of nutrients in the plant, no literature was found to support this claim.

9- Decision for this value was under the guidance of the results and conclusions of Steduto et al. (1997).

Available literature had a range of RUE from 3.55 to 4.96 g MJ⁻¹ (Curt et al., 1998; Dercas and Liakatas, 2006; Mastrorilli et al., 1995), which can be converted into the Biomass Energy Ratio (WA). Values of WA greater than 49.5 Mg ha⁻¹ MJ⁻¹ were possible based on the recommendation of Kiniry (2011, personal comm.), who suggested a 20% increase in RUE (with corresponding increase in WA) to account for root biomass in the model. Mastrorilli et al. (1999) and Ferraris and Edwards (1986) provided guidance on the LAI development curve. Reviewing the data, results and conclusions from Propheter (2009) and Dooley (2010) provided guidance on determining PPL2 for the Maximum Population Density Curve. The first point value for the Plant Population Density Curve (PPL1) was

developed using Texas County, Oklahoma, sweet sorghum yield data.

Table 3.10¹ - Variable definitions from table 3.9.

WA	Biomass Energy Ratio
HI	Harvest Index
TB	Optimal Temperature for Plant Growth
TG	Minimum Temperature for Plant Growth
DMLA	Maximum Potential Leaf Area Index
DLAI	Fraction of the Growing Season when Leaf Area Starts Declining
DLAP1 ²	Point One on the Optimal Leaf Area Development Curve
DLAP2 ²	Point Two on the Optimal Leaf Area Development Curve
RLAD	Leaf Area Index Decline Rate Parameter
RBMD	Biomass-Energy Ratio Decline Rate Parameter
ALT	Aluminum Tolerance Index (1=sensitive; 5=Tolerant)
PPL1 ³	Plant Population Parameter 1
CAF	Critical Aeration Factor
SDW	Seeding Rate
HMX	Maximum Crop Height
RDMX	Maximum Rooting Depth
PPL2 ³	Plant Population Parameter 2
CNY	Fraction of Nitrogen in Yield
CPY	Fraction of Phosphorus in Yield
WSYF	Water Stress Crop Yield Factor
PST	Pest Factor
WCY	Fraction of Water in Yield
BN1	N Fraction in Plant at Emergence
BN2	N Fraction in Plant at Half Maturity
BN3	N Fraction in Plant at Maturity
BP1	P Fraction in Plant at emergence
BP2	P Fraction in Plant at Half Maturity
BP3	P Fraction in Plant at Maturity
VPTH	Threshold Vapor Pressure Deficit
VPD2	Slope of WA:VPD Relationship Above VPTH
GSI	Maximum Stomatal Conductance
EXTINC	Extinction Coefficient for Calculating Light Interception
RTPRT1	Fraction of Weight Partition to Roots for Young Plants
RTPRT2	Fraction of Weight Partition to Roots for Plants Near Maturity

1--Table was adapted from the USDA-ARS tables document: www.ars.usda.gov/main/docs.htm?docid=16601

2--Value before the decimal is the percent of the growing season, the value after the decimal is the fraction of the potential leaf area.

3--Value before the decimal is the plant population in plants per m², value after the decimal is the fraction of the maximum leaf area.

Once sweet sorghum parameters were calibrated to the data in Riley County, the parameters were validated in Caddo County, Oklahoma, Texas County, Oklahoma, and Hale County, Texas. Since so few sweet sorghum data sites were available, results are compared in a table.

Results

The results from the filter method shown in Table 3.11 found the top six C_c for corn in Riley County, Kansas ranging from 0.477 to 0.882, and the three highest P_c^2 ranged from 0.635 to 0.849. The combination selected was the method which added 0.01 m m^{-1} to the minimum soil water value in the SSURGO database and Priestly-Taylor (1972) (SS-PT), whose slope of the linear equation that was the closest to 1 (0.999) of the three P_c^2 values chosen. The result from the statistical analysis of the grain sorghum modeled yields in Riley County found the top six values for C_c ranging from 0.189 to 0.597, the top three P_c^2 value ranged from 0.160 to 0.388. The slope of the three linear regression equations that was closest to 1 was for Ritchie et al. (1999) and Penman-Monteith (Monteith, 1977) (RT-PM) with a value of 0.977. The corn results for the top six C_c values range from 0.779 to 0.876. The highest three values of P_c^2 ranged from 0.924 to 1.196. The selected value with the slope closest to one was the Ritchie et al. (1999) and the Hargreaves and Samani (1985) (RT-HS) with a slope of 0.986. The six highest values of C_c from the grain sorghum modeling scenario ranged from 0.874 to 0.905, with the three highest values for P_c^2 ranging from 0.836 to 0.871. The selected combination with the slope closest to 1 was Ritchie et al. (1999) and Priestley and Taylor (1972) (RT-PT) with a slope value of 1.057.

Since multiple combinations resulted from the filter criteria (SS-PT, RT-PM, RT-HS, and RT-PT) the occurrence method was employed. The combination of Saxton and Rawls (2005) and Priestley and Taylor (1972) (SR-PT) had the highest occurrence (1.0) of all the combinations that were in the P_c^2 portion of the filter selection, and was chosen as the combination for further validation and the sweet sorghum crop parameter development and testing. The actual yield and model yield results associated with the SW-ET combinations are shown in Figures 3.2, 3.3, 3.4, and 3.5.

Table 3.11 – Performance of the ALMANAC model in simulating corn (CO) and grain sorghum (GS) yields using crop yield data from Riley County and Ellis County, Kansas, and nine methods of estimating soil water and ET. Values highlighted in gray are the six highest C_c values; values highlighted in dark gray are the three values with highest P_c^2 and linear regression line slope nearest to 1.0.

