An assessment of the potential for biomass sorghum to be produced as a dedicated bioenergy crop in Iowa, USA

by

Josh Neil Bendorf

A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Agricultural Meteorology

Program of Study Committee:
Andy VanLoocke, Co-major Professor
Emily Heaton, Co-major Professor
Sotirios Archontoulis
Kristie Franz

The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this thesis. The Graduate College will ensure this thesis is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University

Ames, Iowa

2021

DEDICATION

To my late grandfather, Virgil. You taught me the value of hard work and dedication growing up on our family's farm, and how to be a good steward of God's creation. The lessons you taught me have got me to where I am today.

TABLE OF CONTENTS

ACKNOWLEDGMENTS

I would like to extend sincere gratitude to my major professors, Andy VanLoocke and Emily Heaton, whose expertise and guidance has been much appreciated during my time as a graduate student working on this project. They have given me so much helpful feedback at lab meetings and our weekly individual meetings. A special thanks to Andy for allowing me the opportunity to be a TA for his undergraduate agronomy course. It was a great opportunity to grow as an educator and communicator. I also want to thank Sotirios Archontoulis and Kristie Franz for being on my committee and sharing their expertise with me on this project. To the amazing students and staff of the ISU Biomass lab, including Nic Boersma, Dani Clark, Jacob Studt, Patrick Edmonds, Guler (Rojda) Aslan-Sungur, Bryan Petersen, Collin de Graaf, Tyler Donovan, Perla Carmenate, Madelynn Connell, and Aaryn Graeve, thank you all for your help in collecting the field data at SABR in 2019 and 2020. Theo Hartman and Kelsie Ferin, thanks for all your help getting me going with Agro-IBIS and answering my questions along the way. To Shane Hubbard and Chris Kucharik, thank you for encouraging me to pursue graduate school during my time as an undergraduate at the University of Wisconsin, and for inspiring me to take my career in a new direction. Thank you to my family back in Wisconsin who supported my decision to pursue an advanced degree. Lastly, to all my friends in Ames and beyond, I cannot thank you enough for all your love and support over these past two years. It keeps me going!

This research was supported by the Iowa State University Department of Agronomy and the US Department of Energy's Center for Advanced Bioenergy and Bioproducts Innovation (CABBI), Grant No. DE SC0018420.

ABSTRACT

Biomass sorghum (*Sorghum bicolor* L. Moench) is an annual C_4 grass that has gained interest as a dedicated bioenergy crop due to its ability to accumulate large amounts of above-ground biomass even in sub-optimal conditions (i.e. drought). Despite the potential of biomass sorghum as an energy crop, it has not been widely grown in the US as of yet. Corn (*Zea mays* L.), another annual C_4 grass, has been produced on a large scale in the US for biofuels, especially in Midwestern "Corn Belt" states. Iowa is the nation's top producer of corn, which coincides with the state leading the nation in ethanol production. The high productivity of corn in Iowa calls to question if biomass sorghum could be as or more productive than corn in the state in terms of bioenergy. If this is true, what is the spatial pattern of the energy yield differences and what is the land availability in high-yielding regions? These questions are difficult to answer as prior biomass sorghum field trials in the state have been quite limited in space and time. Efforts have been made to use crop models to fill the gaps left by field experimentation, but have also been limited thus far. To address our research question and build on prior studies, we collect biophysical crop data on biomass sorghum grown in Iowa for two growing seasons, which are used to develop a biomass sorghum plant functional type in an agro-ecosystem model (Agro-IBIS) to predict the potential performance and sustainability of biomass sorghum produced in Iowa.

Despite dry conditions in 2019 and severe drought in 2020, biomass sorghum produced $\geq$20 Mg ha^{-1} of aboveground biomass in both years. Below the surface, biomass sorghum root samplings revealed that the crop has most of its roots concentrated near the soil surface, with approximately 73% of the root biomass above 50 cm over a 1 m depth. Using the measured field variables (biomass, leaf area index (LAI), canopy height, evapotranspiration (ET), carbon/nitrogen), the parameters of our biomass sorghum model were calibrated to within close agreement with measured biomass (slope = 1.096, R^2 = 0.91) and ET (slope = 0.784, R^2 = 0.67). Simulated biomass sorghum from our Agro-IBIS model over a 50-year period (1956-2000) revealed a notable north-to-south gradient in biomass yield, with values of >30 Mg ha^{-1} common in the southern US. Yields in Iowa were near 20 Mg ha^{-1}, close to values measured at the field site. A ten-year simulation (1998-2007) of yield across Iowa also indicated a north-to-south pattern, with a strong linear relationship between yield and seasonal growing degree days (R^2 = 0.89). Biomass sorghum had significantly higher simulated aboveground biomass than corn (≥3 Mg ha^{-1}) in the southern tier of Iowa. However, in terms of the energy ethanol yield (EEY), sorghum had the higher EEY in only 25.4% of the total state area, or 16.8% when only lands suitable for sustainable biomass harvest were included. Further research is needed to determine if improvements in climate change resiliency through breeding, efficient methods of harvest and storage, and other revenue options for harvested biomass sorghum could help make the crop a more-viable option to farmers in Iowa.

CHAPTER 1. INTRODUCTION

Background

Petroleum is the leading source for total global energy, which presents both economic and environmental issues as fossil fuels are a finite resource, tend to be sourced from volatile regions, and contribute greatly to greenhouse gas emissions to the atmosphere (IEA, 2002; IPCC, 2018). To reduce fossil fuel dependence, the US enacted the Energy Independence and Security Act (EISA) of 2007, mandating the domestic production of 36 billion gallons of biofuel by 2022, of which 21 billion gallons were to come from cellulosic (non-grain) biomass sources (US EPA, 2010). Residues from forests and agricultural crops are not expected to meet the biomass need, and thus the production of dedicated high-biomass bioenergy crops grown specifically for biofuels and bioproducts is necessary to meet the present EISA goal and future biofuel goals (Rooney *et al.*, 2007; Olson *et al.*, 2012). The IPCC projects that in order to limit global warming to 1.5 °C or less by 2050, up to 6 million km^2 of dedicated bioenergy crops is needed globally by that year, an area equivalent to 75% of the contiguous United States (IPCC, 2018). The need for bioenergy crops is known, but what is not well-know is where bioenergy crops should be grown or what bioenergy crops will be the most viable by region.

A candidate bioenergy crop that has gained strong interest in recent years is biomass (or energy) sorghum (*Sorghum bicolor* L. Moench), a high-biomass C_4 grass. Prior biomass sorghum research has been temporally and spatially limited, and thus long-term regional crop performance is not yet well understood. Therefore, it is necessary to build on previous research by utilizing field experimentation and computational modeling to determine where biomass sorghum has the potential to be a sustainable and profitable crop.

Biomass sorghum cultivars are able to accumulate large amounts of biomass due to their photoperiod sensitivity, which means it will stay in the vegetative phase long into the growing season until terminated by cold temperatures or harvest (Rooney *et al.*, 2007; Rooney, 2008; Shoemaker and Bransby, 2010; Olson *et al.*, 2012). This large amount of biomass accumulation, and the high concentration of fermentable sugars within the biomass, make the crop quite favorable for biofuel production (Shoemaker and Bransby, 2010). Sorghum is the fifth-most produced cereal crop in the world has been domesticated for centuries, it and thus has a well-established breeding program (Rooney *et al.*, 2007). Other candidate C_4 bioenergy grasses, such as perennial miscanthus (*Miscanthus* × *giganteus*) or switchgrass (*Panicum virgatum* L.), have only been domesticated recently (Rooney *et al.*, 2007). Since biomass sorghum is an annual crop, it has the potential to be implemented in existing sorghum or other annual cropping systems (Rooney *et al.*, 2007; Olson *et al.*, 2012). Biomass sorghum is also known for high drought tolerance compared to other C_4 annual grasses, and as a result exhibits higher water use efficiency, by comparison, when grown in dry conditions (Massacci, Battistelli and Loreto, 1996; Rooney *et al.*, 2007; Wagle, Kakani and Huhnke, 2016). These traits can be attributed in part to the origin of the crop in water-limited regions in Africa, as well as the long vegetative growth period of photoperiod-sensitive biomass sorghum (Rooney *et al.*, 2007; Wagle, Kakani and Huhnke, 2016). Sorghum's drought tolerance has also been attributed to a deeper root distribution and an ability to recover from prolonged hot temperatures (Pardales Jr., Yamauchi and Kono, 1991; Monti and Zatta, 2009). Such findings indicate the potential of biomass sorghum to perform well in different environments, including those less suited for corn (*Zea mays* L.) production (Rooney *et al.*, 2007; Maw, Houx and Fritschi, 2017).

High-biomass sorghum cultivars can also have value to a farmer as a forage crop. Forage sorghum varieties tend to have a lower lignin content compared to energy sorghum varieties for improved animal feed value, resulting in lower overall biomass (Rooney *et al.*, 2007; Shoemaker and Bransby, 2010). However, studies have suggested that forage varieties, due to the lower lignin content, have an increased efficiency in conversion to biofuel compared to energy sorghums (Rooney *et al.*, 2007; Shoemaker and Bransby, 2010).

Biofuel Production in Iowa

Biomass sorghum has yet to be grown on a large scale in the US, but there are annual crops currently being produced in the US (i.e. corn) on a large scale for biofuels, particularly in the Midwestern states. As of January 2020, Iowa was the top producer of ethanol in the US at 4.4 billion gallons per year, more than double that of the next-highest producing state (USDA ERS, 2019). This is due in part to Iowa's position as the nation's top producer of corn, estimated at 2.6 billion bushels in total production in the 2017 USDA Census of Agriculture (NASS, 2020). The high amount of corn production in Iowa has resulted in the state becoming the nation's leader in available residue biomass (i.e. corn stover) for cellulosic ethanol production (Ertl, 2013). The high productivity of corn in Iowa raises interest as to if biomass sorghum could have the potential to perform similarly or better than corn in terms of biomass and ethanol productivity in the Iowa agro-ecosystem. If future biofuel markets are favorable for the production of dedicated energy crops in Iowa, it will be important to identify regions where biomass sorghum ethanol yields have the potential to be greater than those of corn.

Prior studies have shown the potential of biomass sorghum to produce high yields across broad regions in the continental US. A four-year yield trial of biomass sorghum varieties reported average biomass yields of 15-25 Mg ha^{-1} across the field sites, with the highest average yields at sites in the southern US (Gill *et al.*, 2014; Lee *et al.*, 2018). Olson et al. (2012) measured yields as high as 49.5 Mg ha^{-1} under irrigated conditions in Texas, and other studies done in the southern US have reported yields of >30 Mg ha^{-1} with sufficient rainfall (Rocateli *et al.*, 2012; Yimam, Ochsner and Kakani, 2015). However, average biomass yields of 30.1 Mg ha^{-1} were achieved in Illinois with sufficient N and moisture (Maughan *et al.*, 2012), and biomass sorghum yields have been reported by Roby *et al.* (2017) to be higher than corn biomass yields under the same environmental conditions in Iowa. Maw, Houx and Fritschi (2017) found biomass sorghum to have higher biomass and ethanol yield compared to corn when grown on marginal land in Missouri. These studies highlight the potential of biomass sorghum to be competitive with corn for biofuel production in Iowa and the general Midwest region.

Although these studies determined the potential yield of biomass sorghum, they did not address the land use/cover in the regions where biomass sorghum has the potential to be produced. Strong demand for biofuels in the late 2000s contributed, in part, to a substantial increase in annual row crop acres in the US Corn Belt, including Iowa (Lark, Salmon and Gibbs, 2015; Morefield *et al.*, 2016). Most of the land converted to annual crops came from existing perennial grasslands and expired Conservation Reserve Program (CRP) lands, which tended to be more environmentally sensitive compared to prime farmland (Secchi *et al.*, 2009; Lark, Salmon and Gibbs, 2015; Morefield *et al.*, 2016). Conversion of perennial grasslands to annual crops has been shown to increase surface runoff and nutrient/sediment loss to waterways (Schilling *et al.*, 2008; Hatfield, McMullen and Jones, 2009; Secchi *et al.*, 2009), losses that are exacerbated when the conversion occurs on lands that are steeply sloped (Bendorf *et al.*, submitted). For sustainable production of an annual crop for biofuels, be it corn or biomass sorghum, the environmental benefits of clean-burning fuels considered alongside land management impacts on natural resources.

Crop Modeling

Although a substantial amount of agronomic field research has been done on biomass sorghum, the research has nonetheless been limited in that it has been performed at point locations for short periods of time. Agro-ecosystem models can be effective tools for addressing the spatial and temporal limitations of these field-based experiments. These models, built off of data from field experiments, can be used to provide agronomic insight into the effectiveness of cropping practices that are difficult to set up in a field experiment (Cabelguenne, Debaeke and Bouniols, 1999; Wallach *et al.*, 2001). Agro-ecosystem models can also be used to evaluate the environmental impacts and ecosystem services associated with crop production and management. For example, agro-ecosystem models have been used to evaluate the effects of cropping systems on water and nutrient cycling, utilizing both past climate data and future projected scenarios (Cabelguenne, Debaeke and Bouniols, 1999). Models can be used to get multi-year estimates over a wide spatial scale that would not have been feasible with field-based experimentation alone (Cabelguenne, Debaeke and Bouniols, 1999). This gives models a great value as deepening the understanding of the impact of a changing climate on our food and natural resource systems (and vice-versa) is imperative given our dependence on these systems (Foley *et al.*, 1996). However, it is emphasized that these models must be put through a thorough calibration and validation process to ensure predictive quality of the output (Wallach *et al.*, 2001).

Previous studies have utilized agricultural/environmental models to perform regional biomass sorghum simulations, which provides insight into the agronomic and environmental performance of biomass sorghum if grown across wide geographic regions. Using the PRISM-ELM model, a statistical-mechanistic model based on observed soils, weather, and yield data, Lee *et al.* (2018) found that biomass sorghum has the potential to yield >20 Mg ha^{-1} across a wide range in the central and eastern US. Kent *et al.* (2020) utilized DayCent, a biogeochemical model, to find that corn tended to have a higher energy yield compared to biomass sorghum in the Midwest, but with lower annual CO_2 emissions from biomass sorghum.

Research Objectives

To date, biomass sorghum studies in Iowa have not been prevalent in the literature and thus the breadth of biophysical data collected is low. Therefore, the data available to calibrate and validate a biophysical biomass sorghum model for Iowa is limited. Biomass yield in Midwestern states has been addressed in prior modeling efforts, but key topics not explicitly addressed include the effects of growing season climate on biomass sorghum growth, land use/land cover in regions of interest for growing biomass sorghum, and land suitability for sustainable biomass sorghum harvest. Biophysical crop models differ in how they simulate crops and ecosystem processes, and thus having multiple models (PRISM-ELM, DayCent, Agro-IBIS) to compare similar processes is necessary (Nair *et al.*, 2012).

To build on prior knowledge and address the aforementioned gaps, the following objectives are addressed in this study: (1) collection of data on several biophysical crop parameters at a research site in central Iowa over two growing seasons; (2) development of a biophysical representation of biomass sorghum in an agro-ecosystem model (Agro-IBIS) through a multi-step, multi-variable calibration/validation procedure using measured field from this and prior studies; and (3) use of our model to simulate production of biomass sorghum across Iowa and perform a comparative analysis with corn. The goal of these analyses is to gain a better understanding of the potential of biomass sorghum to be a viable dedicated energy crop for cellulosic biofuel production when grown across the range of Iowa soils and climate.

CHAPTER 2. METHODS

This study leverages both measurement and modeling practices to gain a better understanding of potential biomass sorghum production in Iowa. The agro-ecosystem model adapted in this study to simulate biomass sorghum production was the Agricultural Version of the Integrated Biosphere Simulator, or Agro-IBIS (Kucharik and Brye, 2003). To develop our biophysical model, field data was collected on biomass sorghum grown at a research farm in central Iowa over two growing seasons. Once code was added into Agro-IBIS to simulate biomass sorghum, an iterative calibration and validation process was performed to estimate values for model parameters based on the collected field data. Using this model and gridded input data, simulations of biomass sorghum production were performed over the state of Iowa. These yields were compared against modeled corn from the same time period to determine regions of interest for biomass sorghum production. Current land cover and topography data were used to determine the characteristics of land projected by our model to be the most productive for biomass sorghum.

Field Site Description

Field trials were located at the Iowa State University (ISU) Sustainable Advanced Bioeconomy Research Farm (SABR) in Boone County, IA near Ames (42.00° N, 93.70° W). During the 2019 and 2020 growing seasons, biomass sorghum was planted in a plot approximately 35,000 m^2 in size. The dominant soils of the SABR farm plot include Webster (fine-loamy, mixed, superactive, mesic typic endoaquolls), Clarion (fine-loamy, mixed, superactive, mesic typic hapludolls), and Canisteo (fine-loamy, mixed, superactive, mesic typic endoaquolls) (Soil Survey Staff, 2020). The sorghum plot at SABR contained an eddy covariance tower in the center of the plot to measure the exchange of mass and energy between the crop canopy and the atmosphere (Aslan-Sungur *et al.*, in preparation). Daily temperatures during the growth period in 2019 and 2020 were near the climatological average, with below-average precipitation in 2019 and severe drought in 2020 (refer to Results for details).

Management

Planting of high biomass sorghum hybrids (TAM varieties) occurred on 1 June 2019 and on 3 June 2020 (Table S1). Row spacing for the biomass sorghum was 0.76 m in both seasons, which is common row spacing for corn grown in central Iowa (Roby et al. 2017). Nitrogen was applied to the biomass sorghum at rates of 80 lbs. acre^{-1} in 2019 and 2020 (Table S1). Harvest was completed on 18 October 2019 and on 22 September 2020 using a large forage chopper. Harvest occurred earlier in 2020 due to a severe lodging event that occurred on 10 August. Cover crops were not planted in the sorghum plot following harvest in either season at SABR.

Biomass Sampling

Aboveground biomass samples were taken during both growing seasons, spaced to correspond with visual assessment of crop development (see Table S2 for dates). A 1 m^2 quadrat was used to randomly select a defined area of plants to sample. However, it was determined that this quadrat did not equally account for rows and inter-row spaces, which could lead to under- or over-estimation of biomass per area depending on quadrat placement. Therefore, we adjusted our sample area to include two rows and two inter-row spaces (1.54 m) along a known length of row (1 m) for a sample size of 1.54 m^2. In the case of some late-season samplings, due to large amounts of biomass, we chose to use a smaller sample size (0.38 m^2). However, due to large late-season variation in sample biomass in 2019 with the smaller sample area, we favored using the 1.54 m^2 sample area in 2020 to reduce late-season variation (refer to Results, Figure 4). For each sampling date, samples were taken at random locations in the plot (n = 4) that (1) were away from the plot edge to avoid edge affects and (2) were far away from the eddy covariance tower to avoid disrupting flux measurements. Following the methods of Roby *et al.* (2017), leaves were separated from stems at the leaf collar, placed in cloth bags, and the biomass was dried at 60 ^{o}C until it reached a constant mass. The final biomass sampling was done as close to mechanical harvest as possible. Late-season lodging occurred in the sorghum plots in both seasons, and thus during samplings only plants from non-lodged areas in the plot were sampled. Biomass samples from three sampling dates in 2019 were selected for carbon and nitrogen analysis, spaced for determining early, middle, and late season concentration differences (Table S3). Dried biomass (separated by leaves and stems) was ground in a Wiley mill (Thomas Scientific, Philadelphia, PA) to a diameter of 1 mm, from which 2-4 mg aliquots were used to determine C and N content (Wilson, 2012) in a combustion analyzer (Elementar Vario MICRO cube, Ronkonkoma, NY) with tungsten oxide added as a catalyst.