Riley	Method	C_c	P_c^2	Slope	Ellis	Method	C_c	P_c^2	Slope
CO	SR-PT	0.882	0.849	0.969	CO	SS-HS	0.876	0.788	0.924
	SS-PT	0.857	0.800	0.999		SR-HS	0.871	0.776	0.996
	SR-HS	0.647	0.573	0.867		RT-HS	0.865	0.802	0.986
	RT-PM	0.642	0.635	0.989		SS-PT	0.841	0.739	1.039
	SS-HS	0.638	0.469	0.905		SR-PT	0.798	0.876	1.196
	RT-PT	0.477	0.572	0.768		RT-PT	0.779	0.776	1.119
	RT-HS	0.345	0.496	0.689		SS-PM	0.714	0.898	1.323
	SS-PM	0.098	0.051	1.084		SR-PM	0.510	0.854	1.477
	SR-PM	0.080	0.030	1.080		RT-PM	0.502	0.809	1.444
GS	RT-PM	0.597	0.388	0.977	GS	SS-PT	0.905	0.826	1.022
	SR-PT	0.392	0.179	0.968		SR-HS	0.903	0.824	0.958
	SS-PT	0.364	0.151	0.991		SS-PM	0.895	0.836	1.058
	SR-PM	0.199	0.160	1.200		RT-HS	0.890	0.821	0.939
	SR-HS	0.198	0.131	0.786		RT-PT	0.885	0.871	1.057
	SS-HS	0.189	0.100	0.802		SR-PT	0.874	0.841	1.083
	SS-PM	0.141	0.135	1.232		RT-PM	0.858	0.852	1.083
	RT-PT	0.110	0.069	0.725		SS-HS	0.848	0.796	0.894
	RT-HS	0.045	0.228	0.594		SR-PM	0.837	0.835	1.124

1 – Abbreviations represent combinations of three soil water methods (SR – Saxton and Rawls, RT - Ritchie, SS - SSURGO) and three ET equations (HS – Hargreaves and Samani (1985), PM - Penman-Monteith (Monteith, 1977), PT – Priestley and Taylor (1972)) used to run the ALMANAC model.

2 – P_c^2 is the Pearson’s Product-Moment Correlation Coefficient-Squared, C_c is the Concordance Correlation Coefficient (Lin, 1989).

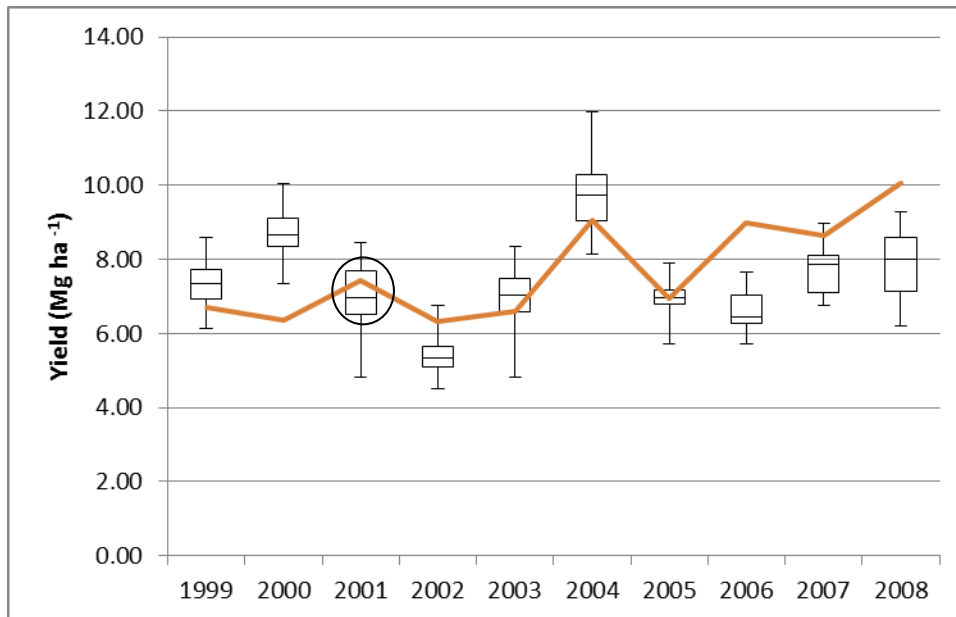


Figure 3.2 – Yield comparison results for grain sorghum SR-PT runs in Riley County, Kansas. Years that are circled were not used to calculate the statistical values due to conditions not modeled in ALMANAC at this time. Box and whisker plots (Max, Min, Median, Q1-25%, Q3-75%) are the field collected data while the line graph is ALMANAC modeled yields.

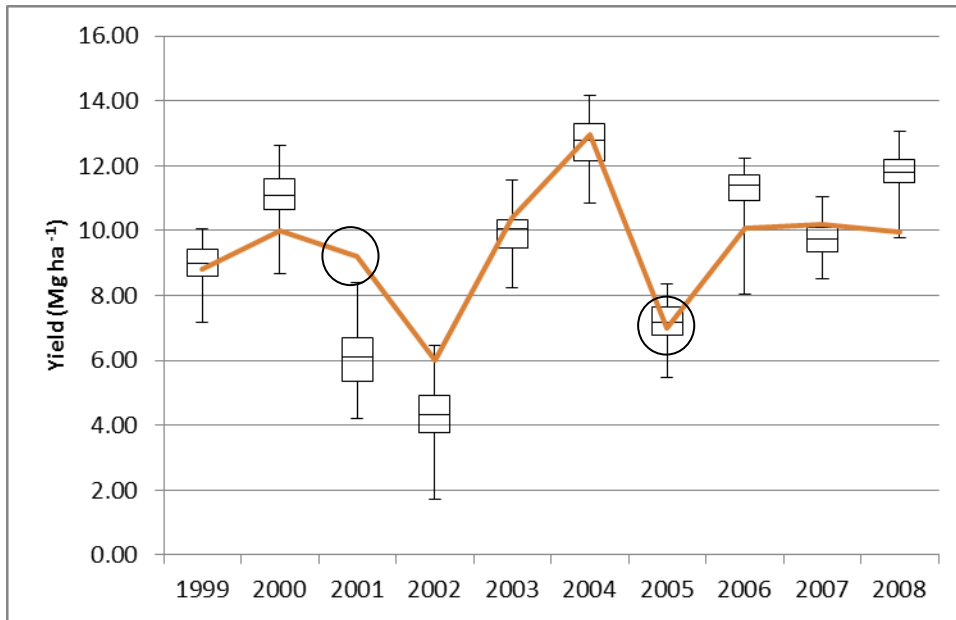


Figure 3.3 - Yield comparison results for corn SR-PT runs in Riley County, Kansas. Years that are circled were not used to calculate the statistical values due to conditions not modeled in ALMANAC at this time. Box and whisker plots (Max, Min, Median, Q1-25%, Q3-75%) are the field collected data while the line graph is ALMANAC modeled yields.

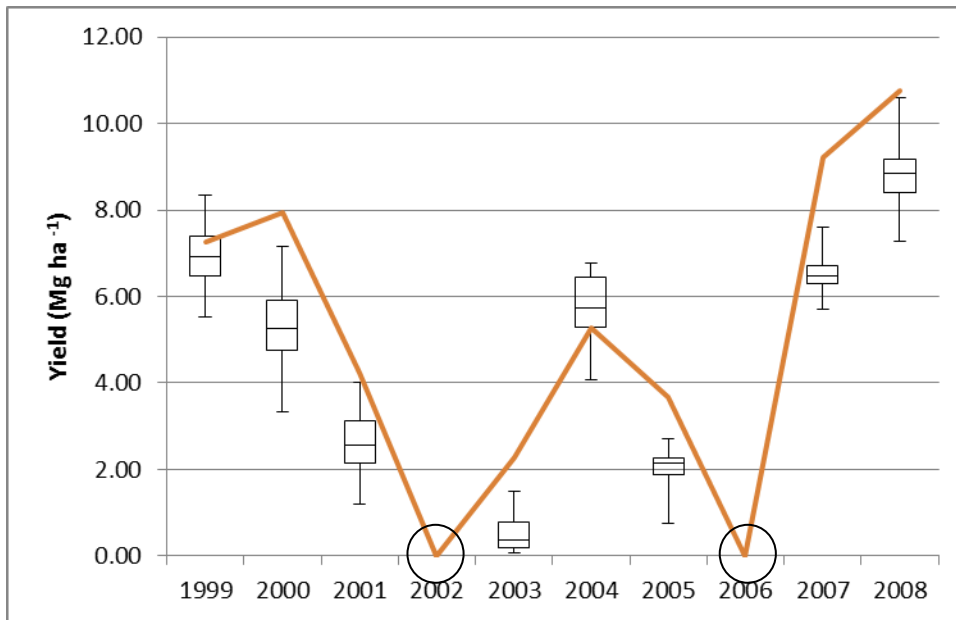


Figure 3.4 - Yield comparison results for corn SR-PT runs from Ellis County, Kansas. Years that are circled were not used to calculate the statistical values due to conditions not modeled in ALMANAC at this time. Box and whisker plots (Max, Min, Median, Q1-25%, Q3-75%) are the field collected data while the line graph is ALMANAC modeled yields.

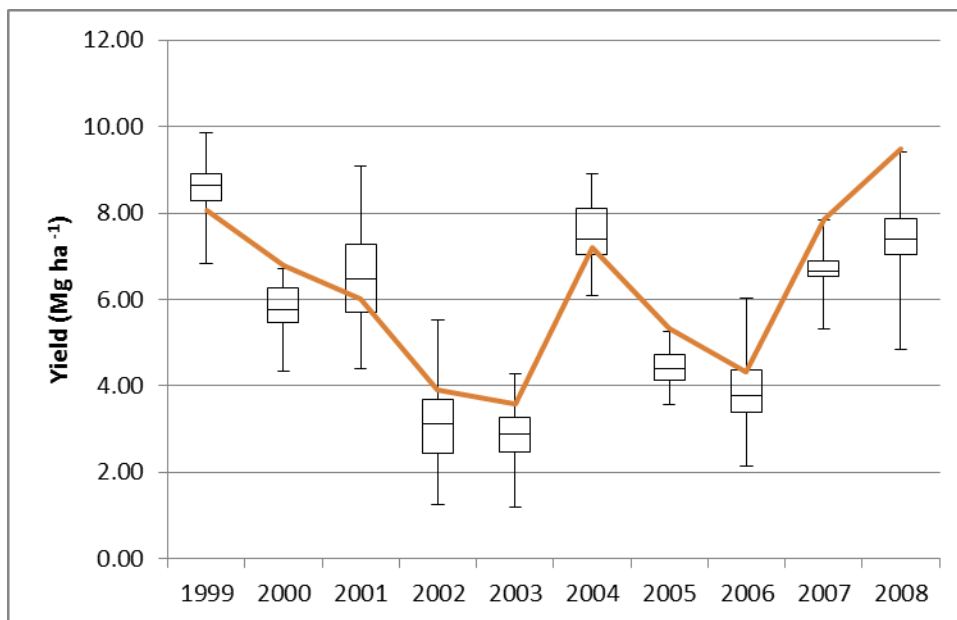


Figure 3.5 - Yield comparison results for grain sorghum SR-PT runs from Ellis County, Kansas. Years that are circled were not used to calculate the statistical values due to conditions not modeled in ALMANAC at this time. Box and whisker plots (Max, Min, Median, Q1-25%, Q3-75%) are the field collected data while the line graph is ALMANAC modeled yields.

Corn and Grain Sorghum Validation (Texas County, Oklahoma)

Using the SR-PT method as the baseline condition in Texas County, Oklahoma, showed grain yields for irrigated corn in 2006 were nearly equal (<1% difference) to the average yield results from Texas County, while those in 2007 and 2008 were overestimated by 0.96 and 0.89 Mg ha⁻¹ (9.3% and 7.6%) (Table 3.12), but still within the maximum and minimum yield values given for 2007 and 2008 measured yield data (Figure 3.6). Irrigated corn silage in 2006 and 2008 were overestimated by 10.83 and 10.74 Mg ha⁻¹ (20.7% and 21.5%) when compared to the average corn silage (Table 3.12). The modeled silage value was higher than the maximum measured value in 2006 but within the maximum and minimum yield values given for 2008 (Figure 3.7). The corn silage yields in 2007 are underestimated by 7.25 Mg ha⁻¹ (11.9%), still falling within the maximum and minimum measure yield values in 2007 (Figure 3.7). Averaged modeled yields for limited irrigation sorghum followed the trend of average yields closely, never deviating by more than 0.42 Mg ha⁻¹ (5.3%), with slight overestimations in 2007 (0.18 Mg ha⁻¹, 3.0%) and slight underestimations in 2006 and 2008 (0.42 and 0.33, 5.3% and 4.2%) (Figure 3.8).

Dryland yields for grain sorghum in Texas County for 2006 and 2007 were overestimated by 1.0 and 0.4 Mg ha⁻¹ (32.9% and 11.7%), and yield in 2008 was underestimated by 0.33 Mg ha⁻¹ (7.8%) (Table 3.12) (Figure 3.9).

Table 3.12 – ALMANAC model crop yield results for corn (CO), corn silage (CS), and grain sorghum (GS) for Texas County, Oklahoma. Modeled results are the average of crop model runs with a range of heat units (Table 3.4), in increments of 100. Each scenario n = 5.

Crop ¹	Irrigated	Year ²	Modeled	Mg ha ⁻¹		
				Average ³	Maximum ³	Minimum ³
CO	Yes	2006	11.02	11.03	12.95	8.94
		2007	11.24	10.28	11.34	9.01
		2008	12.63	11.74	13.20	8.94
CS	Yes	2006	63.17	52.34	61.55	41.78
		2007	53.85	61.10	76.83	49.65
		2008	60.61	49.87	62.22	41.56
GS	Yes	2006	7.44	7.86	9.48	5.54
		2007	6.09	5.91	6.98	4.50
		2008	7.49	7.82	8.77	6.37
GS	No	2006	4.04	3.04	4.41	0.88
		2007	3.81	3.41	4.05	2.72
		2008	3.93	4.26	5.17	3.32

1 – Corn silage is reported in wet Mg ha⁻¹ with a moisture content of 65%, corn and grain sorghum grain yields were reported as 15.5% and 14.0% moisture.