Root biomass was sampled on 4 September 2019 following the methods of Monti and Zatta (2009), for bioenergy crop root sampling. Soil cores (n = 8) were taken in the plot using a hydraulic tractor-mounted soil probe (Giddings Machine Co., Windsor, CO; depth = 100 cm, diameter = 3.81 cm). Half of the cores were done on rows and half were done on inter-rows to get a facilitate accurate representation of the root spatial distribution. Soil cores were segmented into ten increments (in cm: 0-5, 5-10, 10-15, 15-20, 20-30, 30-40, 40-50, 50-60, 60-80, 80-100) and kept in cold storage until washing. Washing was done using a hydraulic centrifuge, from which soil was washed away with pressurized water jets and the roots were collected in a 530-μm sieve (Ordonez *et al.*, 2018). Roots were then separated from other soil organic matter with tweezers and dried at 60 ^{o}C until constant weight. Segmentation of the root biomass was crucial for determining the rooting depth parameter (β), which is a constant in the root density equation determined by root distribution in the soil column. The root density equation is defined by Monti and Zatta (2009) as:

$$Y = 1 - \beta^{d} \quad (1)$$

where “d” is the soil depth in cm and “Y” is the fraction of root biomass above depth “d”. This equation is used in Agro-IBIS to model root biomass. Curve fitting of the root density function to measured root biomass was performed in MATLAB R2018b (MathWorks, 2018) to determine the rooting depth parameter for our study site.

Canopy Height & Leaf Area Index

Biomass sorghum canopy heights and leaf area index (LAI) were measured weekly or bi-weekly during the growing period (see Table S2 for dates). Canopy heights were determined using a simple straight pole with metric length delineations, and LAI measurements were taken using a LI-COR LAI-2200C Plant Canopy Analyzer (LI-COR Biosciences: Lincoln, NE). For height and LAI measurements, data were collected along four equally-spaced random rows in five equally-spaced repetitions ($n = 4 \times 5 = 20$). It was not recommended by LI-COR to take LAI measurements on days with non-uniform sky cover (i.e. broken or scattered clouds), so those days were avoided for samplings (LI-COR, 2013). Crop lodging, which occurred on 14 September 2019 and 10 August 2020, precluded late-season LAI and height measurements in both years. Data from the LAI-2200C was analyzed using the FV2200 software provided by LI-COR. Destructive LAI was also determined during biomass samplings (see Table S2 for dates) using LI-COR 3100C and 3000/3050C table meters (LI-COR Biosciences: Lincoln, NE), to ensure accuracy of the indirect, nondestructive measurements.

Model Background

Agro-IBIS is a modified version of the IBIS model (Foley *et al.*, 1996) that includes agricultural crops, and thus can be used to simulate cropping systems and their associated ecological feedbacks. Agro-IBIS can be run using either gridded climate data or single-site hourly data (Foley *et al.*, 1996; Vanloocke *et al.*, 2010). The input data is used to force a land-surface module, which simulates mass and energy exchange in the soil-plant-atmosphere system at a 60-minute time step (Foley *et al.*, 1996; Kucharik and Brye, 2003). This land-surface module feeds back into the agroecosystem functions defined in the other Agro-IBIS modules (Crop Dynamics, C & N Cycling, Crop Phenology, and Solute Transport) (Kucharik and Brye, 2003). A comprehensive diagram of the model structure is provided by Kucharik and Brye (2003) (Figure S1).

Model Development

The version of Agro-IBIS used in this study did not contain a biomass sorghum plant functional type (PFT), and thus the model code had to be updated to include biomass sorghum. Biomass sorghum code was built off of existing maize PFT code in the model, as maize and sorghum are both C_4 annual grass crops (Rooney *et al.*, 2007; Shoemaker and Bransby, 2010; Roby *et al.*, 2017). Biomass sorghum utilizes the same crop parameters and C_4 physiology (Collatz, Ribas-Carbo and Berry, 1992; Foley *et al.*, 1996) in the model as maize, but has parameter values that are unique for biomass sorghum. Test simulations were run to ensure (1) that a user could choose to run the biomass sorghum PFT and view output and (2) that the maize PFT had not been accidently changed in the code updating process. This process of using the existing C_4 grass code in Agro-IBIS to add in a new C_4 crop into the model is similar to the process used by (Vanloocke, Bernacchi and Twine, 2010) to add a miscanthus PFT into the model.

Measured field data from the SABR farm was used to determine appropriate values for the biomass sorghum model parameters through a multi-step calibration and validation process. The calibration process was done using measured 2019 data, and validation was done using 2020 data from SABR and 2014-15 data from the AEA farm (Roby *et al.*, 2017). A "cascading" calibration approach was used in this study, or a multi-tiered calibration process where two or more variables are used to optimize only a few model parameters at a time, which reduces the loss in predictive quality from estimating too many parameters at once (Wallach *et al.*, 2001). Before the calibration, all biomass sorghum parameters were either (1) set to maize values or (2) set to sorghum values found in literature; several grain-filling parameters were set so that the modeled crop would not set grain (Table 1). Biomass sorghum termination was determined by the first of either (1) cold temperatures (28°F, or -2.2°C: Staggenborg *et al.*, 1996) or (2) an arbitrary latest harvest date of December 1st based on grain sorghum harvest records from USDA NASS. Maximum (38°C) and base temperatures (10°C) for GDD accumulation, along with minimum 10-day average temperature for planting (12°C), were set to representative grain sorghum values (Table 1: Gerik, Bean and Vanderlip, 2003; Roozeboom and Vara Prasad, 2019).

The first tier of the cascading calibration was done by adjusting only parameters for which we had biophysical measurements, with the goal of reducing error between measured SABR and modeled aboveground biomass data (Figures 1, 2). The range of field measurements for LAI, canopy height, root biomass, biomass C & N content, and specific leaf area were used to determine parameter ranges in the calibration. An R script (R Core Team, 2019) was used to run the model for thousands of parameter combinations efficiently (https://github.com/TheoHartman/Agro_IBIS_Sensitivity). Root-mean-square error (RMSE), a common metric for determining model performance, was used to determine the “best-fit” parameter values (Wallach *et al.*, 2001; Esmaeili *et al.*, 2014). The “best-fit” parameter set resulted in the lowest RMSE between measured and modeled biomass data points, and thus was used for simulations.

Once the values for parameters adjusted in the first tier of the calibration were determined, a second-tier calibration was done to optimize canopy parameters (with the first-tier parameter values set) using SABR measured and modeled evapotranspiration data (Figures 1, 2). Parameter ranges were determined based on (1) literature values and/or (2) estimated based on the parameter values of other crops in the model, especially those for maize. Evapotranspiration (ET) data for SABR was measured by the eddy covariance tower (LI-COR Biosciences: Lincoln, NE) in the sorghum plot (Aslan-Sungur *et al.*, in preparation). Following the methodology of the first-tier biomass calibration, daily measured values for the 2019 season were compared against daily modeled ET to determine the best-fit parameter set. Validation was done for three seasons (2014-15 from Roby *et al.* (2017), 2020 from SABR) using measured biomass data. It is important to do a validation to other seasons to determine the predictive quality of the calibrated model parameters (Wallach *et al.*, 2001).

Meteorological Data

For single-site model simulations done for the SABR farm (hereafter referred to as “SABR simulations”), the input weather data used was hourly data from the Iowa State Agricultural Engineering & Agronomy (AEA) Farm in Boone County, IA (42.02° N, 93.78° W) located approximately 10 km from SABR following a similar methodology to Edmonds et al., 2017. Data was retrieved from the Iowa Environmental Mesonet (https://mesonet.agron.iastate.edu/). Precipitation data from SABR rain gauges (Texas Electronics, TR-525) was used for days when it was available for the single-site runs (July 2019 – December 2020). Large-scale regional simulations were run using 0.5-degree gridded climate data from the Climate Research Unit (CRU: University of East Anglia, U.K., 2019) and the National Centers for Environmental Protection (NCEP: NOAA, 2019) reanalysis datasets. The CRU dataset is provided at a monthly timestep for 1901-2018, and the NCEP datasets are provided at a daily timestep for 1948-2018 (Kucharik, 2003; Vanloocke, Bernacchi and Twine, 2010). For the Iowa state-level simulations, a higher-resolution climate dataset (~8 km) developed by ZedX, Inc. (Bellefonte, PA) was used to run the model. The ZedX dataset is provided at a daily timestep for 1948-2007 (Kucharik *et al.*, 2013). This dataset was chosen for the state-level simulation as it provided at a higher resolution compared to the CRU-NCEP dataset.

Model Simulations

Before running a simulation with Agro-IBIS, a “spin-up” and “restart” run has to be completed in order to build up the soil carbon and nitrogen pools (Kucharik, 2003; Vanloocke, Bernacchi and Twine, 2010; Edmonds, 2017; Ferin *et al.*, 2021). The spin-up period was from 1750-1910, where natural vegetation (no agricultural crops) are grown for 160 years to simulate pre-settlement ecology. Following the spin-up, the restart run is a period from 1911 to the first year of the actual simulation. In the restart period, agricultural crops that are representative of regional production are simulated to be grown on the landscape following settlement. For Iowa, the crops grown during the restart period were corn and soybeans. The spin-up and restart runs combined are how the model represents land use/land cover prior to a crop simulation, and thus is not starting from year one for each simulation (Kucharik, 2003).

Model simulations were run at multiple scales in this study. Previous biomass sorghum modeling efforts (Lee *et al.*, 2018; Kent *et al.*, 2020) were performed on the scale of the continental United States, in particular for areas east of the Rocky Mountains. Therefore, using the new Agro-IBIS biomass sorghum module, a long-term simulation (1956-2000) was run using the 0.5-degree resolution CRU-NCAR dataset ("US simulation") for comparison of average biomass yield with prior biomass sorghum modeling results (Lee *et al.*, 2018; Kent *et al.*, 2020) and data from yield trials (Gill *et al.*, 2014; Lee *et al.*, 2018). The domain of this simulation was all US regions between 75.75° W and 115.25° W longitude, which includes the Mississippi Atchafalaya River Basin, or MARB (Ferin *et al.*, 2021). The US simulation is also useful for contextualizing smaller-scale runs, such as those performed for Iowa in this study. State-level runs for Iowa ("Iowa simulations") were performed using the most recent ten years of the ZedX dataset (1998-2007). As mentioned above, the ZedX dataset was used to force the Iowa simulations due to its higher resolution. Soils are described in the model by layer, with 11 layers totaling 2.5 m in depth (Vanloocke, Bernacchi and Twine, 2010). Gridded soil texture by layer, defined on the same grid as the input meteorological data, is used to force model simulations (Soil Survey Staff, 2019).

Corn-Sorghum Comparison

Comparison of corn and biomass sorghum was performed using model output from the Iowa simulations. Mapping and analysis of model output was performed using ArcGIS Desktop 10.8.1 (ESRI, 2018). Model output (NetCDF file format) was imported into ArcGIS as a raster file, and was then subsequently converted into a shapefile. Biomass yield comparison was done using yearly biomass yield output from Agro-IBIS. Modeled corn biomass yields were averaged to the Iowa counties and compared against actual county-level yield data to ensure accuracy

(NASS, 2020). For a comparison of energy ethanol yield (EEY), total aboveground biomass was first converted into theoretical ethanol yield (TEY) using the conversion factors for corn stover (0.29 L ethanol $[kg\ DM]^{-1}$), corn grain (0.42 L ethanol $[kg\ DM]^{-1}$), and sorghum leaf and stem biomass (0.27 L ethanol $[kg\ DM]^{-1}$) used by Roby *et al.* (2017) (Chandel *et al.*, 2010; RFA, 2016). TEY was converted to EEY using the lower heating value for ethanol (21.2 MJ $[L\ ethanol]^{-1}$) (Persson *et al.*, 2010). Harvest fraction for corn biomass included all grain and 45% stover removal, which is the recommended sustainable stover removal fraction (Ertl, 2013). For biomass sorghum, 90% of above-ground biomass was harvested (Kent *et al.*, 2020). These harvestable fractions were then converted to EEY using the conversion factors stated above.

Current land cover characteristics of the ZedX grid cells were determined using the 2019 USDA Cropland Data Layer to assess the land cover in regions of interest for biomass sorghum production (CDL: NASS, 2019). The CDL is provided as a 30m resolution raster dataset. For each grid cell, ArcGIS was used to calculate (1) the amount of area in corn production and (2) the amount of "plantable" (land that could be potentially converted to row crops) per grid cell. Plantable lands included lands that were (1) not currently in row crop production and (2) not in urban/developed, forests, or open water land covers. Common plantable land covers included grasslands/pasture, alfalfa, hay, and small grains (Bendorf *et al.*, submitted).

Slope characteristics of each grid cell was calculated following a similar methodology, using 30m USGS 3DEP elevation data (USGS, 2020). For each grid cell, the area of land at 2% slope or less was calculated. It is not recommended to remove corn stover on lands that are greater than 2% slope (Ertl, 2013), and thus removing large amounts of sorghum biomass on such lands is likely to not be sustainable. Thus, for any pixels where <10% of the total area was at or below 2% slope, it was assumed no sorghum would be produced. This 90:10 percentage ratio is comparable to the logic used in Schulte *et al.* (2017), with at least 10% of steeply-sloped cropland in a conservation-minded practice (i.e. only removing large amounts of biomass on lands ≤2% slope) to reduce soil and nutrient loss. Sorghum was also assumed to not be grown in pixels where corn production comprised <10% of the cell area, indicative of small amounts of land dedicated to annual row crops.

CHAPTER 3. RESULTS

Here we present the findings from our analysis of potential biomass sorghum production in Iowa. These findings include growing season climate at the field site; crop growth and development; carbon and nitrogen content of the leaves, stems and roots; model calibration and validation to current and prior data; and regional simulations of biomass sorghum and corn using the Agro-IBIS model.

Climate

For both the 2019 and 2020 growing seasons, daily mean temperatures tended to be close to the 1981-2018 climatological average (Figure 3, Table 2). Both seasons started out with periods of above-average temperatures in June and early July, with colder-than-average temperatures noted at the end (Figure 3). Monthly growing degree day (GDD) accumulation was higher in 2020 than in 2019 through August. However, there were 115 more GDD (°C) accumulated by harvest in 2019 due in part to a later harvest and above-average September temperatures in that year (Table 2). Accumulated precipitation was below the climatological average for the majority of both seasons (Figure 3, Table 2). The 2019 season began with near-average precipitation, followed by a dry period in August and then a rebound to above-average precipitation in the fall (Figure 3, Table 2). This resulted in drought conditions in the late summer of 2019 (Table 3; USDM, 2020). A more-severe drought affected parts of central Iowa in the summer of 2020, as noted in monthly precipitation totals of <50% of the long-term average in June-August (Tables 2, 3). Every month of the 2020 season was below average (Table 2), which resulted in seasonal accumulated precipitation of <50% of the climatological average by harvest in 2020 (Figure 3).

Crop Growth & Development

Despite the drought conditions in 2020, aboveground biomass accumulation was similar between the two seasons. During the summer months, average biomass in 2020 was approximately 2-4 Mg ha^{-1} higher than on the same respective day in 2019 (Figure 4). However, by mid-September, the 2019 crop had the higher biomass, which coincided with cooler and drier conditions during this time in 2020 (Table 2). Final end-of-season average aboveground biomass was 16.6 (±5.9) Mg ha^{-1} and 17.8 (±2.1) Mg ha^{-1} in 2019 and 2020, respectively (Figure 4). However, there was a large amount of variation around these means due to highly-variable stem densities between hand harvests (data not shown). In 2019, the final harvest date had a lower mean biomass than the preceding date, but there was no indication in the plot of biomass decline as no leaf drop or senescence was noted. Also, the day-of-year (DOY) 261 standard error is within the DOY 274 standard error, and thus it was assumed that crop biomass was not declining after DOY 261.

Canopy height and leaf area index (LAI) measurements reveal similar crop development patterns compared to biomass. Both the canopy height and LAI in the 2020 crop were greater than the 2019 crop until late August (DOY 230-235, Figure 5). Mean sorghum canopy height reached maximums of 3.2 (±0.3) m and 3.1 (±0.1) m in 2019 and 2020, respectively. However, in both seasons, the maximum height was measured during the last sampling date before harvest and thus further growth may have been possible (Figure 5). Destructive and non-destructive LAI measurements were in close agreement with each other, but non-destructive measurements were stopped early in both in 2019 and 2020 after severe lodging events from strong thunderstorms (Figure 5). Maximum mean LAI measured between the two methods were 9.51 (±1.5) and 8.33

(±1.7) in 2019 and 2020, respectively; these values were measured using the destructive LAI methodology (Figure 5).

Root cores pulled in 2019 reveal that the biomass sorghum grown at SABR had most of its roots concentrated near the soil surface. On average, over 50% (52 ± 9%) of the sorghum root biomass were above 20 cm depth in the soil profile, with over 70% (73 ± 6%) above the 50 cm depth (Figure 6). Performing a curve-fit of the root density equation to the average root biomass fraction by depth, a rooting depth parameter (β) of 0.9682 (R^2 = 0.92) was found (Figure 6). Root biomass was larger and more concentrated towards the soil surface with on-row cores (β = 0.9611) versus inter-row cores (β = 0.9729).

Biomass Composition

Chemical analysis was performed on samples from three hand harvests (DOY 198, 241, & 274) in 2019. On average, the biomass sorghum above-ground dry matter was 42.52% (±3.65%) carbon and 2.20% (±1.28%) nitrogen by mass (Table S3). Average leaf biomass concentrations of carbon (44.2%) and nitrogen (2.7%) were higher than those of the stem biomass (40.9%; 1.7%). Biomass composition changed from early to late season, with average carbon concentration increasing between the first and last hand harvests (40.4 vs 44.9%, respectively). Nitrogen concentration, however, decreased over the same time period (3.8% vs 0.9%, respectively).

Model Calibration & Validation

In the first tier of the two-tiered calibration process, five above-ground parameters (vegetative leaf carbon fraction, maximum LAI, maximum canopy height, specific leaf area, dry biomass carbon concentration) and two below-ground parameters (β, vegetative root carbon fraction) relevant to biomass accumulation were adjusted within a range of measured values from the field. The parameters optimized in the second tier of the calibration included five crop canopy parameters (quantum efficiency, leaf respiration coefficient, slope & intercept of stomatal conductance-water vapor relationship, maximum Rubisco activity at 15°C (V_{max})) to find an overall "best-fit" set between biomass and ET. These values are represented in Table 1. Some notable parameters values that distinguish biomass sorghum from maize include higher heat tolerance, no grain fill, higher LAI, taller crops, minimal root biomass, lower specific leaf area, and a higher V_{max}.

The overall "best-fit" parameter set yielded a strong linear relationship (slope = 1.096, R^2 = 0.91) between measured vs. simulated aboveground biomass, with simulated values being slightly high (Figure 2). The comparison of measured vs. simulated ET also shows a strong linear relationship (R^2 = 0.67), but simulated ET was slightly underestimated (slope = 0.784, Figure 2). Simulated root biomass was evaluated against measured data from 2019; on the sampling date (4 September), the simulated root biomass (1.40 Mg ha^{-1}) was within the standard error of the measured data (1.46 ± 0.37 Mg ha^{-1}). For the three validation seasons (2014, 2015, 2020), a linear regression reveals that Agro-IBIS under-estimated the early-season data points (intercept = -3.2 Mg ha^{-1}) and over-estimated the higher biomass values (slope = 1.325). Despite this, there was a strong linear relationship between measured and simulated biomass (R^2 = 0.88) and the 95% confidence interval on the linear fit on the data points included the 1:1 line (Figure S2). The sorghum grown in 2020 was the same genotype as was grown in the calibration year (different than 2014-15), and of the three validation years 2020 had the strongest correlation (R^2 = 0.99) and slope closest to the 1:1 line (1.126) between measured and modeled output (data not shown). A qualitative comparison of the measured vs. modeled 10 cm soil temperature and moisture was performed and confirmed that the crop's physical soil environment was simulated with reasonable accuracy (Figure S3, S4). Modeled crop variables other than above-ground biomass, including 2020 ET (Figure S5) and 2019-20 LAI (Figure S6), reveal some notable deviations from measured values but overall are reasonable. Leaf area index, however, is consistently underestimated in our simulations early in the season.

Regional Sorghum Simulations

The fifty-year (1956-2000) simulation of biomass sorghum across the portion of the US included in the MARB show a distinct north-to-south gradient in the aboveground biomass produced. Aboveground biomass ranged from <5 Mg ha^{-1} near the Canada-US border to >35 Mg ha^{-1} close to the Gulf of Mexico (Figure 7). Simulated average biomass totals of ≥20 Mg ha^{-1} reached into the Corn Belt states, including southern portions of Iowa, Illinois, Indiana, and Ohio. When compared to results from a four-year (2009-12) yield trial of biomass sorghum (Gill *et al.*, 2014; Lee *et al.*, 2018), the simulated values were within the range of measured values for the northern and central sites (Iowa, Kansas, Kentucky, North Carolina; Figure 7). However, simulated values were higher than the range of measured yield in Texas and Mississippi. It should be noted, however, that the modeled biomass sorghum was harvested later (late November, on average) in the far southern US compared to the yield trial (September-October).

Simulated average biomass sorghum aboveground biomass in Iowa also showed a distinct north-to-south pattern, ranging from less than 18 Mg ha^{-1} in the far north to over 27 Mg ha^{-1} in the southeastern corner (Figure 8). Overall, simulated biomass tended to be higher in the south compared to the north. Near the calibration/validation site, simulated biomass averaged between 21-24 Mg ha^{-1}, close the Iowa state average of 22 Mg ha^{-1} (Figure 8). Yield variability around the mean was in the range of 15-25% of the mean, with higher year-to-year variability noted in the north (Figure S7). Biomass exhibited a high linear correlation to accumulated GDD

($R^2 = 0.89$), with biomass above the state average associated with total GDD above the state average and vice-versa (Figures 9, S8). Sites with below-average simulated sorghum biomass tended to have precipitation on the extremes, whereas sites with near-average precipitation tended to have higher biomass. For sites with similar total GDD, simulated biomass tended to be higher as precipitation increased, especially for sites with below-average biomass (Figure 9). The relationship between simulated biomass and seasonal precipitation was notable but not as strong as with GDD ($R^2 = 0.44$, quadratic fit). Simulated growing season length also varied substantially between northern and southern Iowa. Planting occurred, on average, 10-15 days earlier in the south compared to the north, and vice-versa for the geographic pattern of harvest dates (Figure 10a, b).

Corn-Sorghum Comparison

Relative to simulated corn from 1998-2007, biomass sorghum aboveground biomass tended to be at or above corn aboveground biomass. On average, simulated biomass sorghum had 1 Mg ha^{-1} or more biomass than corn in the southern counties of Iowa (Figure 11a). The higher simulated sorghum biomass was statistically significant ($p < 0.05$) in most of south central and southeast Iowa, where biomass was ≥3 Mg ha^{-1} greater than corn (Figure 11a). Simulated corn produced more biomass, on average, in northeast and north central Iowa. Northwest Iowa was either neutral or had slightly (1-3 Mg ha^{-1}) higher biomass with sorghum. However, it should be noted that simulated corn grain yields trended below county-level averages in the northwest, as well as above-average in the south (data not shown).

The majority of the model grid cells in Iowa met our criteria for being suitable for sustainably harvesting sorghum biomass (>10% of area at <2% slope; Figure 12). Grid cells not suitable for harvesting sorghum are concentrated in the northeast and south central parts of the state (Figure 12b, in red). These cells, along with cells that have low (<10% of total area) existing corn production, were denoted as areas where sorghum production area would be minimal based on our criterion for sustainable harvest (Figure 11b). In comparison to the total biomass yield, the energy ethanol yield (EEY) analysis reveals that biomass sorghum had a higher EEY compared to corn in only 22.5% of the state (8,106,761 ac, Table 4). Areas in the far southern parts of Iowa and along the Missouri River had higher average EEY yields from biomass sorghum, but this difference was not statistically significant (Figure 11b). In the far southeast, biomass sorghum EEY was at most ≥2 MJ m^{-2} more than corn. The south central region had a notable amount of grid cells that were non-sorghum producing based on our land use/slope criterion, and of the total area in which biomass sorghum had the higher EEY, 25.4% was in such regions. This reduced our area of potential biomass sorghum production in Iowa to 6,049,763 acres, 16.8% of the entire state area (Table 4). On a state level, the areas in Iowa where simulated biomass sorghum dry biomass yields tended to be highest were in regions where plantable land area was higher (R^2 = 0.23, Figure 13). This coincide with the higher-yielding areas in southern Iowa as being characterized by low amounts of land in corn production and more in plantable lands (Figure 14).

CHAPTER 4. DISCUSSION

Context of Study

The purpose of our study was to use simulated agronomic and environmental variables from our biomass sorghum model to determine regions in Iowa where biomass sorghum has the most potential to be a viable option for farmers if a cellulosic ethanol market develops. We developed our model through the collection of field data from biomass sorghum grown at a research farm (including aboveground biomass, root biomass, canopy height, LAI, evapotranspiration, and specific leaf area), performing a two-tiered, multi-variable model calibration-validation process using this collection of measured field data, and running state-level yield simulations of corn and biomass sorghum. To date, biomass sorghum modeling efforts have been limited due to limited measured field data. The current study is unique to biomass sorghum research in that we include both a field measurement and modeling analysis to address the aforementioned limitations, with an explicit examination of potential future land use conversion to biomass sorghum. Our results indicate that while biomass sorghum does have the potential to produce biomass yields of $\geq$20 Mg ha^{-1} across the majority of Iowa, the crop produced a higher EEY compared to corn in only a small southern fraction of the state. The implications of these findings and considerations for the future competitiveness of biomass sorghum in Iowa are discussed in the proceeding sections.

Measurements Build on Prior Studies

The average end-of-season aboveground biomass measured at the SABR farm plots were 16.6 ($\pm$5.9) Mg ha^{-1} in 2019 and 17.8 ($\pm$2.1) Mg ha^{-1} in 2020 (Figure 4). These values are similar to findings from prior studies conducted in central Iowa. At a site near Ames, Roby *et al.* (2017) measured mean biomass sorghum leaf and stem dry matter of 19.1 Mg ha^{-1} in over two seasons with ample rainfall. Gill *et al.* (2014) measured similar values in a four-year yield trial of energy sorghum varieties in Ames (11.5-17.4 Mg ha^{-1}) with a September harvest. Yields of high-biomass sorghum varieties grown in Missouri (just to the south of Iowa) range from 8.7-20.9 Mg ha^{-1} (Maw, Houx and Fritschi, 2017; Maw, Houx and Fritschi, 2017). In a fertilizer rate trial at sites in Illinois (lower latitudes than Ames), peak yields ranged from 20.4-35.1 Mg ha^{-1}, with highest yields at the southernmost site (Maughan *et al.*, 2012). Moore *et al.*, 2020 measured an average peak biomass sorghum aboveground dry matter yield of 23.0 Mg ha^{-1} near Urbana, IL in 2018. Peak LAI in both seasons at SABR exceeded 8 m^2 m^{-2} across methods of measurement. These values are higher than prior measured values of 5.1-5.6 for sorghum grown in central Iowa using similar methodology (Roby *et al.*, 2017). However, peak LAI values exceeding 8 m^2 m^{-2} have been measured in Illinois (Moore *et al.*, 2020) and Texas (Olson *et al.*, 2012). To our knowledge, these crop did not suffer from lodging. Our measured canopy heights of 3-4 m correspond with those measured by Roby *et al.* (2017).

It has been widely suggested in prior literature that biomass sorghum is very tolerant of dry conditions (Massacci, Battistelli and Loreto, 1996; Rooney *et al.*, 2007; Olson *et al.*, 2012; Wagle, Kakani and Huhnke, 2016; Roby *et al.*, 2017). Our study corroborates this suggestion in that during two dry growing periods, which include a severe drought in 2020, no substantial impacts to crop productivity were observed. In 2019, a year in which precipitation was below normal during the peak growing period, total growing season ET (June-October) was measured at 411 mm, which corresponds to an average water-use efficiency (cumulative biomass to total water lost through ET) of 4.04 g C [mm H_2O]$^{-1}$. This value is higher than the mean water-use efficiencies of 3.47 g C [mm H_2O]$^{-1}$ (Roby *et al.*, 2017) and 3.04 g C [mm H_2O]$^{-1}$ (Moore *et al.*, 2020) measured in the Midwest during more-optimal conditions. Other studies, however, have found that biomass sorghum yields did substantially decrease under drought conditions. During an exceptional drought (D4, USDM) in Oklahoma in the summer of 2011, biomass sorghum yields reached 4.4 Mg ha^{-1} (Yimam, Ochsner and Kakani, 2015). During the same time period in Missouri (D0, USDM), yields of 8.7-13.0 Mg ha^{-1} were observed, notably lower than in more-optimal conditions (Maw, Houx and Fritschi, 2017). This suggests that biomass sorghum grown on Iowa soils may be more resilient to drought compared to other regions of the US.

Comparison of Modeling Results

Our model output for a 50-year simulation suggest that yields tend to increase at lower latitudes, with the highest yields in the far southeastern US. These values corroborate with measured values from field trials, which suggest a similar geospatial pattern (Figure 7). Results from Kent *et al.* (2020) suggest a very similar pattern across the US, with both the DayCent and Agro-IBIS models suggesting average biomass sorghum potential dry matter yields of near 20 Mg ha^{-1} in Iowa and other Corn Belt states. Likewise, Lee *et al.* (2018) report similar findings from their statistical modeling of biomass sorghum with PRISM-ELM. However, larger differences between model projections occur further to the south. Agro-IBIS predicts higher simulated biomass (≥30 Mg ha^{-1}) in the in the southeastern US compared to regions further north. However, this trend is not evident in the output of the DayCent or PRISM-ELM models, where yields in the far southeast are similar to those in the Corn Belt. Biomass sorghum parameters in Agro-IBIS allow the plant to grow until either (1) frost termination or (2) December 1st, with planting occurring as soon as soil temperatures are sufficiently warm enough. Therefore, the growing period will be longer in the south (warmer spring and fall compared to the north) and thus higher yields can be achieved. This was shown in the linear regression of GDD and biomass sorghum yield in Iowa (Figure 9). The yield trial results mapped on Figure 7 indicate that average yields are highest in the southeastern sites, with yields of near or above 30 Mg ha^{-1} measured in non-drought years in this and other experiments in southeastern locations (Olson *et al.*, 2012; Rocateli *et al.*, 2012; Yimam, Ochsner and Kakani, 2015). It is unclear as to when planting and harvest were assumed for the DayCent and PRISM-ELM simulations, and thus growing season length is uncertain. Therefore, we are confident that our results are representative of potential future biomass sorghum production.

The north-to-south gradient was again evident in Iowa in that biomass sorghum produced higher biomass yields than corn in the south, corresponding to GDD increasing from north to south (Figures 11a, S3). However, when we converted these biomass numbers to EEY, corn was the higher-producing crop across the vast majority of Iowa with the exception of the far southern counties (Figure 11b). A corn-biomass sorghum EEY comparison performed with DayCent by Kent *et al.* (2020) found similar results in that corn produced 1-2 MJ m^{-2} yr^{-1} of EEY more than sorghum in Iowa, with the largest difference in the north. Analysis of output from DayCent and Agro-IBIS indicate that southern Iowa is the region in the state where biomass sorghum has the potential to be competitive with corn in terms of energy/biofuel production. In the southeast and south-central counties, where biomass sorghum yields were projected to be highest, average corn yields tend to be the lowest in the state due in part to issues brought about by poorly-drained soils (Al-Kaisi *et al.*, 2015; Iowa State University Extension & Outreach, 2020).

It should be noted that our modeled corn yields were compared against county-level NASS yields (Iowa State University Extension & Outreach, 2020) to ensure that model output was accurate. It was determined that modeled corn grain yields were within 0.63 Mg ha^{-1} (10 bu ac^{-1}) of measured values in the majority of Iowa counties, with greater over-estimation of yield in the south and under-estimation in the northwest (Figure S9). Yield discrepancies could potentially be a result of management changes that have been implemented to improve yields that are not included in our model. One example of such a practice is tile drainage, which is prevalent in Iowa agricultural fields and has been estimated to significantly increase corn yields (Helmers et al., 2012; Kassel, 2018; Valayamkunnath et al., 2020). Another management practice that was tested in this study to resolve model under-estimation of yield was adding manure application (Lark *et al.*, in review) in our fertilizer inputs to the corn crop in our model simulations. However, this did not result in any substantial yield changes in our corn output (data not shown). Regional yield over-estimation, such as that in southern Iowa, may be due to a topography with a wide range of slopes being over-simplified by a more-coarse simulation resolution (illustrated in Figure 12), leading to steeper areas being “flattened-out” in the simulations. In a prior Agro-IBIS study comparing modeled and measured corn yield, Kucharik (2003) found similar model error in these portions of Iowa for corn yield. Thus, it is possible that biomass sorghum could likely have more of a dry matter yield advantage in southern Iowa than our results suggest. The fraction of corn stover harvested is also an important factor in determining which crop has the advantage, with sorghum having a larger advantage as less stover is harvested for cellulosic ethanol (data not shown).

Implication of Findings

Our field measurements and model projections indicate that biomass sorghum has the potential to yield, on average, over 20 Mg ha^{-1} across the majority of Iowa, but on a state level, corn is projected to be the more-productive annual crop in terms of biofuel conversion. However, model results suggest that biomass sorghum has the potential to do well in regions not as well-suited for corn (i.e. southern counties). Maw, Houx and Fritschi (2017) found that on land classified as marginal, biomass and sweet sorghums tended to produce significantly higher dry matter yields compared to corn, which corresponded to significantly higher TEY. However, it has been shown that energy sorghum hybrids produce much higher TEY when grown on more suitable cropland (Tang *et al.*, 2018). Thus, meeting ethanol production goals will be challenging if biomass sorghum production is focused only on marginal lands.

From our analysis of potential future land use conversion to biomass sorghum in Iowa, it was found that where biomass sorghum was projected to produce the highest yields (southern region) are dominated by plantable lands versus existing corn land. This region is also characterized by more steeply-sloped highly erodible land (Figure 12; Secchi *et al.*, 2009). Southern Iowa has a large area of land in the CRP program compared to the rest of the state, but increased demand for ethanol is expected to reduce this amount as growing crops for biofuels becomes more profitable for farmers (Secchi *et al.*, 2009). Conversion of CRP and/or other plantable lands (pasture, hay, grasslands, small grains, etc.) to an annual crop like energy sorghum could lead to substantial environmental impacts, such as increased nitrogen leaching, soil erosion, and surface runoff (Schilling *et al.*, 2008; Hatfield, McMullen and Jones, 2009; Secchi *et al.*, 2009; Qi *et al.*, 2011; Bendorf *et al.*, submitted). In the Raccoon River basin in central Iowa, increases in annual row crop production have shown strong correlation to flow-weighted NO_3 concentration in rivers (Hatfield, McMullen and Jones, 2009). Annual precipitation has been on the rise in Iowa over the last several decades, with 1990-2013 being the wettest 23-year period on record dating back to the early 1600s (Ford, 2014). Given the steep topography of this region, environmental issues associated with increased rainfall, such as increased surface runoff and flooding, may be more pronounced than in a less-sloped region (Schilling *et al.*, 2008; Secchi *et al.*, 2009; Bendorf *et al.*, submitted). Therefore, if market conditions are favorable for producing biomass sorghum in Iowa, management practices will be crucial to ensuring that the production of this crop is sustainable.

One such management practice would be to plant cover crops, such as winter rye, which have been shown to significantly reduce nitrate leaching from corn and soybean systems in Iowa without any significant changes in the cash crop yield (Qi *et al.*, 2011). In a study conducted by Rocateli *et al.* (2012) in Alabama, biomass sorghum produced as much as 30.1 Mg ha^{-1} of biomass with a rye cover crop, but it was not determined explicitly if the cover crop treatment significantly changed yields. A separate research study at the SABR farm is being conducted at the time of this study to determine biomass sorghum performance under a rye cover crop in Iowa. No-till is another conservation practice that can reduce soil erosion without significant decreases in biomass sorghum yield (Rocateli *et al.*, 2012); corn yields at sites in Southern Iowa were found to not be significantly different between reduced and conventional tillage (Al-Kaisi *et al.*, 2015). In cellulosic biomass cropping systems, no-till or reduced tillage in encouraged to retain soil organic carbon on landscapes where large amount of biomass for ethanol are being removed (Ertl, 2013). Lastly, precision agriculture platforms can be leveraged to strategically implement conservation practices, such as the placement of perennials in low-yielding areas in fields (Brandes *et al.*, 2018) or as buffer (prairie) strips on hillslopes (Schulte *et al.*, 2017). These practices allow annual crops to be grown in the majority of the field while greatly reducing the loss of nutrients to waterways. Precision agricultural tools can also be used to determine optimum fertilizer rates for different parts of the field, which helps increase farmer return on investment as well as reduce NO_3 leaching and N_2O emissions (McNunn *et al.*, 2019). Cropping system models, such as Agro-IBIS, could be used to investigate potential land management changes and inform precision ag support tools.