2 – Corn and grain sorghum data for years 2009 and 2010 were not available for comparison, once published online this data would be invaluable to the combination validation.

3 – Values are taken from Goodwell, KS crop performance reports (OSU-CRP, 2006-2008). The average value is an average of multiple crop varieties while the Minimum and Maximum values are the highest and lowest performing variety.

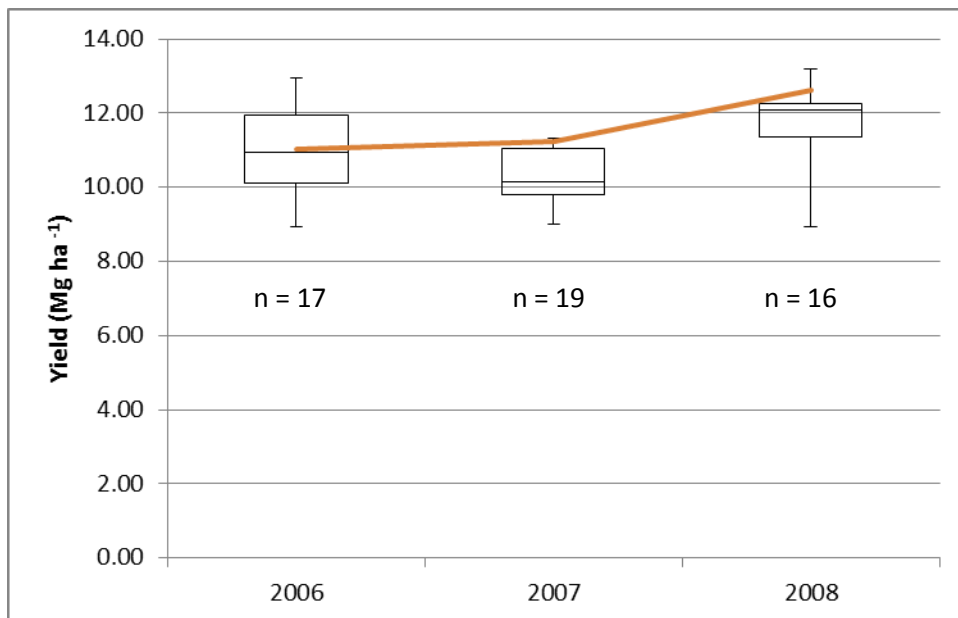


Figure 3.6 –Irrigated corn (CO) dry matter yields from Texas County, Oklahoma. Values for the collected data are given in a box and whisker (Max, Min, Median, Q1-25%, Q3-75%) plot. Modeled results are shown with the line. The sample numbers (n) for field measured yields are given.

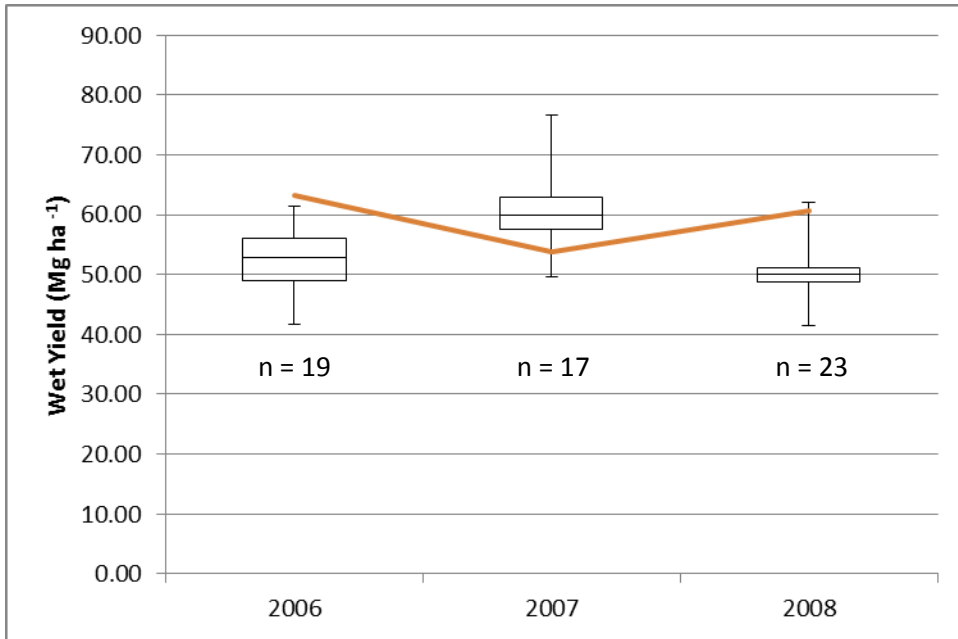


Figure 3.7 –Irrigated corn silage (CS) wet matter yields from Texas County, Oklahoma. Values for the collected data are given in box and whisker(Max, Min, Median, Q1-25%, Q3-75%) plot. Modeled results are shown with the line. The sample numbers (n) for field measured yields are given.

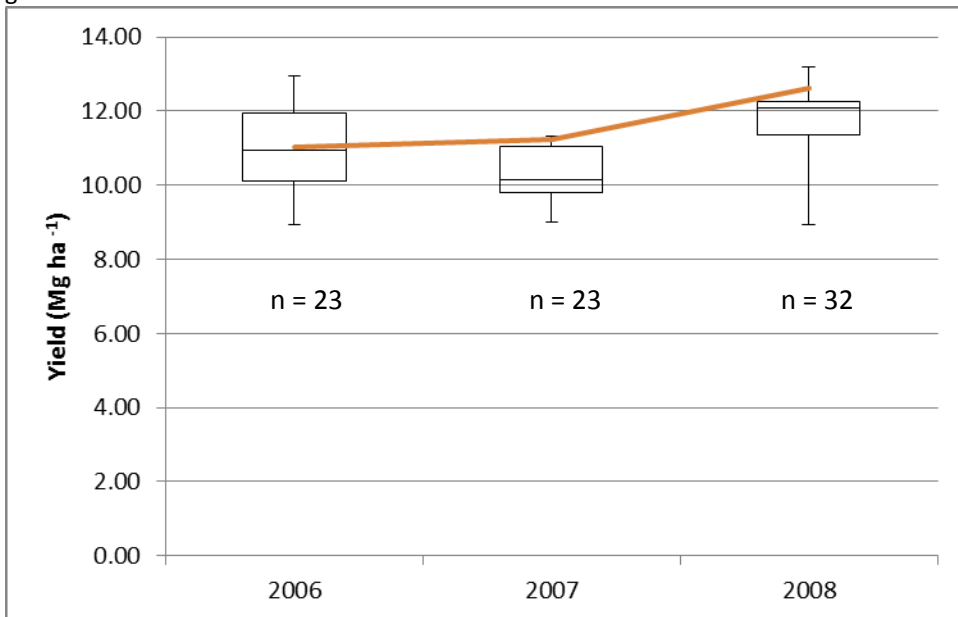


Figure 3.8 –Grain sorghum (GS) yields under conditions of limited irrigation from Texas County, Oklahoma. Values for the collected data are given in box and whisker (Max, Min, Median, Q1-25%, Q3-75%) plot. Modeled results are shown with the line. The sample numbers (n) for field measured yields are given.

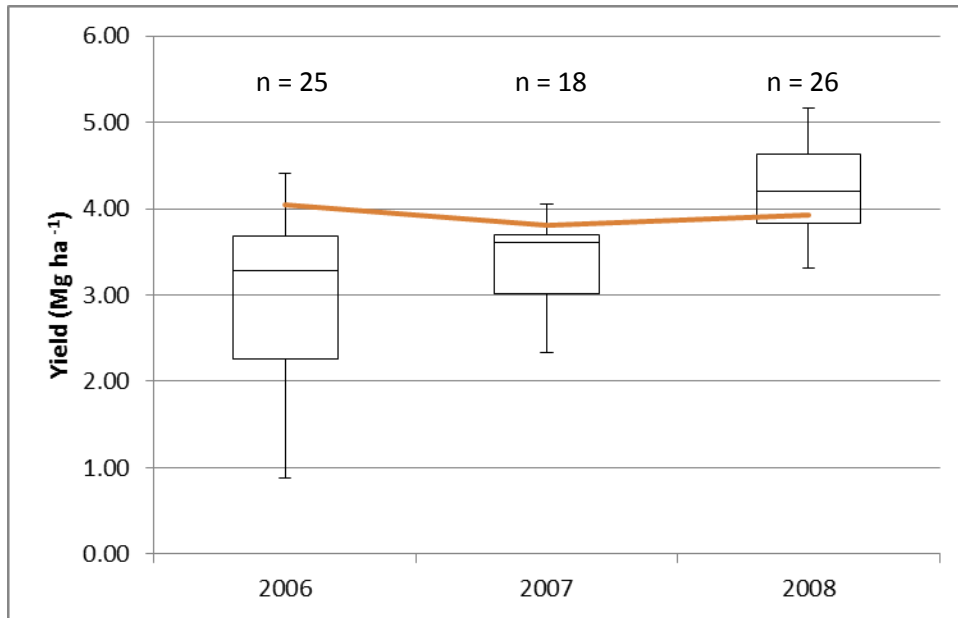


Figure 3.9 – Dryland grain sorghum (GS) yields from Texas County, Oklahoma. Values for the collected data are given in box and whisker (Max, Min, Median, Q1-25%, Q3-75%) plot. Modeled results are shown with the line. The sample numbers (n) for field measured yields are given.

Sweet Sorghum

The final sweet sorghum crop parameter set in ALMANAC had a Biomass Energy Ratio for sweet sorghum of $55 \text{ Mg ha}^{-1} \text{ MJ}^{-1}$; leaf area curve points (DLAP1 and DLAP2 defined in Table 3.10) for sweet sorghum were estimated using data from Ferraris and Edwards (1986) and Mastroilli (1999). The values were 15.05 and 42.95, and plant population curve values were 10.38 for PPL1 and 15.84 for PPL2 (Table 3.9). The value before the decimal for PP1 and PP2 is the number of plants per m^2 , and value after the decimal is the fraction of the leaf area at that population. ALMANAC underestimated sweet sorghum actual yield by 0.90 Mg ha^{-1} (3.3%) in Riley County in 2007 and overestimated yield by 0.89 Mg ha^{-1} (2.8%) in 2008 (Table 3.13). In Caddo County, Oklahoma, irrigated sweet sorghum yield was underestimated by 1.60 Mg ha^{-1} (4.9%) in 2006, but remained within the range of values given by the collected data (Table 3.13), while in 2007 the two dryland output yields overestimated yield by 13.66 (132.6%) and 12.31 Mg ha^{-1} (100.2%). In Texas County, Oklahoma, yield results were underestimated in both 2006 (1.13 Mg ha^{-1} , 6.7%) and 2007 (1.76 Mg ha^{-1} , 9.8%). Finally in Hale County, Texas, 2007 yields were underestimated by 0.83 Mg ha^{-1} (4.6%), and 2008 yields were overestimated by 1.38 Mg ha^{-1} (7.7%).

Table 3.13 – Results from the sweet sorghum trials development and validation.

State	County	Year	Irrigated	Modeled	Average	Maximum ²	Minimum ²
					Mg ha ⁻¹		
Kansas							
	<i>Riley</i>	2007	No	26.70	27.60	--	--
		2008	No	33.09	32.20	--	--
Oklahoma							
	<i>Caddo</i>	2006	Yes	30.94	32.54	41.66	26.21
		2007	Yes	N/A ¹	11.22	13.80	8.22
		2007	Yes	N/A ¹	21.03	23.34	19.17
		2007 ³	No	23.96	10.30	13.64	8.38
		2007 ³	No	24.60	12.29	15.70	9.70
	<i>Texas</i>	2006	Yes	15.83	16.96	19.32	13.03
		2007 ⁴	Yes	16.24	18.00	19.47	16.39
Texas							
	<i>Hale</i>	2007	Yes	18.99	18.16	25.93	14.15
		2008	Yes	19.22	17.84	24.22	10.41

1– Was not modeled since no accurate information was given about irrigation during this year.

2 – Average values are an average of the sweet sorghum trials in a given study area. The maximum and minimum values are those of the recorded data. Maximum and Minimum values were not given with data from Riley County.

3 – Two harvest Dates for dryland were available (9/24/07, 10/31/047), the data given are in chronological order.

4—Values for the dry weight were estimated based on the moisture content from 2006 trials as the dry weight for this area was not given.