There is the potential, given sorghum's long history as a domesticated crop and robust breeding program, that continued efforts can be made to increase crop productivity through breeding (Rooney, 2008; Leakey *et al.*, 2019). Such improvements could include increased drought stress tolerance, more favorable composition for efficient biofuel conversion, and/or increased photosynthetic capacity (Rooney, 2008; Leakey *et al.*, 2019). These traits will likely become even more advantageous in future climates. Another advantage biomass sorghum has over corn in terms of climactic stress is that it is non-grain filling. Grain is a substantial amount of the aboveground biomass of corn, and it has been shown that heat stress during the grain filling period can greatly reduce grain (and biomass) yields (Rooney, 2008; Ferin, 2020). In a study where Agro-IBIS was forced with projected future climate data, corn yields in Iowa were expected to decline in the warmer environment (Xu, Twine and Girvetz, 2016; Ferin, 2020). Sorghum has been shown to be resilient to increased climactic stresses and can recover after the stressed period (Pardales Jr., Yamauchi and Kono, 1991; Massacci, Battistelli and Loreto, 1996), and that the genetic improvements mentioned above can increase this resiliency under future climates (Leakey *et al.*, 2019).

Future Considerations

This study has provided insight into the potential of biomass sorghum to be a dedicated energy crop in the state of Iowa, from which new research questions can arise. Our modeling results suggest that biomass sorghum's highest potential in Iowa is in the southern tier of the state. Extensive agronomic field trials of biomass sorghum in Iowa have thus far been concentrated in the Ames area, and so to test the predictions of Agro-IBIS, it would be highly beneficial to establish trials across the state. A major agronomic and environmental issue to address with the production of a crop is how much nitrogen fertilizer should be applied. Prior field studies suggest that biomass sorghum does not require over 56 kg N ha^{-1} to produce high yields (Maughan *et al.*, 2012; Maw, Houx and Fritschi, 2017; Schetter *et al.*, 2020). Yield response to fertilizer applied can be simulated in Agro-IBIS through "FNOPT", a critical leaf nitrogen level parameter (below which nitrogen-stress occurs), as low levels have leaf nitrogen levels have been shown to inhibit plant growth (Archontoulis *et al.*, 2012). Testing the sensitivity of biomass sorghum yield in Ames to fertilizer rate by setting a representative value for FNOPT from the literature (0.018, Table 1), it was determined that yields decline below 56 kg N ha^{-1} by 1-2 Mg ha^{-1}, but stay relatively constant above that rate (Figure S10). This is similar to what was found in prior studies, but lack of fertilizer rate field data in Iowa limited this analysis and thus it was tabled for future work. Agro-IBIS can also be used to simulate the effects of future climate on biomass sorghum in Iowa using modeled future climate data, and crop improvements through breeding can also be modeled due to the detailed canopy-level parameterization of plants in the model.

The biomass sorghum model that we developed in this study is, in essence, a "prototype" biomass sorghum model developed around a single genotype to be harvested for biofuel. The detailed biophysical parameterization of the Agro-IBIS biomass sorghum module means that crop improvements (such as those stated above) can be simulated and/or tested through the adjustment of model parameters in current or future climates. Parameters can also be adjusted to simulate other biomass sorghum genotypes, which is valuable given the genetic diversity of sorghum (Rooney *et al.*, 2007). A yield trial of biomass sorghum in southeast Iowa containing over 500 hybrids revealed a wide range in end-of-season yield (<10 – >30 Mg ha^{-1}) at a single site (Salas-Fernandez, 2016). The hybrid that was grown at SABR may in fact not be the highest-yielding option for production in Iowa. In fact, given the modeled vs. measured differences in the current study, especially in LAI, it may be that our model is more representative of one of the other high-biomass sorghum cultivars. Technological improvements in the biofuel conversion process could increase the amount of biofuel derived from biomass sorghum feedstock. Research is currently being conducted to determine the available methods for increasing the lipid production and extraction from cellulosic feedstock, which would increase the quantity and quality of the biofuels produced (Singh, Arora and Singh, 2021). Biomass sorghum feedstock may also have value in other usages outside of biofuels. As mentioned above, certain high-biomass sorghum cultivars can have value to a livestock producer as forage for their animals. Sorghum has also been studied as a potential feedstock for biogas production, a methane-rich gaseous product which can be derived through the anaerobic digestion of biomass feedstock. Similarly to biofuels, biogas produced from biomass sorghum feedstock would help offset greenhouse gas emissions when used in place non-renewable fuels for heat, power, and/or electricity (Weiland, 2010; Wannasek *et al.*, 2017). The potential usage and/or conversion of feedstock to product will be key drivers in determining what sorghum genotypes are grown, and the Agro-IBIS model can be adapted to simulate the productivity of that genotype.

Future work should also focus on factors, other than yield, that will impact the economic viability of growing dedicated energy crops. One such factor is the distance to the biorefinery where farmers will be taking their biomass for conversion to ethanol. Increased distance to the biorefinery results in greater monetary and energy costs associated with transporting the biomass (Persson *et al.*, 2010). Right now, there are very few ethanol plants that can produce cellulosic ethanol in Iowa (Ertl, 2013). There are also the costs associated with harvesting and storing the biomass, and if any extra equipment or infrastructure will be needed for harvest and/or storage (Ertl, 2013).

CHAPTER 5. CONCLUSION

In the current study, we utilized both field measurements and computational crop modeling to increase the agronomic and environmental knowledge of potential biomass sorghum production in Iowa, a highly productive agricultural state in the Midwest US. This work was motivated by the increasing interest in growing dedicated bioenergy crops to help offset the negative environmental impacts of non-renewable energy sources (i.e. fossil fuels). Results from our research site show that biomass sorghum can produce over 20 Mg ha^{-1} of aboveground dry matter even during a dry growing season; during a severe drought in 2020, no substantial crop impacts were noted. This finding speaks highly of the potential of biomass sorghum to be quite resilient of drought conditions in Iowa. Through the biophysical model that was developed in Agro-IBIS from our collected field data, a distinct north-to-south gradient was found in potential average biomass yield. Biomass yields showed a high linear correlation to growing season length, with average yields of >25 Mg ha^{-1} in the southern tier of Iowa where the accumulated growing degree days are highest. When the modeled aboveground biomass from biomass sorghum was compared to that of corn, an annual bioenergy crop currently being produced in Iowa, it was found that biomass sorghum produced significantly higher biomass yields in the south and vice-versa for corn in the north. However, when we assume a harvest fraction of the aboveground dry matter and convert that amount to an EEY, corn is the more productive crop across the majority of the state. Biomass sorghum has a marginally higher EEY in the far southern portion of Iowa, however this number may be underestimated due to overestimated corn productivity in this region by Agro-IBIS.

In conclusion, although biomass sorghum shows the potential to produce high yields in Iowa even under sub-optimal conditions, it struggles to be competitive with corn in the state in terms of biofuel production. It is possible that through improvements through breeding, biomass sorghum will become more competitive, particularly through increased crop resiliency to changing climate. Best management of biomass sorghum must also be considered in future studies in Iowa as our results show that in areas where the crop is the most productive are regions characterized by more-sloped land in plantable land covers. Lastly, biomass sorghum's competitiveness with corn will be a factor of the producer costs associated with the management, harvest, and storage of the crop material. However, it is possible that other revenue sources of harvested biomass sorghum will be available to a producer, such as from forage or biogas. As demand for clean-burning fuels and renewable energies increases, further investigation on these topics will become increasing valuable.

REFERENCES

Al-Kaisi, M. M. *et al.* (2015) ‘Tillage and Crop Rotation Effects on Corn Agronomic Response and Economic Return at Seven Iowa Locations’, *Agronomy Journal*, 107(4). doi: 10.2134/agronj14.0470.

Archontoulis, S. V *et al.* (2012) ‘Leaf photosynthesis and respiration of three bioenergy crops in relation to temperature and leaf nitrogen: how conserved are biochemical model parameters among crop species?’, *Journal of Experimental Botany*, 63(2), pp. 895–911. doi: 10.1093/jxb/err321.

Aslan-Sungur, G. *et al.* (2021) ‘SABR Farm ET Flux Paper’. Manuscript in preparation.

Bendorf, J. *et al.* (2021) ‘Farming on a Slippery Slope: Rapid Changes in Agricultural Land Use & Hydrology in the Driftless Region’. Manuscript submitted for publication.

Brandes, E. *et al.* (2018) ‘Targeted subfield switchgrass integration could improve the farm economy, water quality, and bioenergy feedstock production’, *GCB Bioenergy*, 10, pp. 199–212. doi: 10.1111/gcbb.12481.

Cabelguenne, M., Debaeke, P. and Bouniols, A. (1999) ‘EPICphase, a version of the EPIC model simulating the effects of water and nitrogen stress on biomass and yield, taking account of developmental stages : validation on maize, sunflower, sorghum, soybean and winter wheat’, *Agricultural Systems*, 60, pp. 175–196.

Chandel, A. K. *et al.* (2010) ‘Key drivers influencing the commercialization of ethanol-based biorefineries’, *Journal of Commercial Biotechnology*, 16(3), pp. 239–257. doi: 10.1057/jcb.2010.5.

Climatic Research Unit (CRU), University of East Anglia, U.K. (2019) *High-resolution gridded datasets (and derived products).* Available at: https://crudata.uea.ac.uk.

Collatz, G. J., Ribas-Carbo, M. and Berry, J. A. (1992) ‘Coupled Photosynthesis-Stomata1 Conductance Model for Leaves of C4 Plants *’, *Austrailian Journal of Plant Physiology*, 19.

Edmonds, P. M. (2017) *A Comparison of Conventional Annual and Alternative Perennial Cropping Systems Under Contemporary and Future Precipitation Scenarios in the US Prairie Pothole Region*, *Graduate Theses and Dissertations*. Available at: https://lib.dr.iastate.edu/etd/15298.

Ertl, D. (2013) ‘Sustainable Corn Stover Harvest’. Available at: https://www.researchgate.net/publication/319493290.

Esmaeili, S. *et al.* (2014) ‘Quantitative global sensitivity analysis of the RZWQM to warrant a robust and effective calibration’, *Journal of Hydrology*. Elsevier B.V., 511, pp. 567–579. doi: 10.1016/j.jhydrol.2014.01.051.

ESRI (Environmental Systems Research Institute). ArcGIS Desktop, Version 10.6.1 (2018) Redlands, CA.

Ferin, K. M. (2020) *A multi-spatial scale analysis of land use and climate change impacts on water quality and crop productivity for major US cropping systems*, *Graduate Theses and Dissertations*. Available at: https://lib.dr.iastate.edu/etd/18307.

Ferin, K. M. *et al.* (2021) 'Water Quality Effects of Economically Viable Land Use Change in the Mississippi River Basin under the Renewable Fuel Standard', *Environmental Science & Technology*, 55, pp. 1566–1575. doi: 10.1021/acs.est.0c04358.

Foley, J. A. *et al.* (1996) 'An integrated biosphere model of land surface processes, terrestrial carbon balance, and vegetation dynamics', *Global Biogeochemical Cycles*, 10(4), pp. 603–628.

Ford, T. W. (2014) 'Precipitation anomalies in Eastern-Central Iowa from 1640 - Present', *Journal of Hydrology*. Elsevier B.V., 519(PA), pp. 918–924. doi: 10.1016/j.jhydrol.2014.08.021.

Gerik, T., Bean, B. and Vanderlip, R. (2003) *Sorghum Growth and Development*. Available at: http://texasextension.tamu.edu.

Gill, J. R. *et al.* (2014) 'Yield Results and Stability Analysis from the Sorghum Regional Biomass Feedstock Trial', *Bioenergy Research*, 7, pp. 1026–1034. doi: 10.1007/s12155-014-9445-5.

Hatfield, J. L., McMullen, L. D. and Jones, C. S. (2009) 'Nitrate-nitrogen patterns in the Raccoon River Basin related to agricultural practices', *Journal of Soil and Water Conservation*, 64(3), pp. 190–199. doi: 10.2489/jswc.64.3.190.

Helmers, M. J. et al. (2012) 'Nitrogen loss on tile-drained Mollisols as affected by nitrogen application rate under continuous corn and corn-soybean rotation systems', *Canadian Journal of Soil Science*, 92, pp. 493–499. doi: 10.4141/CJSS2010-043.

IEA (2002) *World Energy Outlook 2002*. Paris: OECD Publishing. Available at: https://doi.org/10.1787/weo-2002-en.

Iowa State University (2020) *Iowa Environmental Mesonet*. Available at: https://mesonet.agron.iastate.edu.

Iowa State University Extension & Outreach (2020) *Historical Corn Yields by County in Iowa*. Available at: www.extension.iastate.edu/agdm.

IPCC (2018) 'Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change', in Masson-Delmotte, V. et al. (eds).

Kassel, P. (2018) ‘Field Drainage’, *Field & Feedlot - Iowa State University Extension & Outreach Northwest Region*.

Kent, J. *et al.* (2020) ‘Simulated Biomass Sorghum GHG Reduction Potential is Similar to Maize’, *Environmental Science & Technology*, 54, pp. 12456–12466. doi: 10.1021/acs.est.0c01676.

Kucharik, C. J. (2003) ‘Evaluation of a Process-Based Agro-Ecosystem Model (Agro-IBIS) across the U . S . Corn Belt : Simulations of the Interannual Variability in Maize Yield’, *Earth Interactions*, 7(14).

Kucharik, C. J. *et al.* (2013) ‘Miscanthus Establishment and Overwintering in the Midwest USA : A Regional Modeling Study of Crop Residue Management on Critical Minimum Soil Temperatures’, *PLOS ONE*, 8(7). doi: 10.1371/journal.pone.0068847.

Kucharik, C. J. and Brye, K. R. (2003) ‘Integrated BIosphere Simulator (IBIS) Yield and Nitrate Loss Predictions for Wisconsin Maize Receiving Varied Amounts of Nitrogen Fertilizer’, *Journal of Environmental Quality*, 32, pp. 247–268.

Lark, T. J., et al. ‘Environmental outcomes from the US Renewable Fuel Standard.’ Manuscript under review.

Lark, T. J., Salmon, J. M. and Gibbs, H. K. (2015) ‘Cropland expansion outpaces agricultural and biofuel policies in the United States’, *Environmental Research Letters*. IOP Publishing, 10(4), p. 44003. doi: 10.1088/1748-9326/10/4/044003.

Leakey, A. D. B. *et al.* (2019) ‘Water Use Efficiency as a Constraint and Target for Improving the Resilience and Productivity of C3 and C4 Crops’, *Annual Review of Plant Biology*, 70, pp. 781–808.

Lee, D. K. *et al.* (2018) ‘Biomass production of herbaceous energy crops in the United States : field trial results and yield potential maps from the multiyear regional feedstock partnership’, *GCB Bioenergy*, 10, pp. 698–716. doi: 10.1111/gcbb.12493.

LI-COR (2013) *LAI-2200 Plant Canopy Analyzer Instruction Manual*. Lincoln, NE: LI-COR, Inc. Available at: www.licor.com.

Massacci, A., Battistelli, A. and Loreto, F. (1996) ‘Effect of Drought Stress on Photosynthetic Characteristics , Growth and Sugar Accumulation of Field-grown Sweet Sorghum’, *Austrailian Journal of Plant Physiology*, 23, pp. 331–340.

MATLAB (2018) *version 9.5.0 (R2018b)* Natick. Massachusetts: The MathWorks Inc.

Maughan, M. *et al.* (2012) ‘Forage and Energy Sorghum Responses to Nitrogen Fertilization in Central and Southern Illinois’, *Agronomy Journal*, 104(4), pp. 1032–1040. doi: 10.2134/agronj2011.0408.

Maw, Michael J.W., Houx, J. H. I. and Fritschi, F. B. (2017) 'Maize, sweet sorghum, and high biomass sorghum ethanol yield comparison on marginal soils in Midwest USA', *Biomass and Bioenergy*. Elsevier Ltd, 107, pp. 164–171. doi: 10.1016/j.biombioe.2017.09.021.

Maw, Michael J W, Houx, J. H. I. and Fritschi, F. B. (2017) 'Nitrogen Use Efficiency and Yield Response of High Biomass Sorghum in the Lower Midwest', *Agronomy Journal*, 109(1), pp. 115–121. doi: 10.2134/agronj2016.01.0044.

McNunn, G. *et al.* (2019) 'Using a Crop Modeling Framework for Precision Cost-Benefit Analysis of Variable Seeding and Nitrogen Application Rates', *Frontiers in Sustainable Food Systems*, 3. doi: 10.3389/fsufs.2019.00108.Creative.

Monti, A. and Zatta, A. (2009) 'Root distribution and soil moisture retrieval in perennial and annual energy crops in Northern Italy', *Agriculture, Ecosystems and Environment*, 132, pp. 252–259. doi: 10.1016/j.agee.2009.04.007.

Moore, C. E. *et al.* (2020) 'Ecosystem-scale biogeochemical fluxes from three bioenergy crop candidates : How energy sorghum compares to maize and miscanthus', *GCB Bioenergy*, 0, pp. 1–14. doi: 10.1111/gcbb.12788.

Morefield, P. E. *et al.* (2016) 'Grasslands, wetlands, and agriculture: The fate of land expiring from the Conservation Reserve Program in the Midwestern United States', *Environmental Research Letters*, 11(9). doi: 10.1088/1748-9326/11/9/094005.

Nair, S. S. *et al.* (2012) 'Bioenergy crop models: descriptions, data requirements, and future challenges', *GCB Bioenergy*, 4, pp. 620–633. doi: 10.1111/j.1757-1707.2012.01166.x.

National Oceanic & Atmospheric Administration (NOAA) (2019) *NCEP/NCAR Global Reanalysis Products: 1948-continuing.* Available at: /data/gridded/data.ncep.reanalysis.html.

Olson, S. N. *et al.* (2012) 'High biomass yield energy sorghum: developing a genetic model for C4 grass bioenergy', *Biofuels, Bioproducts, & Biorefining*, 6, pp. 640–655. doi: 10.1002/bbb.

Ordonez, R. A. *et al.* (2018) 'A solution for sampling position errors in maize and soybean root mass and length estimates', *European Journal of Agronomy*, 96, pp. 156–162. doi: 10.1016/j.eja.2018.04.002.Rights.

Pardales Jr., J. R., Yamauchi, A. and Kono, Y. (1991) 'Growth and Development of Sorghum Roots after Exposure to Different Periods of a Hot Root-Zone Temperature', *Environmental and Experimental Botany*, 31(4), pp. 397–403.

Persson, T. *et al.* (2010) 'Simulating the production potential and net energy yield of maize-ethanol in the southeastern USA', *European Journal of Agronomy*. Elsevier B.V., 32(4), pp. 272–279. doi: 10.1016/j.eja.2010.01.004.

Qi, Z. *et al.* (2011) 'Nitrate-Nitrogen Losses through Subsurface Drainage under Various Agricultural Land Covers', *Journal of Environmental Quality*, 40(September). doi: 10.2134/jeq2011.0151.

R Core Team (2019) *R: A language and environment for statistical computing.* R Foundation for Statistical Computing, Vienna, Austria. Available at: https://www.R-project.org/.

RFA (2016) *Pocket Guide to Ethanol 2016*. Renewable Fuels Association. Available at: www.EthanolRFA.org.

Roby, M. C. *et al.* (2017) 'Biomass sorghum and maize have similar water-use-efficiency under non- drought conditions in the rain-fed Midwest U.S.', *Agricultural and Forest Meteorology*. Elsevier, 247, pp. 434–444. doi: 10.1016/j.agrformet.2017.08.019.

Rocateli, A. C. *et al.* (2012) 'Biomass sorghum production and components under different irrigation/tillage systems for the southeastern U.S.', *Industrial Crops & Products*. Elsevier B.V., 36, pp. 589–598. doi: 10.1016/j.indcrop.2011.11.007.

Rooney, W. L. *et al.* (2007) 'Designing sorghum as a dedicated bioenergy feedstock', *Biofuels, Bioproducts, & Biorefining*, 1, pp. 147–157. doi: 10.1002/bbb.

Rooney, W. L. (2008) 'Sorghum', in *Cellulosic Energy Cropping Systems*. John Wiley & Sons, Ltd., pp. 109–129.

Roozeboom, K. L. and Vara Prasad, P. V. (2019) 'Sorghum Growth and Development', in *Sorghum: A State of the Art and Future Perspetives*. John Wiley & Sons, Ltd. doi: 10.2134/agronmonogr58.2014.0062.

Salas-Fernandez, M. (2016) 'Sorghum Biomass Yield for Biofuel Production in Iowa Sorghum Biomass Yield for Biofuel Production in Iowa', *Farm Progress Reports*: Vol. 2015: Iss. 1, Article 153.

Schetter, A. *et al.* (2020) 'Photoperiod Sensitive Energy Sorghum Responses to Environmental and Nitrogen Variabilities', pp. 1–37. Available at: https://doi.org/10.1101/2020.11.03.366898.

Schilling, K. E. *et al.* (2008) 'Impact of land use and land cover change on the water balance of a large agricultural watershed: Historical effects and future directions', *Water Resources Research*, 45(7), pp. 1–12. doi: 10.1029/2007WR006644.

Schulte, L. A. *et al.* (2017) 'Prairie strips improve biodiversity and the delivery of multiple ecosystem services from corn–soybean croplands', *Proceedings of the National Academy of Sciences of the United States of America*, 114(42), pp. 11247–11252. doi: 10.1073/pnas.1620229114.

Secchi, S. *et al.* (2009) 'Corn-Based Ethanol Production and Environmental Quality : A Case of Iowa and the Conservation Reserve Program', *Environmental Management*, 44, pp. 732–744. doi: 10.1007/s00267-009-9365-x.

Shoemaker, C. E. and Bransby, D. I. (2010) 'The Role of Sorghum as a Bioenergy Feedstock', in Braun, R., Karlen, D., and Johnson, D. (eds) *Sustainable Feedstocks for Advanced Biofuels*. Soil and Water Conservation Society, pp. 149–159.

Singh, R., Arora, A. and Singh, V. (2021) 'Bioresource Technology Biodiesel from oil produced in vegetative tissues of biomass – A review', *Bioresource Technology*. Elsevier Ltd, 326. doi: 10.1016/j.biortech.2021.124772.

Soil Survey Staff, Natural Resources Conservation Service (NRCS), United States Department of Agriculture (2020) *Web Soil Survey*. Available at: http://websoilsurvey.sc.egov.usda.gov.

Soil Survey Staff, Natural Resources Conservation Service (NRCS), United States Department of Agriculture (2019) *Gridded Soil Survey Geographic (gSSURGO) Database for Iowa.* Available at: http://websoilsurvey.sc.egov.usda.gov.

Staggenborg, S. A. *et al.* (1996) *Fall Freeze Damage in Summer Grain Crops*. Manhattan, Kansas.

Tang, C. *et al.* (2018) 'Bioethanol Potential of Energy Sorghum Grown on Marginal and Arable Lands', *Frontiers in Plant Science*, 9. doi: 10.3389/fpls.2018.00440.

United States Drought Monitor (USDM) (2020) *Comprehensive Statistics.* Available at: https://droughtmonitor.unl.edu/Data/DataDownload/ComprehensiveStatistics.aspx.

United States Geological Survey (USGS) (2020) *3D Elevation Program*. Available at: https://www.usgs.gov/core-science-systems/ngp/3dep.

US Environmental Protection Agency (EPA) (2010) 'Regulation of Fuels and Fuel Additives: Changes to Renewable Fuel Standard Program', *Federal Register*, 75(58), pp. 14670–14904.

USDA Economic Research Service using data from: Renewable Fuels Association (2019) *RFA Ethanol Industry Outlook.* Available at: https://www.ers.usda.gov/data-products/us-bioenergy-statistics/.

USDA National Agricultural Statistics Service (2019) *CropScape – Cropland Data Layer*. Available at: http://nassgeodata.gmu.edu/CropScape.

USDA National Agricultural Statistics Service (2020) *Quick Stats*. Available at: https://quickstats.nass.usda.gov.

Valayamkunnath, P. et al. (2020) 'Mapping of 30-meter resolution tile-drained croplands using a geospatial modeling approach', *Scientific Data*, 7, pp. 1–10. doi: 10.1038/s41597-020-00596-x

Vanloocke, A. *et al.* (2010) 'A regional comparison of water use efficiency for miscanthus , switchgrass and maize', *Agricultural and Forest Meteorology*. Elsevier B.V., 164(December), pp. 82–95. doi: 10.1016/j.agrformet.2012.05.016.

Vanloocke, A., Bernacchi, C. J. and Twine, T. E. (2010) 'The impacts of Miscanthus x giganteus production on the Midwest US hydrologic cycle', *GCB Bioenergy*, 2, pp. 180–191. doi: 10.1111/j.1757-1707.2010.01053.x.

Wagle, P., Kakani, V. G. and Huhnke, R. L. (2016) 'Evapotranspiration and Ecosystem Water Use Efficiency of Switchgrass and High Biomass Sorghum', *Agronomy Journal*, 108(3), pp. 1007–1019. doi: 10.2134/agronj2015.0149.

Wallach, D. *et al.* (2001) 'Parameter Estimation for Crop Models : A New Approach and Application to a Corn Model', *Agronomy Journal*, 93(4), pp. 757–766.

Wannasek, L. *et al.* (2017) 'Sorghum, a sustainable feedstock for biogas production? Impact of climate, variety and harvesting time on maturity and biomass yield', *Biomass and Bioenergy*. Elsevier Ltd, 106, pp. 137–145. doi: 10.1016/j.biombioe.2017.08.031.

Weiland, P. (2010) 'Biogas production : current state and perspectives', *Applied Microbiology and Biotechnology*, 85, pp. 849–860. doi: 10.1007/s00253-009-2246-7.

Wilson, D. M. (2012) 'Where's the nitrogen ? The timing and impacts of internal nitrogen cycling on switchgrass (Panicum virgatum L .) yield and biofuel quality', *Graduate Theses and Dissertations*, 12518.

Xu, H., Twine, T. E. and Girvetz, E. (2016) 'Climate Change and Maize Yield in Iowa', *PLOS ONE*, pp. 1–20. doi: 10.1371/journal.pone.0156083.

Yimam, Y. T., Ochsner, T. E. and Kakani, V. G. (2015) 'Evapotranspiration partitioning and water use efficiency of switchgrass and biomass sorghum managed for biofuel', *Agricultural Water Management*. Elsevier B.V., 155, pp. 40–47. doi: 10.1016/j.agwat.2015.03.018.

FIGURES & TABLES

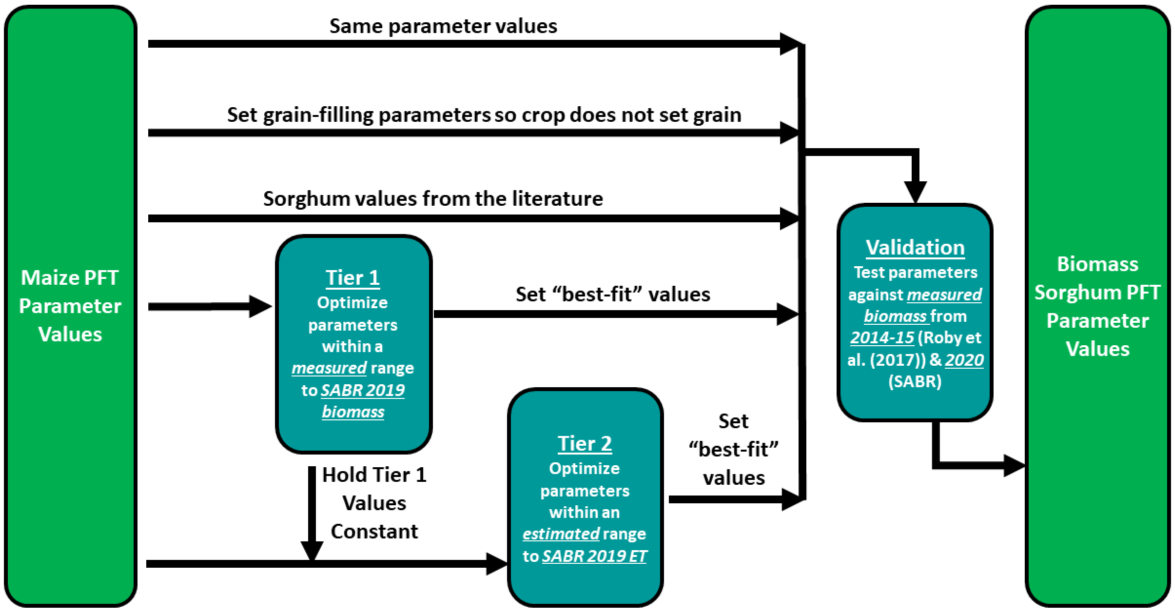

Figure 1: Schematic diagram of the process used to determine the biomass sorghum PFT parameter values in Agro-IBIS

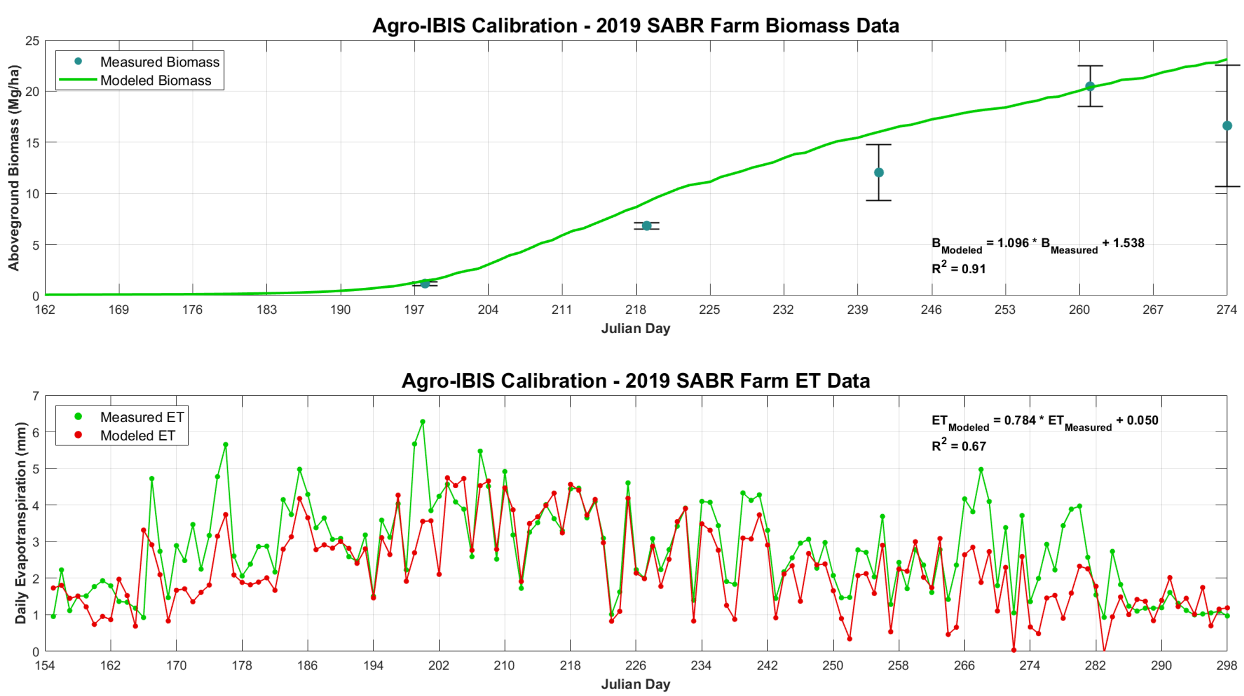

Figure 2: Calibration of the Agro-IBIS biomass sorghum PFT to measured biomass and ET data from the SABR farm in 2019

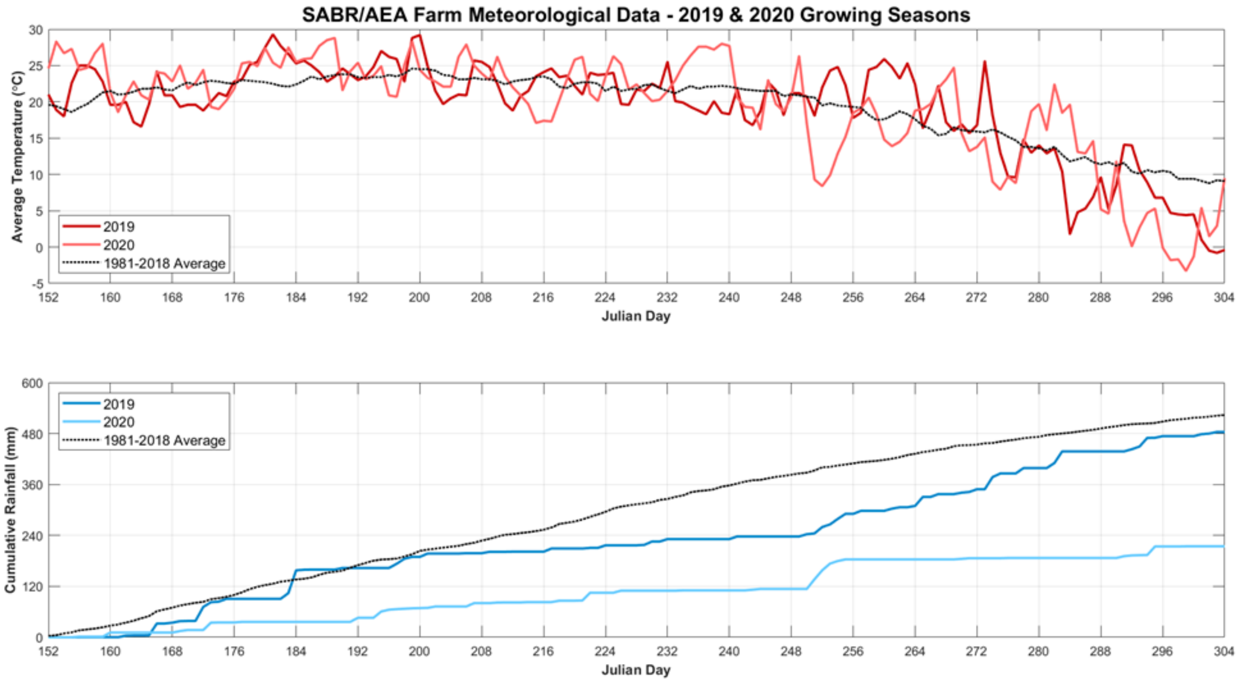

Figure 3: SABR/ISU-AEA farm meteorological data from 2019 and 2020, including daily climatological means (1981-2018)

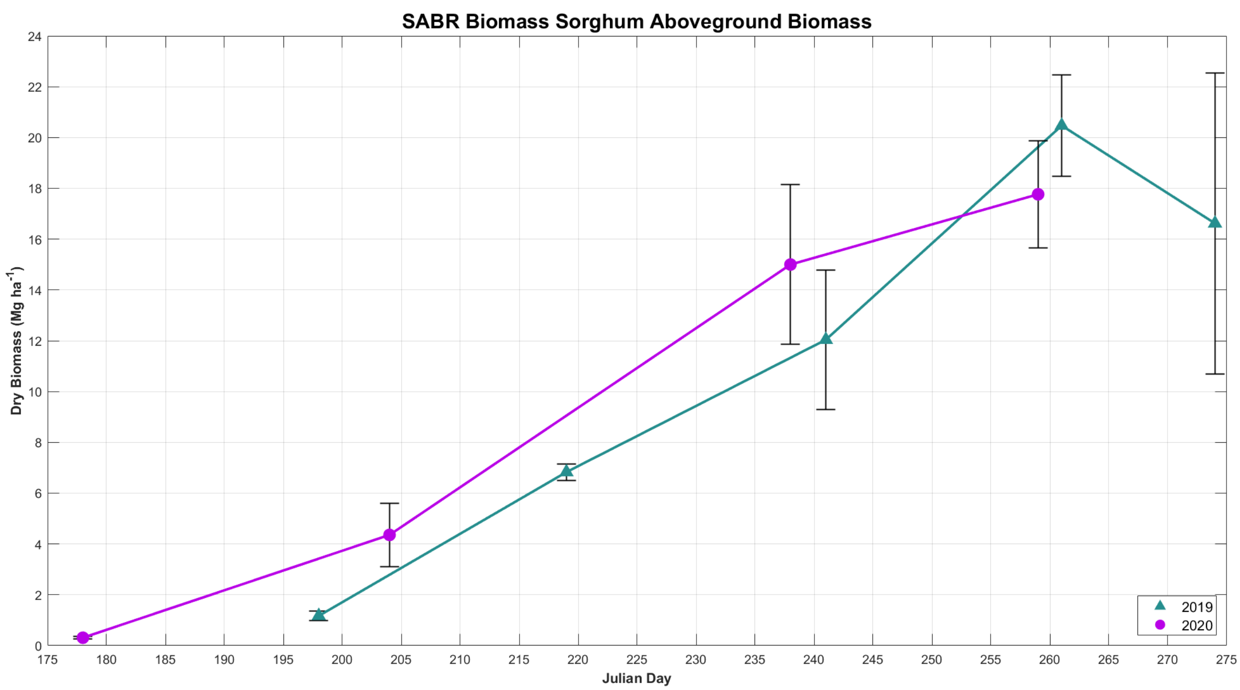

Figure 4: SABR farm biomass sorghum aboveground dry leaf & stem biomass, 2019 & 2020 seasons