Discussion

SS-PT, RT-PM, RT-HS, and RT-PT were selected for each individual scenario (Riley County, Corn and Grain Sorghum; Ellis County, Corn and Grain Sorghum). The multiple selections allowed for the occurrence method to be employed to determine a single appropriate SW and ET combination to use across all counties in the study. Though Saxton and Rawls (2005) and Priestley and Taylor (1972) (SR-PT) combination was not selected statistically as the best suited SW-ET combination for any of the four scenarios, the SW and ET combination of SR-PT had the highest overall occurrence (1.0), which means it occurred in the last stage of selection of the four scenarios (Table 3.11). This suggests the SR-PT combination has good potential for wide applicability in the Midwest. Choosing one most appropriate combination was important in this study so there was consistency in modeling among sites. Using multiple combinations would have complicated the application of these combinations in different geo-climate regions, by making it difficult to specify which combination should be used for crop modeling sweet sorghum or any other crop. Consistent use of a single combination (SR-PT) made it possible to

apply calibrated parameters from one region to other regions, even though it was not the best fit for any of the scenarios in this study. Use of these methods and statistical analysis of the yields (greater than 8-10 real world yield/model output comparison points) could solidify SR-PT further as a useful combination for crop modeling in the geo-climate regions of the central US.

Reasonable agreement was observed between RT-PM and SR-PT for grain sorghum in Riley County, even with eliminating 2001 grain yields due to hail damage. It appeared two years, 2007 and 2008, added difficulty in modeling grain sorghum with ALMANAC since those years provided substantially more rainfall in a short duration during the growing season, both in high monthly sums and multiple large events (data not shown). The long term average rainfall for April through August for Riley County area is about 500.4 mm (19.70 inches) (KSU-AESCES, 2008a); during the 2007 and 2008 seasons, rainfall was approximately 721.6 mm (28.41 inches) and 727.5 mm (28.64 inches). Much of the rainfall occurred early in the growing season, with 303.0 mm (11.93 inches) in May 2007 and 295.7 mm (11.64 inches) in June 2008, which might have provided stresses that were not adequately modeled in ALMANAC. Nonetheless, the crop performance reports (KSU-AESCES, 2007-2008b) did not suggest that the additional rainfall in short duration directly affected overall yields, so these dates were not removed from the statistical analysis. In this case ALMANAC may not represent growth conditions adequately, by overestimating average grain yields for grain sorghum during 2007 and 2008 (data not shown), and assuming the high amount of rainfall is providing adequate growth conditions for high biomass accumulation earlier in the growing season. This may be a problem with grain sorghum's small HI range (0.45–0.5) for Riley County in the original ALMANAC parameters, as biomass accumulation in Riley may be higher since there is adequate rainfall. Even with the higher biomass accumulation there is still potential for low yields due to stresses later in the growing season (specifically during flowering and grain fill for grain sorghum) which may limit grain fill even with high biomass accumulation (KSU-AESCES, 1999-2008a). This is why a wider range HI was used for Riley County's grain sorghum modeling (Table

3.4). Grain yield over estimation was not an issue for the corn yields during modeling and was not investigated further, though a wider range for HI was used due to the larger annual rainfall and increased biomass accumulation potential in Riley County (Table 3.4).

The variations in the validation scenarios used for the grain sorghum and corn may be due to inadequate information about management and planting operation details and dates. For example, for the irrigated crops, no information was available when the irrigation was applied during the months of the growing season, only the amount that was applied (OSU-CES, 2006-2008a; OSU-CES, 2006-2008b Corn, 2009). Therefore, the assumption was made that irrigation was applied in accordance with ET demand (one week with no precipitation), which may have differed from actual conditions. It would be useful for future crop performance reports to include irrigation dates and amounts to ensure accurate modeling. For the dryland grain sorghum scenario, field management for grain sorghum and previous crops might have helped improve results.

Possible plant biomass efficiency values for sweet sorghum development ranged from RUE of 3.9 to 4.95 g MJ⁻¹ (Mastrorilli, 1999; Mastrorilli, 1994; Dercas and Liakatas, 2006; Curt et al., 1998), corresponding to WA of 39.0 to 49.5 Mg ha⁻¹ MJ⁻¹. With the 20% increase recommended by Kiniry (2011, personal comm.), WA of 55 Mg ha⁻¹ MJ⁻¹ was possible, which with the 20% increase was near the theoretical estimate (4.65 g MJ⁻¹) for the maximum RUE for C₄ species calculated by Loomis and Williams (1963). Having no specific leaf area development values from literature for sweet sorghum, the leaf area development curves from Ferraris and Edwards (1986) and Mastrorilli (1999) helped provide the LAI estimates over the growing season (Table 3.9). Ferraris et al (1986) reported a list of variables for sweet sorghum, including a maximum potential leaf area index of 6, which matched grain sorghum in the ALMANAC model. Ferraris (1986) also provided harvest indices (HIs) between 0.25 and 0.6; the low values were attributed to a ratoon type harvest method, and were not used for this study. Instead the value 0.98 was chosen for the HI to represent the above ground biomass recoverable during harvest

with the assumption that not all above ground biomass is recoverable, even if crop biomass was harvested by hand. Data for biomass nutrient concentrations were only available for anthesis (used as value halfway through the growing season) (Han et al., 2010), and maturity (Han et al., 2010; Propheter, 2009). Values for nutrients concentrations were lowered until stresses for nitrogen and phosphorus were nearly zero since model results (not shown) showed stresses during development and lower yields, which may be due to the differences in nutrient concentrations for roots and shoots during development and maturity. The extinction coefficient for the final model parameters (0.59) was based on an extinction coefficient (0.58) taken from Curt et al. (1998). The value was raised slightly to 0.59 to account for a higher density of the plant populations, which Kiniry (1995) showed increased for corn and grain sorghum with higher population densities. The vapor pressure deficit/RUE (VPD2) slope value was adjusted from the literature to be slightly greater than that of corn, to account for sweet sorghum's optimal stomatal behavior over a wide range of VPD values (2.3 to 5.6 kPa), including well watered and water stressed conditions, as described by Steduto et al. (1997). There is reasonable amount of data to show that VPD has an effect on RUE as VPD increases (Stockle and Kiniry 1990; Kiniry, 1999). Further research to define the responsiveness of sweet sorghum growth to VPD would improve performance of this sweet sorghum models by confirming or providing an improved value for the VPD2 slope within the ALMANAC crop model parameter set.

Model results for sweet sorghum in Riley County in 2007 (26.70 Mg ha⁻¹) and 2008 (33.09 Mg ha⁻¹) come close to the actual values given by Propheter (2009) (27.60 and 32.20 Mg ha⁻¹), though it is important to note that these years had elevated rainfall that made it difficult to model grain sorghum grain yields in Riley County. As stated above the excess rainfall increased the biomass accumulation and may have skewed the grain sorghum grain yields in using a narrow HI range (0.45-0.5) for estimating grain yields. Widening the maximum HI and stressed HI range improved ALMANAC modeled yields in the Riley County. Since the focus of this sweet sorghum study was on total above-ground biomass

yields, and not specifically grain yields, it did not appear that, even with the access rainfall, development of the parameters were affected.

In Texas County, Oklahoma, for example, modeled output yields were close to the harvested biomass (Bellmer and Huhnke, 2007) in 2006, only being underestimated by 1.13 Mg ha^{-1} (6.7%). While the larger variance in 2007 (underestimated by 1.76 Mg ha^{-1}) may be caused by lack of management and yield information, since no dry weight value was given for the 2007 performance report (Bellmer and Huhnke, 2008), the dry weight of the biomass had to be estimated using the previous year's average moisture content average.

The deviation from the yield values in Caddo County, Oklahoma, may be due to lack of management and yield information. The sweet sorghum crop performance trials in 2006 had no dryland sweet sorghum data, while for the irrigated crop 25.4 mm (1 inch) of irrigation was applied per week during the growing season (Bellmer and Huhnke, 2007), in addition to the rainfall, which brings the total water added to the system to around 711.2 mm (28 inches) during the growing season (personal calculation). It appears with the abundant available water and the heat unit maturity value of 2300, the plant reached full maturity approximately 12 days before the first harvest date (on or before September 21, 2006 (Bellmer and Huhnke, 2007)) for the 2006 ratoon crop. The modeled value came close the recorded biomass value for the full biomass accumulation (32.54 Mg ha^{-1} -actual; 30.94 Mg ha^{-1} -modeled) suggesting that the WA was too high. After further investigation, it appeared that the higher average temperature, combined with the high WA, during May through September (data not shown) may be influencing the rapid heat unit accumulation and plant development, skewing the biomass accumulation in this region. The skewed results for this model seemed to be reflected in the development of the crop parameters in a cooler temperate climate with a shorter growing season, and average temperatures that are lower early in the growing season (calculations not shown). The variation in Caddo County, Oklahoma modeled biomass may also be in choosing the vapor pressure

deficit (VPD) slope value, suggesting the VPD2 value and WA relationship may need to be reviewed further. Only one year of comparison for irrigated sweet sorghum biomass was available for Caddo County, Oklahoma since the following year (2007) no irrigation information for the sweet sorghum trials was given. Dryland data were available for both years in the Caddo County comparison but were grossly overestimated by ALMANAC. A detailed look at the weather during this year showed an unusual rainfall pattern. In a four-month period (May-August 2007) Caddo County received approximately 863.6 mm (34 inches) of rain, which was substantially greater than the previous year's 254 mm (10 inches). This large amount of rainfall mixed with the low average biomass yields (Table 3.12) suggests that the field conditions were not adequately depicted for this region, or the sweet sorghum plants may have undergone stresses not adequately modeled in ALMANAC at this time. As described above this may be a reflection of the crop parameter development in a cooler climate region.

In Hale County, Texas, though, values fell within the range of the gathered biomass data. The limited management information combined with the variability in the rainfall amounts added difficulty in determining which variables contributed to the yield variability modeling sweet sorghum with ALMANAC.

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Chapter 4 – Conclusions and Future Work

Conclusions

The concept of modeling has been useful in many applications as described above, also seen with crop modeling in this study with development of sweet sorghum crop parameters. Various conclusions can be drawn from the review of the models in Chapter 2 and the implementation of the ALMANAC model in sweet sorghum crop parameter development in Chapter 3. The literature review during this study and conclusions from Chapters 2 and 3 bring about a variety of future research ideas for modeling and sweet sorghum crop parameter development. In the following sections conclusions from Chapters 2 and 3 will be addressed. Along with needs and potentials for future research in the area of general model development, and sweet sorghum crop parameter development that have become apparent during the time of this study.

Chapter 2

In Chapter 2 five models were reviewed (CropSyst, CERE-Sorghum, APSIM, ALMANAC, and SORKAM), with ALMANAC selected as the best suited for the development and testing of sweet sorghum crop parameters. The conclusion that ALMANAC was the best suited for sweet sorghum crop parameter development was based on a general comparison. From this generalized comparison, based on current sweet sorghum literature available and physiological data, no real conclusion can be drawn supporting superiority of one model over another. The elimination of a model from selection does not discount the usefulness or applicability of the model, although the results of the model comparison did provide a conclusive view of what published data are needed to make the non-selected models more suited for widespread sweet sorghum simulation.

From Chapter 2 results it can also be concluded that more data are needed on the physiological development stages of sweet sorghum and specific growth development factors for the other models to

be better suited for sweet sorghum crop modeling. Further research of sweet sorghum physiology could also be helpful in improving modeling results for the ALMANAC model.

Tables 2.7(ALMANAC), and 2.8(SORKAM) , 2.9 (Ceres-SORGHUM), 2.10 (CropSyst) show the results from the Chapter 2 comparison, with variables with a value of one in column A and zero in Column B would be useful in modeling sweet sorghum. From the general comparison tables future research a conclusive research focus on growth temperature (maximum, minimum, and optimal average), root dynamics (water/nutrient uptake/concentration), Leaf area behavior (senescence, specific leaf area), and maturity factors (grain fill, responses to stress) would provide the needed detail for modeling sweet sorghum.

Chapter 3

Two main conclusions can be drawn from this chapter. First the combination of Saxton and Rawls (2006) and Priestley-Taylor (1972) (SR-PT) methods in ALMANAC has the potential for wide applicability for estimating grain yields in the Central Plains, even though this combination was not selected as the best fit for any of the individual scenarios. Based on the corn silage validation scenario in Texas County, Oklahoma, ALMANAC did not appear to model corn silage biomass consistently, since it overestimated or underestimated yields each year (11.9 to 21.5%); however, the modeled values fell within or just outside the real-world harvested values given in the panhandle crop performance reports. From the available real-world/model yield results (8-10 for each scenario) few statistically conclusive statements can be made about the most suitable ET-soil water combination. Further replicates are needed from multiple sites and soil types to further gauge the statistical effectiveness of each of the combinations over a variety of scenarios. Also during the combination testing, a single set of parameters was used in both Riley and Ellis County for the ET-soil water determinations. More detailed site calibration may improve statistical values taken from each of the scenarios in the study.

Secondly, based on the development of the sweet sorghum crop model parameters, it can be concluded that ALMANAC provides reasonable accuracy in simulated biomass yields across many geo-climate regions; simulated biomass yield deviated by 0.89 to 1.76 (2.8 to 9.8%) in Kansas (Riley), Oklahoma (Texas), and Texas (Hale). As long as those regions do not provide large amounts of irrigation or have excessive rainfall (e.g., 508 mm (20 in) more than the previous year) for the geo-climate region. This occurred both years in Caddo County, Oklahoma, which allowed ALMANAC to overestimate yields for irrigated (13.66 Mg ha⁻¹, 2006) and dryland (12.31 Mg ha⁻¹, 2007) sweet sorghum. The plants in this area reached maturity much faster than any of the other regions in this study (data not show). From this it can be concluded that parameters involving RUE/WA and RUE/VPD and subroutines in ALMANAC dealing with heat unit accumulation may need to be examined further to provide clearer

representations in areas with high irrigation and or infrequent high volume rainfall events. Additionally investigation of parameter development in different geo-climate regions needs to be understood, to understand its effect on the utilization of developed crop parameters in different climate regions. The limited available sweet sorghum biomass data (>3 years) for each of these sites suggests more sweet sorghum harvested data is needed to draw further conclusions from the ALMANAC model crop parameter development.