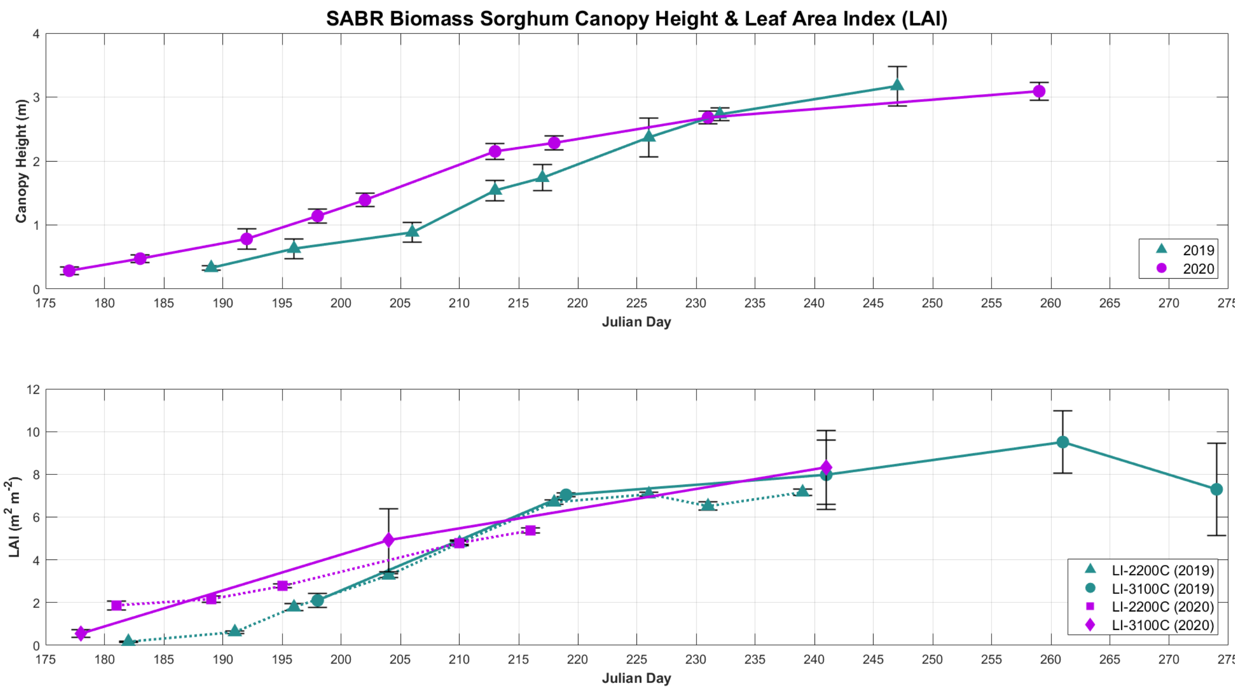

Figure 5: SABR farm biomass sorghum canopy height & leaf area index (LAI), 2019 & 2020 seasons

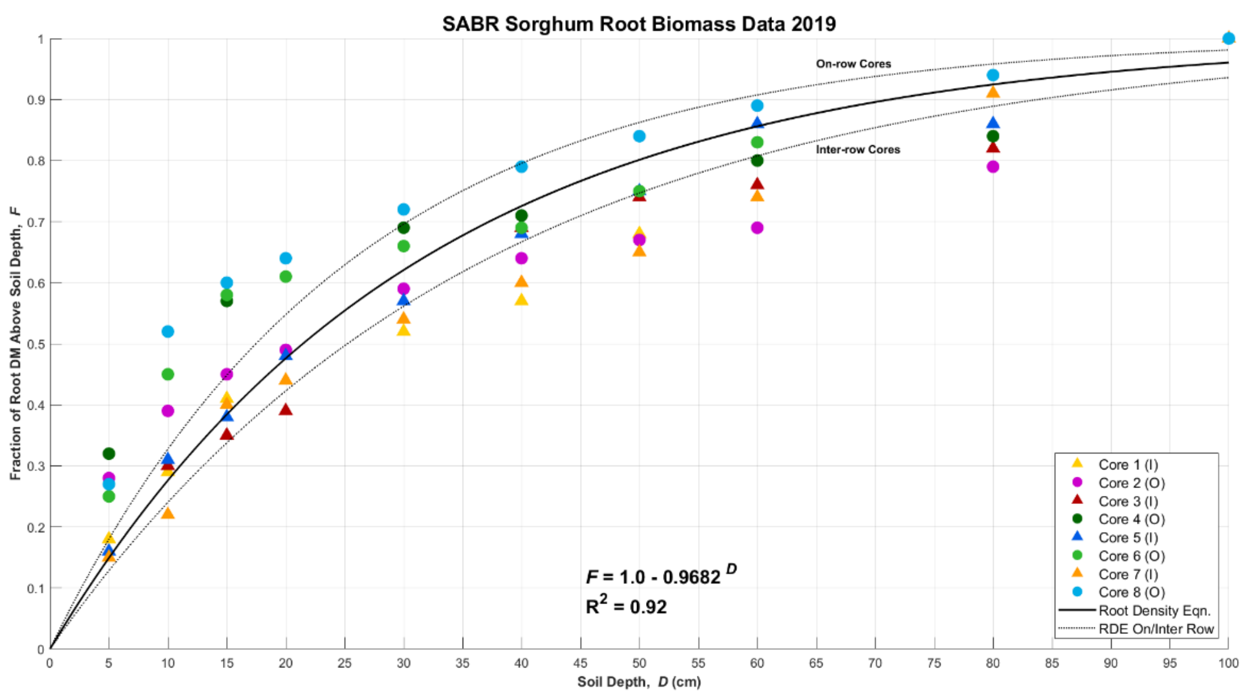

Figure 6: SABR farm biomass sorghum root biomass fraction by soil depth, 2019

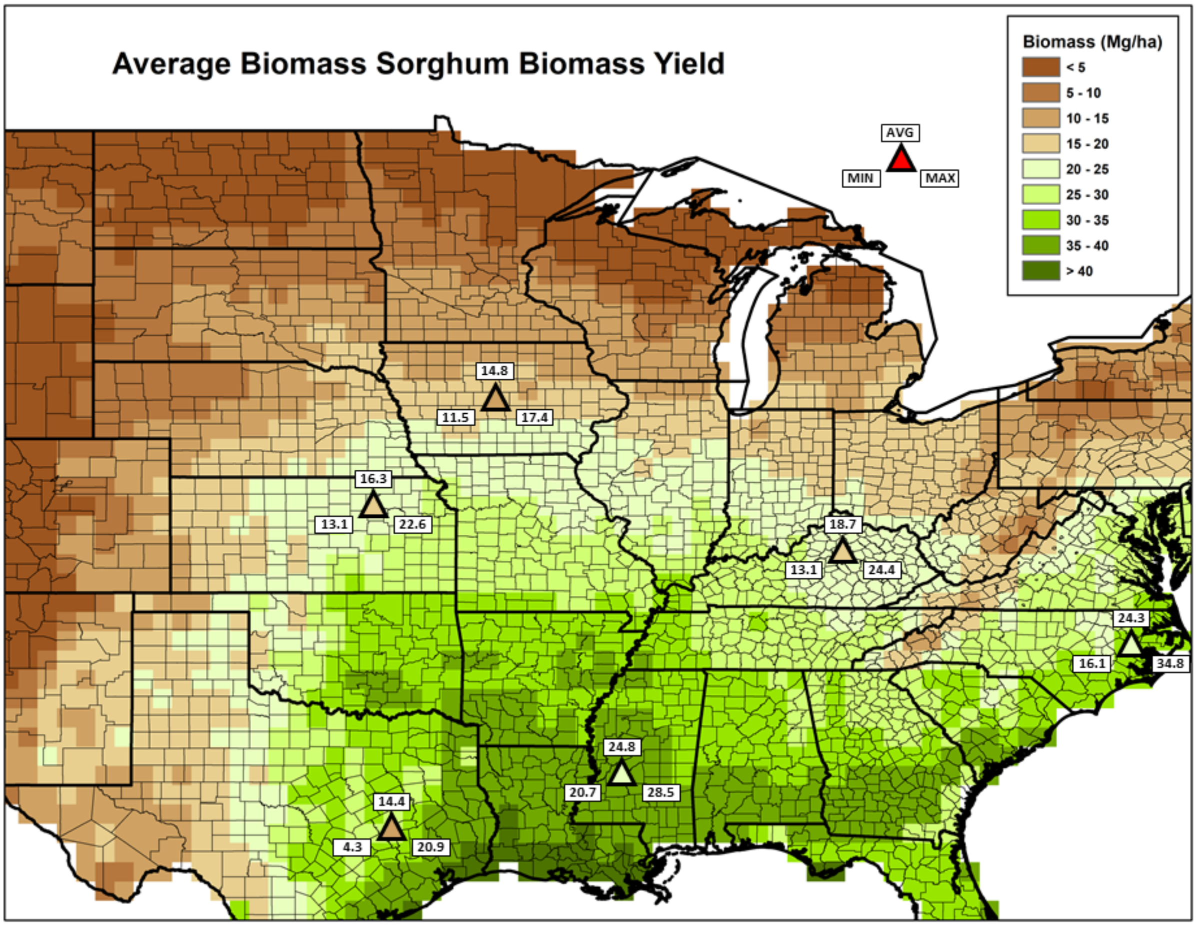

Figure 7: Agro-IBIS simulated biomass sorghum biomass yield for the region of the US included in the MARB (1956-2000 average). Triangles represent data from a 2008-12 yield trial of biomass sorghum (Gill *et al.* (2014)), shaded by average yield.

Figure 8: Average Agro-IBIS simulated biomass sorghum biomass yield across the state of Iowa (1998-2007)

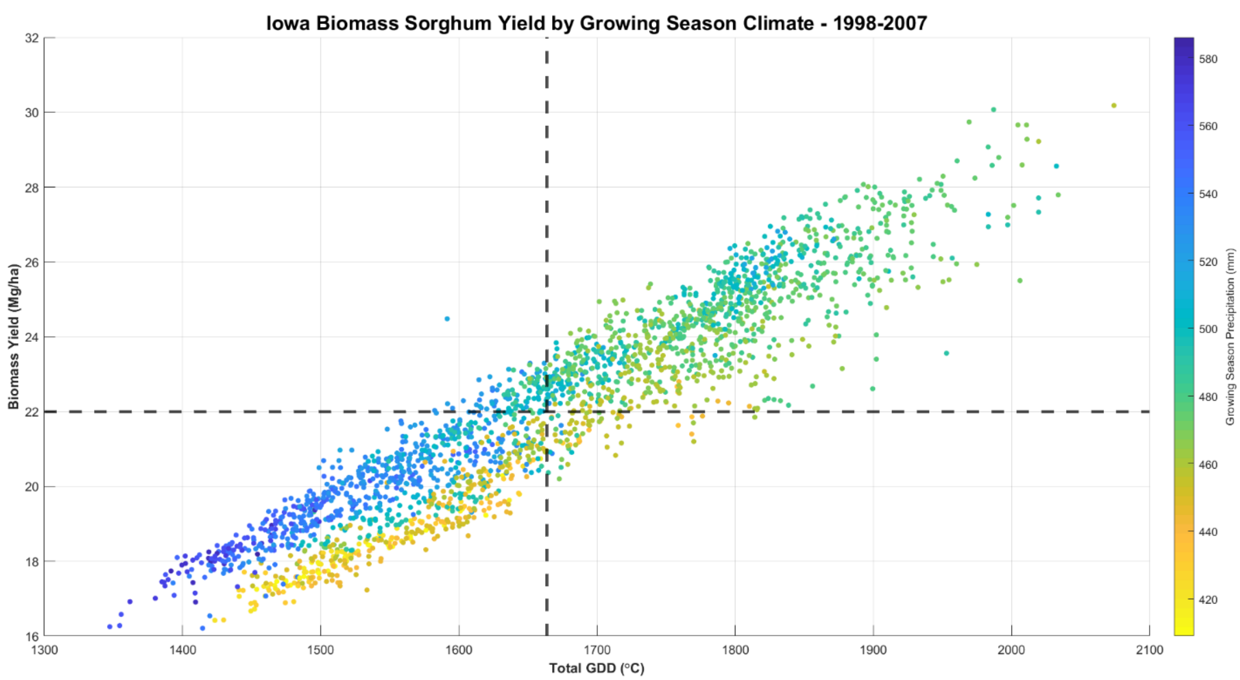

Figure 9: Total growing degree days (planting-harvest) and precipitation (May-November) versus average Agro-IBIS modeled biomass yield in Iowa (1998-2007). Each dot represents and Agro-IBIS grid cell in Iowa.

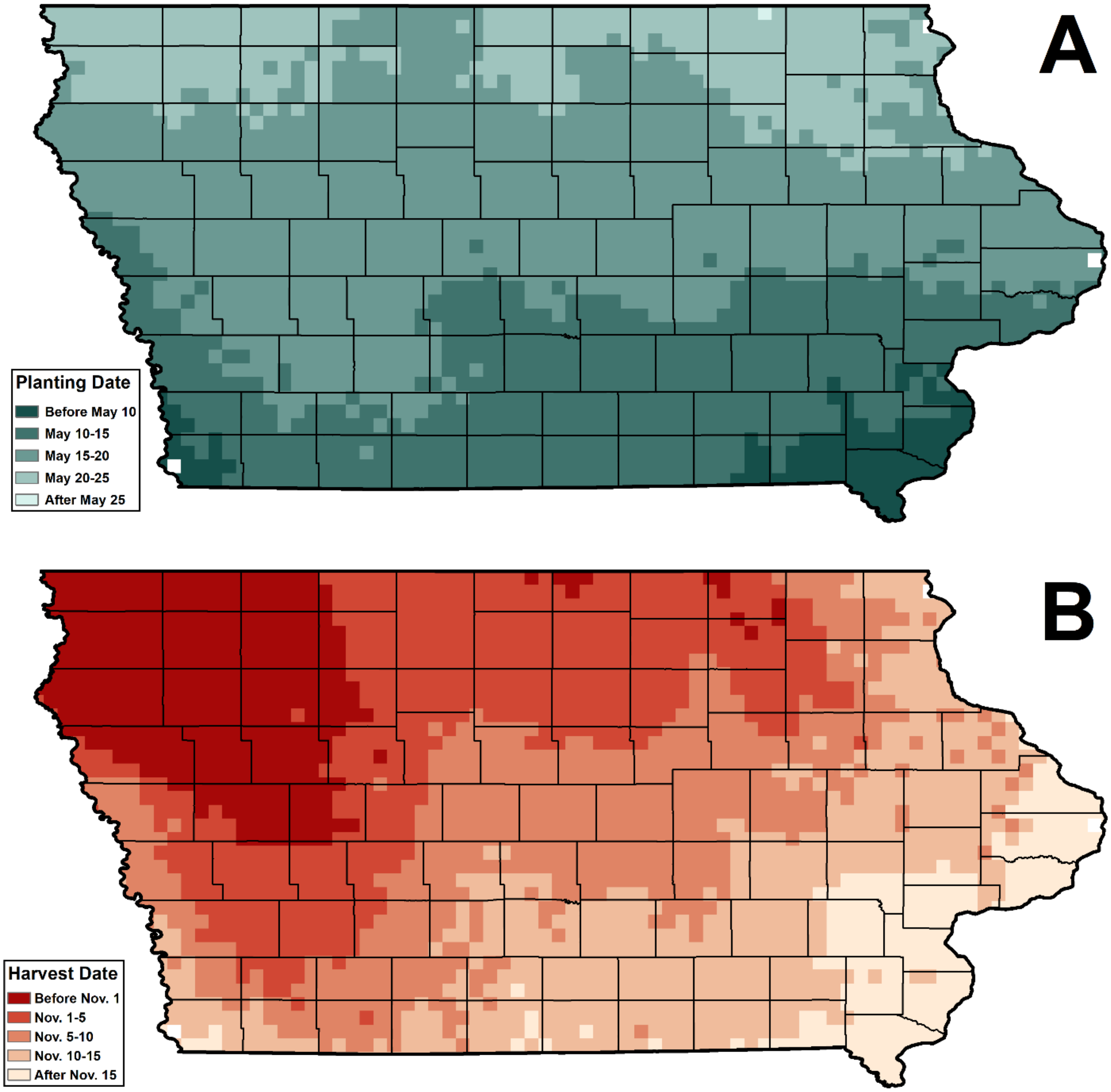

Figure 10: Agro-IBIS simulated average biomass sorghum planting (A) & harvest (B) dates in Iowa based on climatological data & temperature thresholds

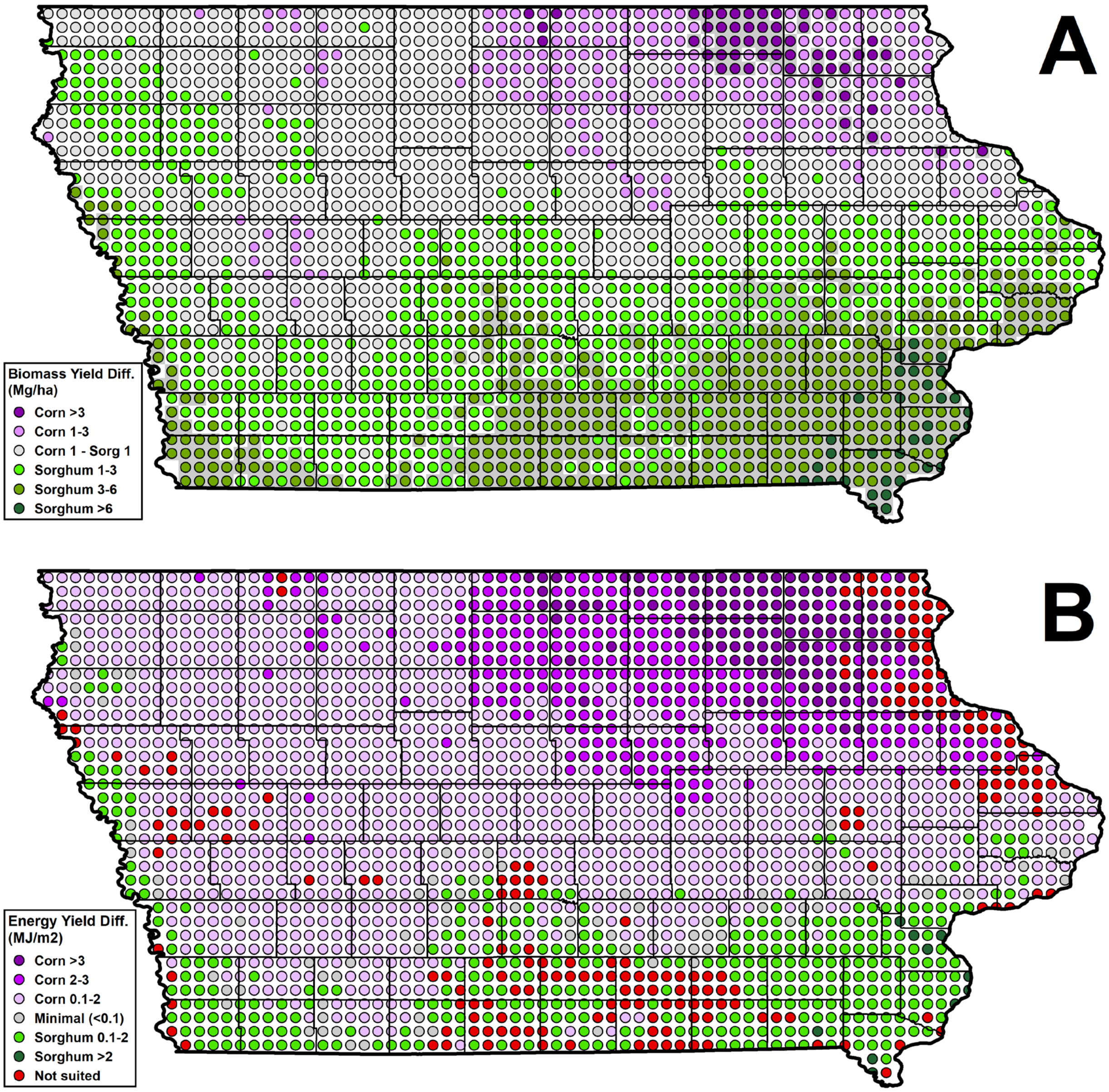

Figure 11: Difference in aboveground biomass (A) and energy ethanol yield (B) between Agro-IBIS simulated biomass sorghum & corn. Dots with a grey shadow indicate statistical significance ($p < 0.05$). In (B), the red dots represent are where land is not suited for harvesting large quantities of biomass due to land cover &/or slope.

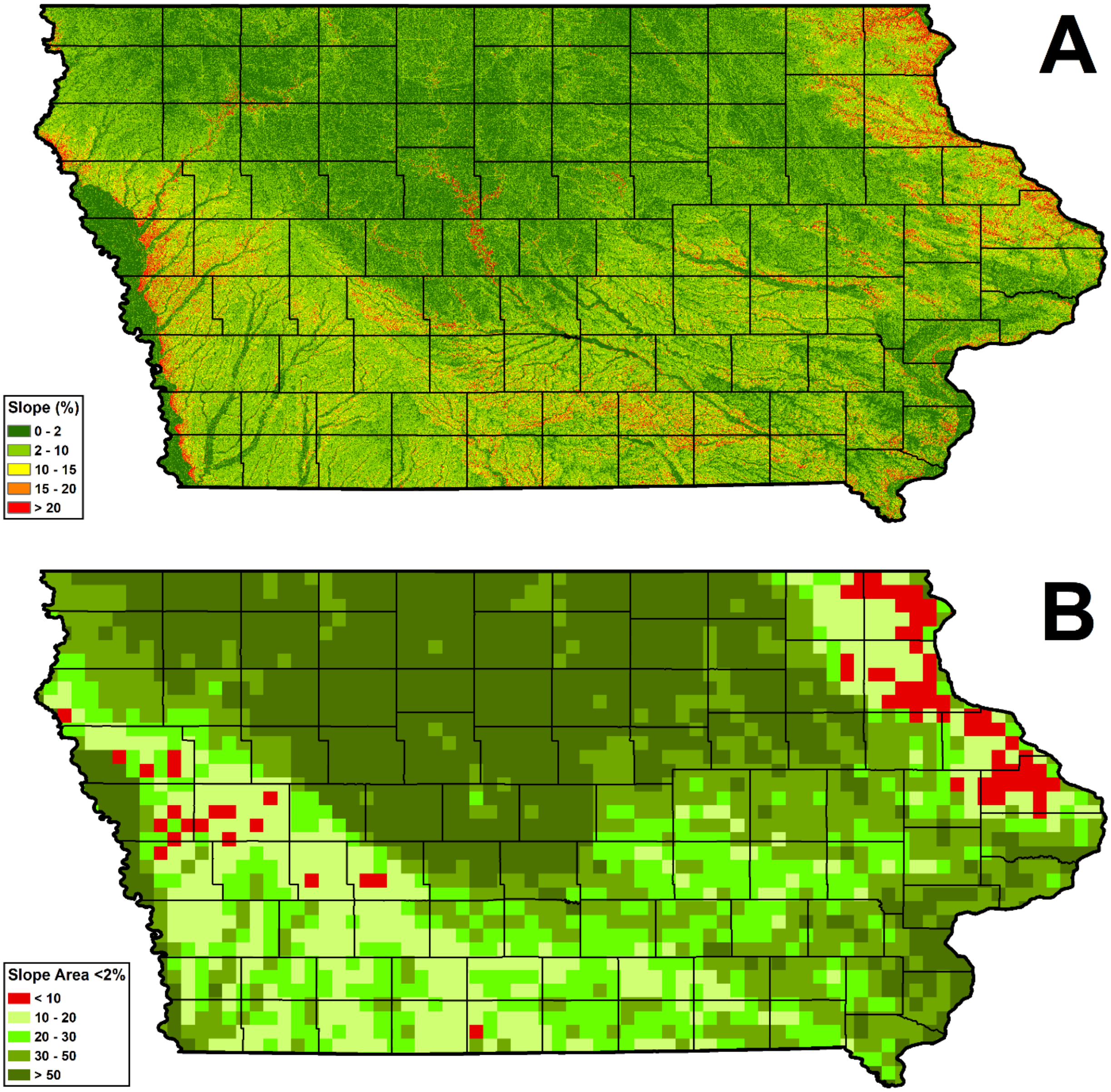

Figure 12: (A) Iowa slope (%) derived from USGS 3DEP elevation data. (B) Percent of the Agro-IBIS grid cell area in slopes <2%; slope.

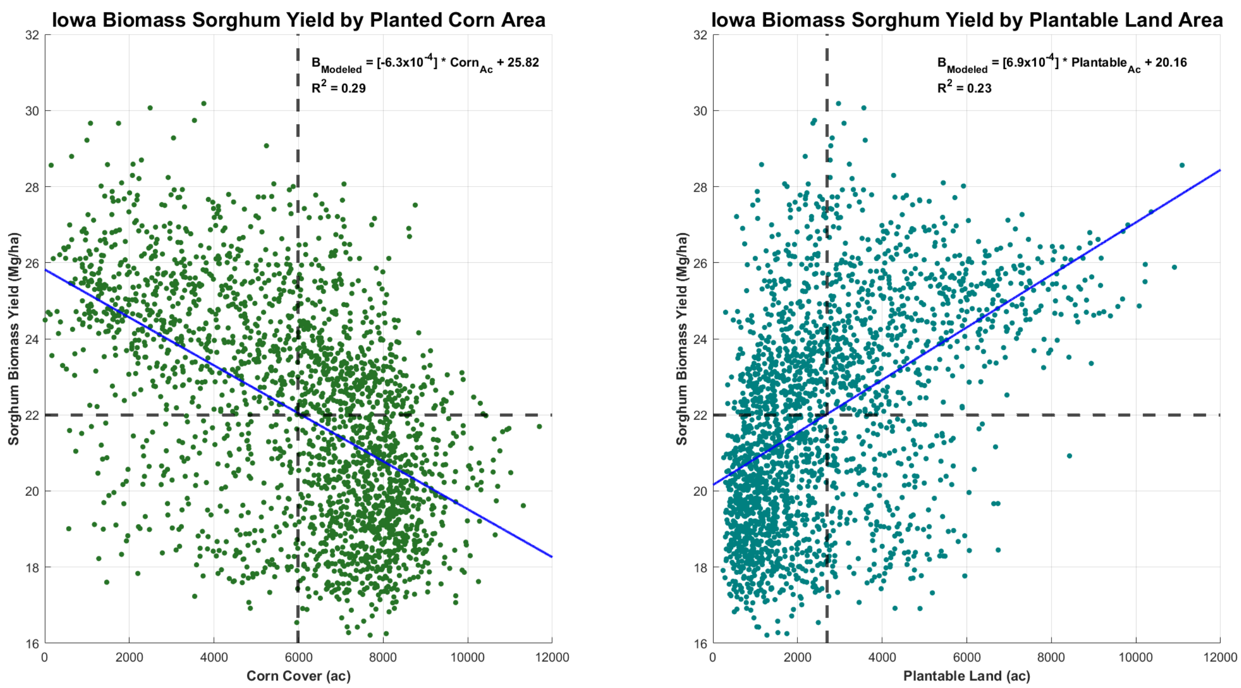

Figure 13: Corn area (A) and plantable land area (B) versus biomass sorghum biomass yield in Iowa (1998-2007). Blue lines represent the linear model fit to the data. Land cover data sourced from the 2019 USDA Cropland Data Layer (CDL).

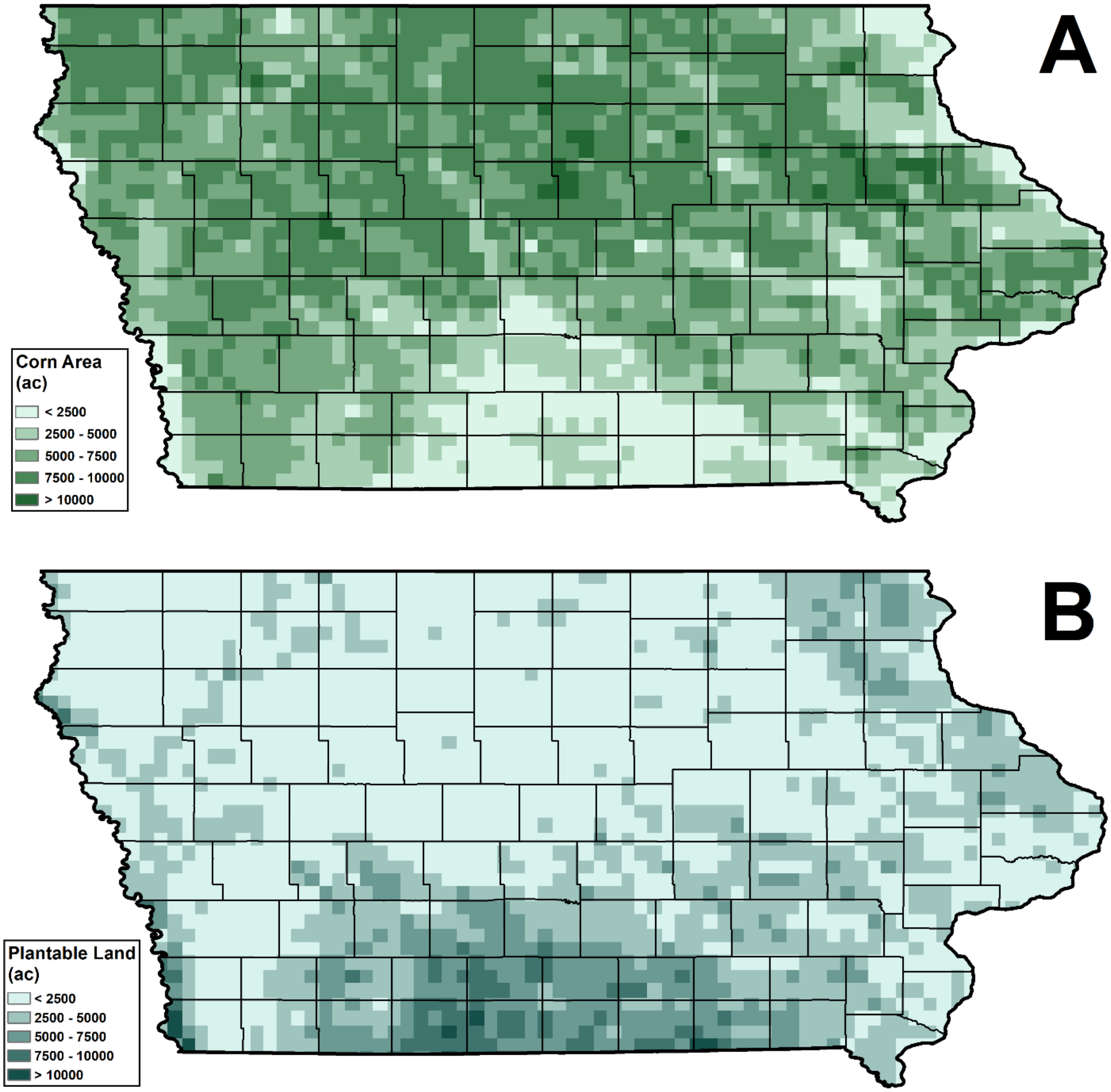

Figure 14: Corn area (A) and plantable land area (B) by Agro-IBIS grid cell. Land cover data sourced from the 2019 USDA Cropland Data Layer (CDL).

Table 1: Agro-IBIS biomass sorghum and maize (corn) PFT parameters used in the simulations in this study

Agro-IBIS Biomass Sorghum PFT Parameters				
Grain Fill & Phenology				
Parameter	**Description**	**Maize**	**Biomass Sorghum**	**Source**
MXTMP	Maximum temp. (C) for GDD accumulation	30	38	Roozeboom & Vara Prasad (2016)
BASET	Base temperature (K) used for daily GDD summation	283.16	283.16	Roozeboom & Vara Prasad (2016)
PTEMP	Minimum 10 day average temperature for planting (K)	283.16	285.16	Gerik, Bean, & Vanderlip (2003)
HYBGDD	Maximum GDD (C) required for hybrid physiological maturity	1700	9999	This study, Set for no grain fill
MXGDFI	Maximum days past planting allowed before shift to grain fill	110	999	This study, Set for no grain fill
MXMAT	Maximum days past planting allowed before maturity is reached	165	999	This study, Set for no grain fill
GRNFILL	Annual GDD fraction (to reach maturity) needed for grain fill initiation	0.65	999	This study, Set for no grain fill
MAXHI	Maximum harvest index	0.60	0.00	This study, Set for no grain fill
BETA	Rooting depth parameter	0.96	0.96	This study, Calibrated value - biomass
C/N Allocation				
AROOTI	Initial allocation of carbon to roots	0.40	0.01	This study, Calibrated value - biomass
FLEAFI	Initial allocation of carbon to leaf (split with stem)	0.80	0.50	This study, Calibrated value - biomass
CFRAC	Fraction of dry matter production that is carbon	0.50	0.45	This study, Calibrated value - biomass
FNLFMX	Maximum amount of N allowed in leaf at end of growing season	0.013	0.020	This study, SABR farm leaf C/N analysis
SRATIO	Stem:Leaf N allocation ratio	0.05	0.65	This study, SABR farm leaf C/N analysis
FNOPT	Minimum leaf nitrogen content before onset of N stress	0.0285	0.0180	Maw et al. (2017), Schetter et al. (2020)
Canopy Development				
LAIMX	Maximum leaf area index (LAI)	5.0	12.0	This study, Calibrated value - biomass
ZTOPMX	Canopy height maximum (m)	2.5	3.0	This study, Calibrated value - biomass
ALPHA4	C_4 intrinsic quantum efficiency (dimensionless)	0.05	0.07	This study, Calibrated value - ET
GAMMA	Leaf respiration coefficient	0.010	0.008	This study, Calibrated value - ET
COEFM	Slope of stomatal conductance-water vapor relationship	4.0	2.0	This study, Calibrated value - ET
COEFB	Intercept of stomatal conductance-water vapor relationship	0.03	0.04	This study, Calibrated value - ET
VMAX_PFT	Max Rubisco activity at 15 C, at top of canopy ($\mu mol[CO_2]\ m^{-2}\ s^{-1}$)	34.14	60	This study, Calibrated value - ET; Massacci et al. (1996)
SPECLA	Specific leaf area ($m^2\ kg^{-1}$)	51	30	This study, Calibrated value - biomass

Table 2: SABR/ISU-AEA farm meteorological data for the 2019 & 2020 growing seasons; climatology from 1981-2018

Month	**2019**				**2020**				**Climatology (1981 - 2018)**		
	Max T [C]	**Min T [C]**	**Precip [mm]**	**GDD [C day]**	**Max T [C]**	**Min T [C]**	**Precip [mm]**	**GDD [C day]**	**Max T [C]**	**Min T [C]**	**Precip [mm]**
June	27.1	16.2	90.4	349	29.3	18.0	36.3	376	27.5	15.4	126.5
July	29.4	18.7	111.0	785	30.2	19.1	45.7	831	29.3	17.5	102.1
August	26.9	15.8	35.8	1137	29.2	16.2	30.0	1223	28.0	16.1	111.0
September	26.5	15.4	111.3	1465	23.7	10.8	74.2	1376	24.6	11.4	84.8
October	13.7	2.4	134.9	1491	14.0	2.4	27.9	N/A	17.9	4.9	63.5
Average/Total	24.7	13.7	483.4	1491	25.3	13.3	214.1	1376	25.5	13.1	487.9

NOTE: GDD is cumulative beginning at planting date, and ends at harvest date

Table 3: Percent of Boone County, IA in a USDM Drought Monitor category (D0-D4); including the Drought Severity and Coverage Index (DSCI) value and departure from climatological (2000-18) mean

Area (%) in US Drought Monitor Category - Boone County, IA								
Year	**DOY**	**D0**	**D1**	**D2**	**D3**	**D4**	**DSCI**	**DSCI Departure from 2000-18 Mean**
2019	92	0	0	0	0	0	0	-68
	127	0	0	0	0	0	0	-25
	155	0	0	0	0	0	0	-30
	183	0	0	0	0	0	0	-54
	218	26.0	0	0	0	0	26	-32
	246	62.6	35.7	0	0	0	134	54
	274	0	0	0	0	0	0	-89
	309	0	0	0	0	0	0	-84
2020	98	0	0	0	0	0	0	-68
	126	0	0	0	0	0	0	-25
	154	19.5	0	0	0	0	19	-11
	189	19.8	80.2	0	0	0	180	126
	217	0	0	69.3	30.7	0	331	273
	245	0	0	9.8	90.2	0	390	310
	280	0	0	100	0	0	300	211
	308	0	62.1	38.0	0	0	238	154

Table 4: Area of Iowa (total area and % of total area) included in the corn-biomass sorghum comparison categories

ID	Domain	Area (km^2)	Area (ac)	% of State	% of (2)
1	Iowa	145,765	36,019,260	100%	*N/A*
2	Biomass sorghum has the larger EEY v. corn	32,807	8,106,761	22.5%	*N/A*
3	Non-sorghum producing due to land cover/slope	12,964	3,203,423	8.9%	*N/A*
4	Area in (2) and not in (3)	24,483	6,049,763	16.8%	74.6%

**Values rounded to nearest whole number*

APPENDIX A. SUPPLEMENTARY MATERIALS

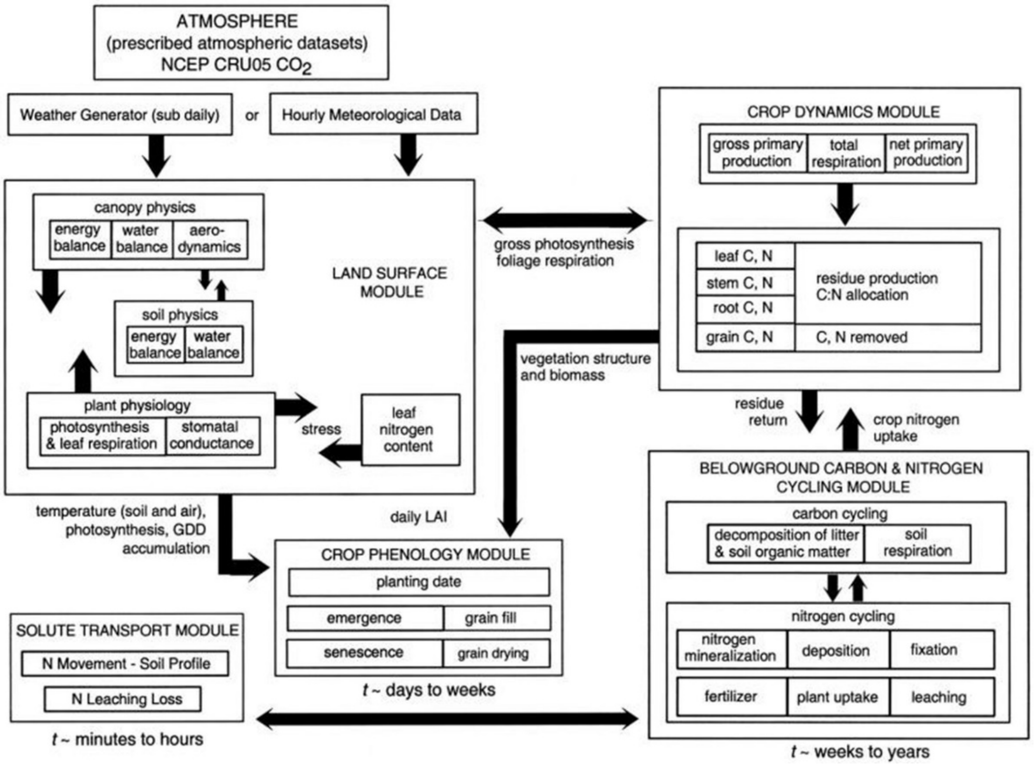

Figure S1: From Kucharik & Brye (2003) - Schematic of the dynamic ecosystem model IBIS (the Integrated BIosphere Simulator) adapted for agroecosystems.