Future Work

This section is a reflection of the model review, sweet sorghum parameter development, and the available literature for sweet sorghum. All potential future work mentioned in this section reflects thoughts about information that may provide improved model results or increased applicability of the models for sweet sorghum modeling for each of the models reviewed by providing missing sweet sorghum physiology data. These potential future work ideas may also provide data for improving the sweet sorghum crop parameters developed in this study.

Sweet Sorghum Physiology

The Radiation use efficiency (REU) values found for sweet sorghum during the literature search in this study ranged from 3.6-4.95 g MJ⁻¹ (Curt et al., 1998; Dercas and Liakatas, 2006; Mastrorilli et al., 1995). Understanding the cause of the wide range of variations of the RUE value could significantly help modeling efforts by providing means of geo-climate specific modeling parameters or providing a standard value for the RUE for sweet sorghum biomass accumulation while giving insight into the environmental effects that reduce RUE in addition to the current know reduction factors (i.e. - VPD, nutrient deficits, water stress... etc.).

Revisiting older published literature may provide answers to these questions For example radiation use efficiency across environments was determined to not vary across environments (Dewit, 1965; Sinclair and Horie, 1988; Hammer and Wright, 1994) but provided standardized field based RUE

calculations across latitudinal or geo-climate regions may provide the needed insight for the variations of the RUE values due to regional factors not apparent in regions with similar attributes (i.e., rainfall, average temperature, soil texture, incident solar radiation and or cloud cover. .. etc.). These tests may also uncover additional environmental factors that provide increased/decreased productivity providing additional information to determine the feasibility of sweet sorghum as an ethanol feedstock. Sinclair and Munchow (1999) list a variety of factors that could affect the RUE value in the environment (i.e. water/nutrient stress, direct/diffuse radiation, VPD) in their RUE literature review. They are confounded by the simple relationship proposed by Kiniry et al. (1998). Sinclair and Muchow (1999a, 1999b) suggest that such a simple relationship eliminates extensive environmental factors that affect the RUE throughout the growing season. With such a staunch conflict of on the VPD/RUE relationship, it should be investigated further. Kiniry (1999) did offer a response to Sinclair and Muchaw (1999b) offering more detail than his previously publish article.

The optimal growth temperature for sweet sorghum is also important in modeling efforts. This is important since Steduto et al. (1997) measured that sweet sorghum has optimal stomatal functions across a wide range of vapor pressure deficits (2.3 to 5.6 kPa). This may suggest that sweet sorghum may grow at wider optimal temperature range than those currently given for corn or grain sorghum.

As described above a need for research for sweet sorghum modeling is the VPD/RUE slope relationship proposed by Kiniry (1998, 1999). The bases for VPD/RUE slope was not based on an actual measured value but on the conclusions from Steduto et al. (1997) which suggested that sweet sorghum stomata operate optimally over a wide VPD range (2.3 to 5.6 kPa). In the paper published by Kiniry (1998) the vapor pressure deficit was calculated on a daily average averaged over the growing season and the value is then plotted with the RUE calculated during the none reproductive growth stages. What would help with the correlation of VPD with RUE relationship would be a comparison that was not seasonal but show more resolution throughout the growing season. Perhaps a daily comparison, if

possible, would provide the necessary information for understanding the impact of VPD on RUE, which would certainly improve modeling efforts, perhaps determining if VPD has a greater effect on RUE at lower soil moisture contents. Resolving the disagreements between Kiniry (1999) and Sinclair and Munchow (1999a, 1999b) and bring a clearer understanding how VPD effects RUE and whether or not it is as significant, as Kiniry (1998, 1999) concludes.

To allow for further development and validation of sweet sorghum physiological stages through crop modeling a better understanding of the grain fill development stages of sweet sorghum would allow some of the models compared in this study to be better suited for sweet sorghum modeling, with the review method discussed in this thesis, if this data were available.

Other specific physiological factors would also be useful in allowing the models being review better suited, such as factors for the uptake of nutrients, specifically Nitrogen/Phosphorus. For example, for further development and understanding of nutrient accumulation in sweet sorghum biomass, providing nutrient concentrations at different stages of growth (i.e., emergence, flowering, during grain fill) would provide additional values for sweet sorghum parameters to allow for other crop models, with this method of review, to be better suited for modeling sweet sorghum.

Additional biomass data provided as dry and wet biomass values and measurements with large scale field tests (≥ 1 ha (2.5 ac)) may help provide the field condition comparison for modeled data to further the development and validate sweet sorghum modeling, providing a means of solidifying sweet sorghum as a potential ethanol feedstock crop.

General Modeling

After reviewing models and climate data in during this study, it became evident that providing an alternate means for runoff estimation may provide a more accurate depiction of field conditions especially for the field scale crop models used in this study. This idea stemmed from an article found during the literature review process written by Garen and Moore (2005; Walter and Shaw, 2005), who

expressed concerns that the curve number method was being applied in ways which it was not originally designed to be implemented. The suggestions were not meant to discredit models that have used the curve number method but to urge members of the scientific community to move toward the development of an alternative estimation method. The misuses described in this article may contribute to variations in modeled field conditions that reduce modeling accuracy and precision when compared to real world environments. The development of a new runoff estimation model may provide a better understanding of surface dynamics of the soil with residue, and nutrient/sediment loss.

In general, after reviewing all the crop models in this study, it seems apparent that a modification to the radiation absorption function may be needed. Focusing on climates that have more cloud cover during the growing season, and how plants absorb radiation during clouding days is important for future work. Plant growth during the growing season in these areas may be underestimated due to a higher fraction of dispersed/direct radiant energy, which has been shown to increase radiation use efficiency as much as 0.4 g MJ^{-1} . In order to incorporate this into new models or existing models additional information may need to be collected, specifically daily cloud cover.

In recent years modeling has begun to incorporate more spatially appropriate rainfall data (Gali et al., 2007). Gali et al. (2007) incorporated Nexrad rainfall data into the SWAT model to improve modeling results. Incorporating these types of rainfall data may reduce error by ensuring rainfall distribution is more accurate and not extrapolated from rain gauge sites. Additionally, a factor incorporating storm intensity may help with erosion and runoff calculations.

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