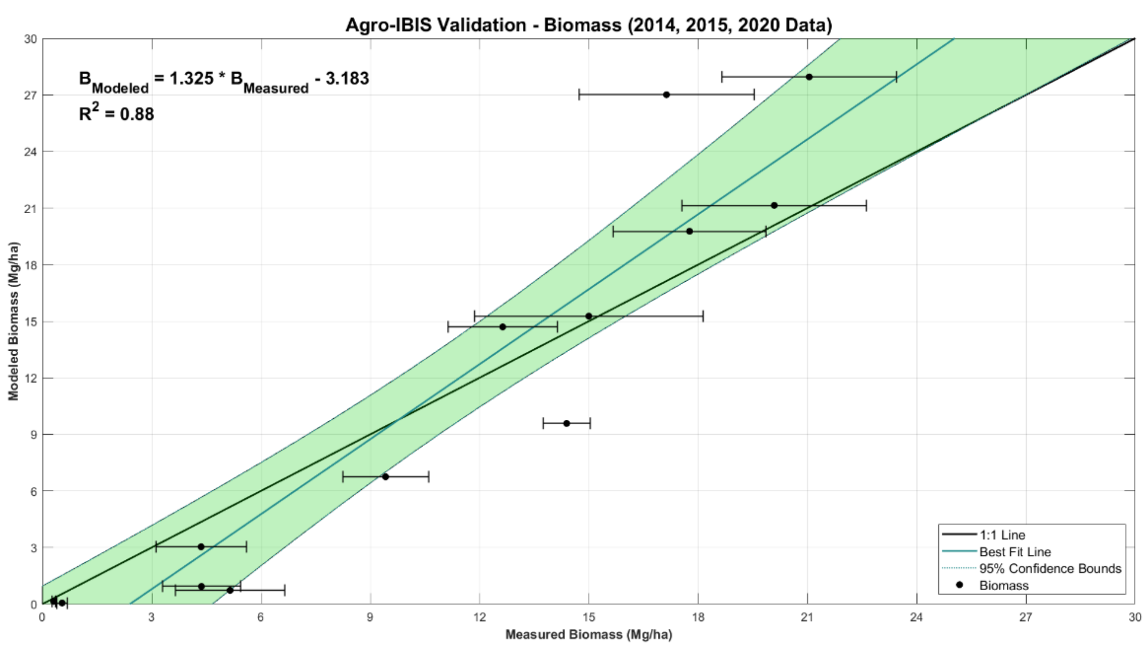

Figure S2: Validation of Agro-IBIS biomass sorghum PFT to measured leaf & stem biomass from three seasons - 2020 (SABR); 2014-15 (Roby et al. (2017)). Green line represent linear model fit to the data, with 95% confidence bounds (shaded in light green).

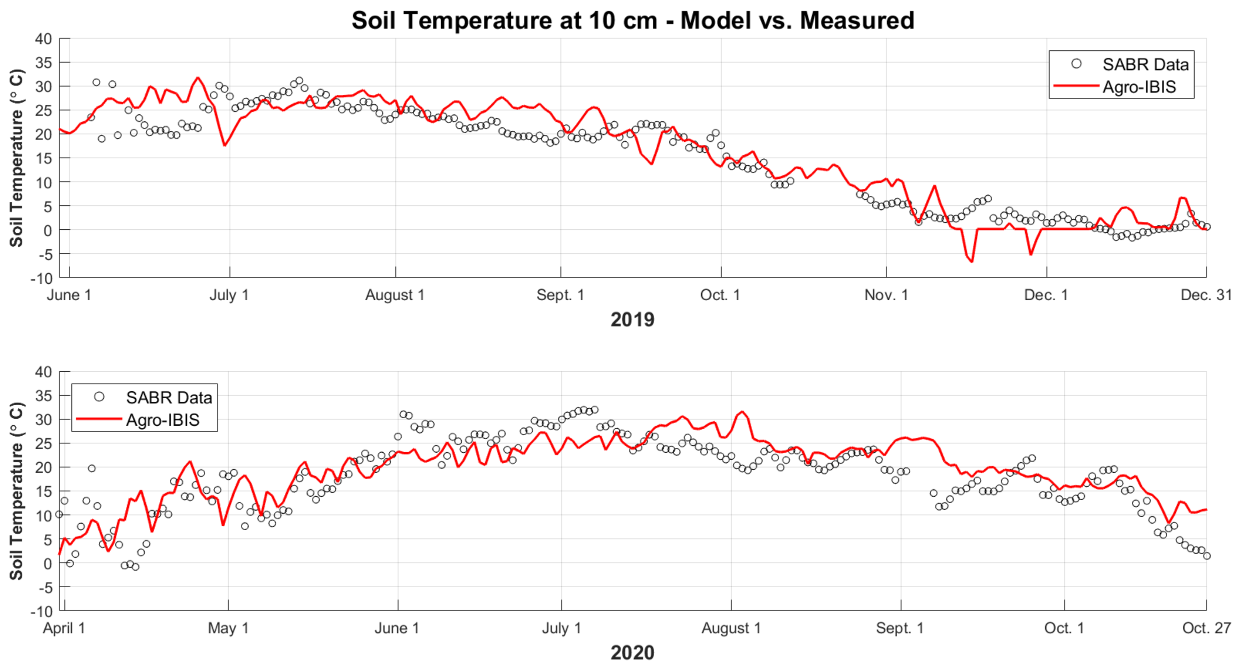

Figure S3: Soil temperature at 10 cm depth, 2019 & 2020 seasons – measured data from the SABR farm (open circles) and simulated values from Agro-IBIS (red line).

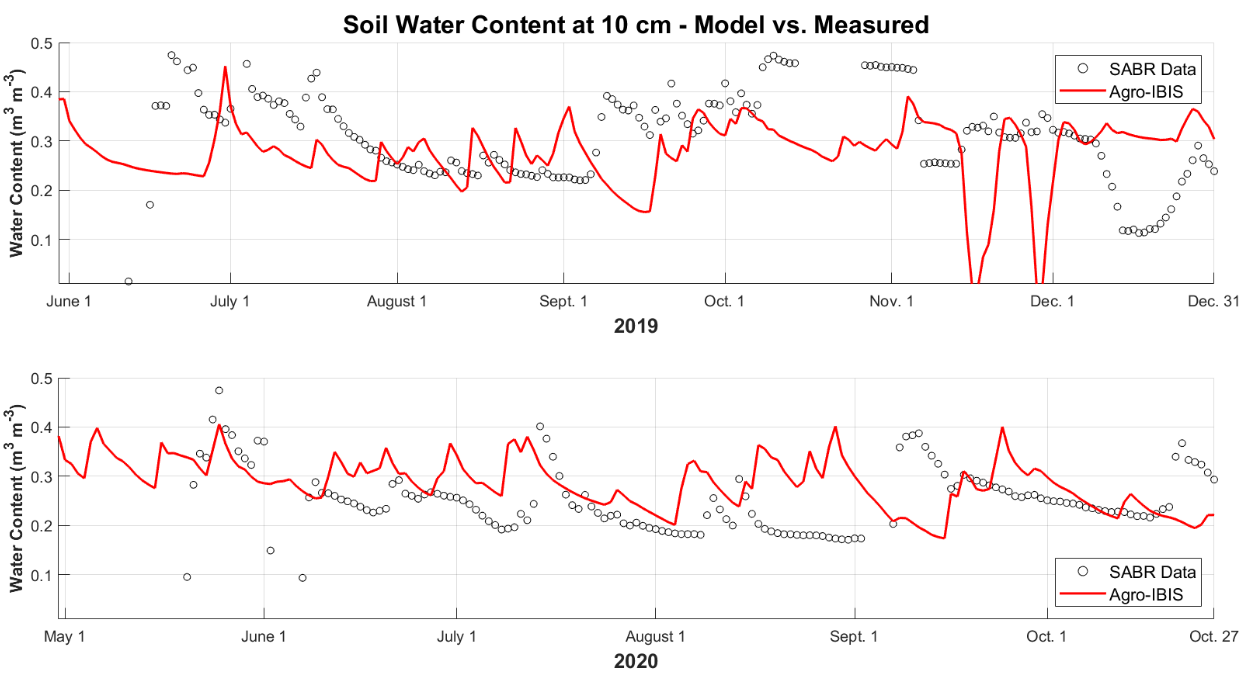

Figure S4: Soil water content ({vol. of water} / {vol. of soil}) at 10 cm depth, 2019 & 2020 seasons – measured data from the SABR farm (open circles) and simulated values from Agro-IBIS (red line).

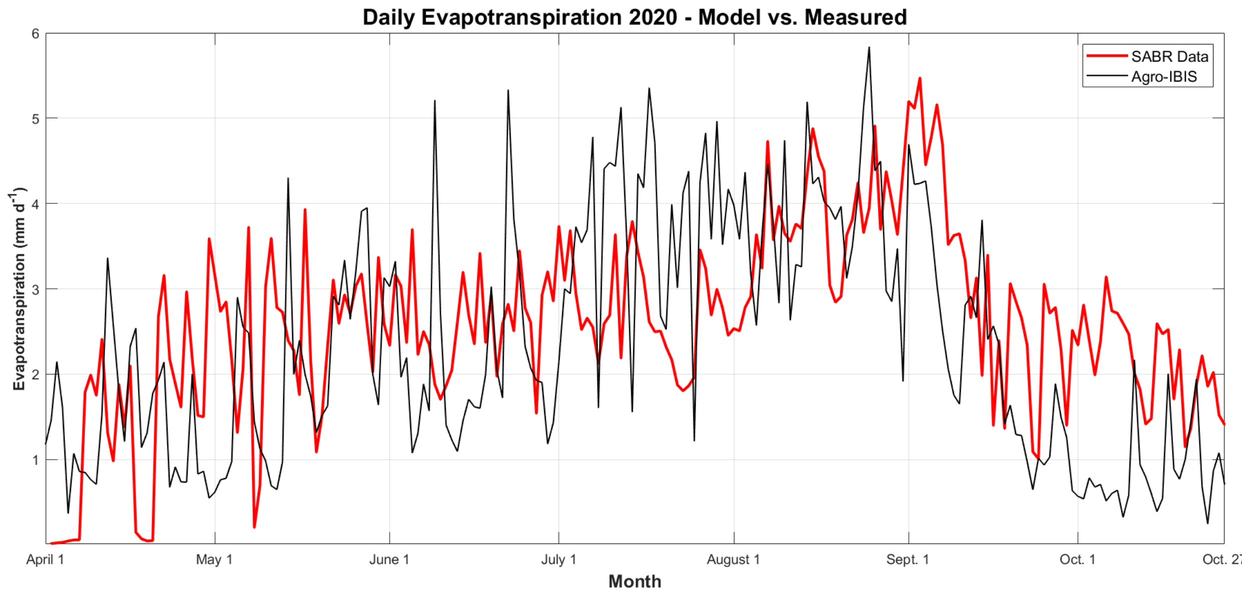

Figure S5: Daily evapotranspiration (mm), 2020 season – measured data from the SABR farm (black line) and simulated values from Agro-IBIS (red line).

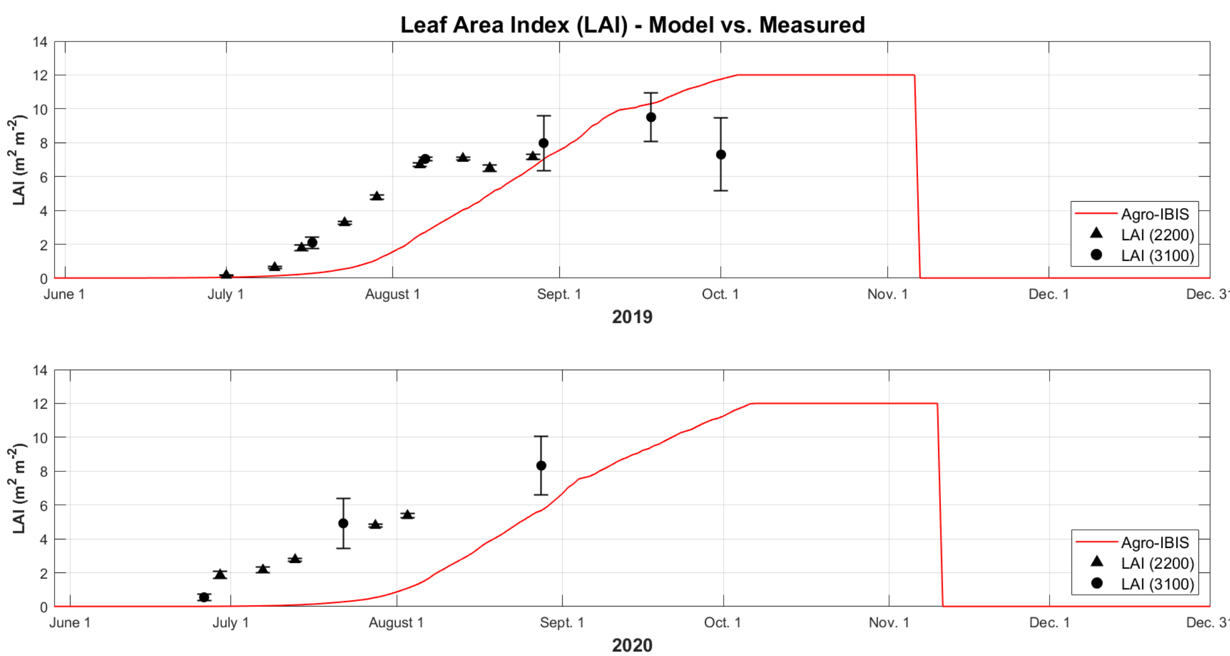

Figure S6: Leaf area index (LAI), 2019 & 2020 seasons – measured data from the SABR farm (black triangles, 2200; black circles, 3100) and simulated values from Agro-IBIS (red line).

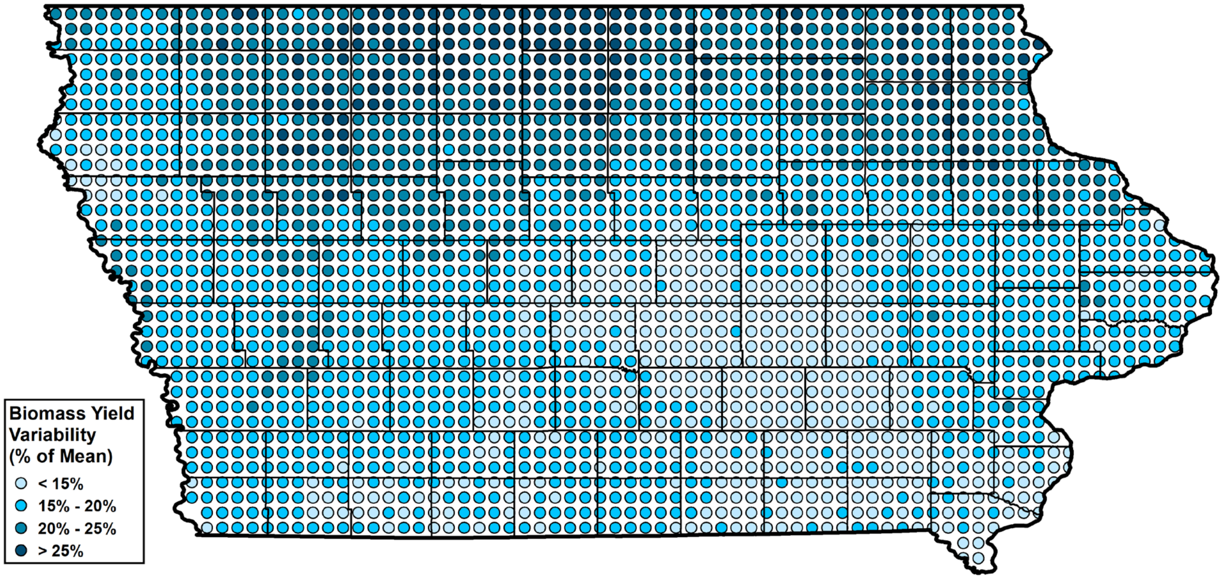

Figure S7: Agro-IBIS variability (± 1 standard deviation from the mean) of biomass sorghum yield (1998-2007). Values are represented as a percentage of the 10-year average yield.

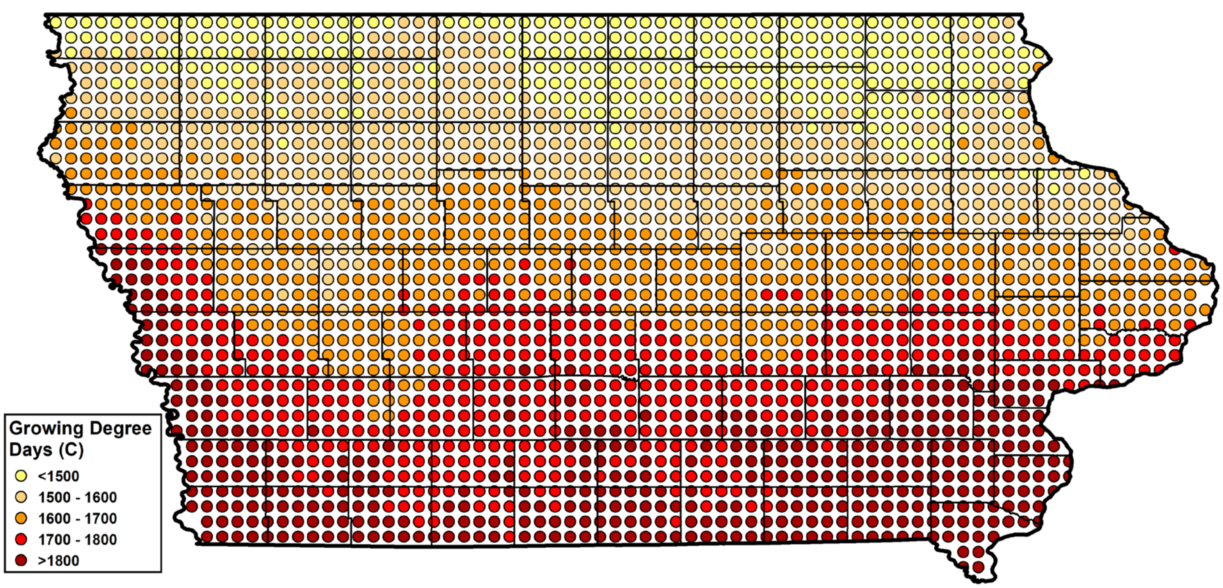

Figure S8: Agro-IBIS average growing degree days (°C) between planting and harvest of biomass sorghum (1998-2007).

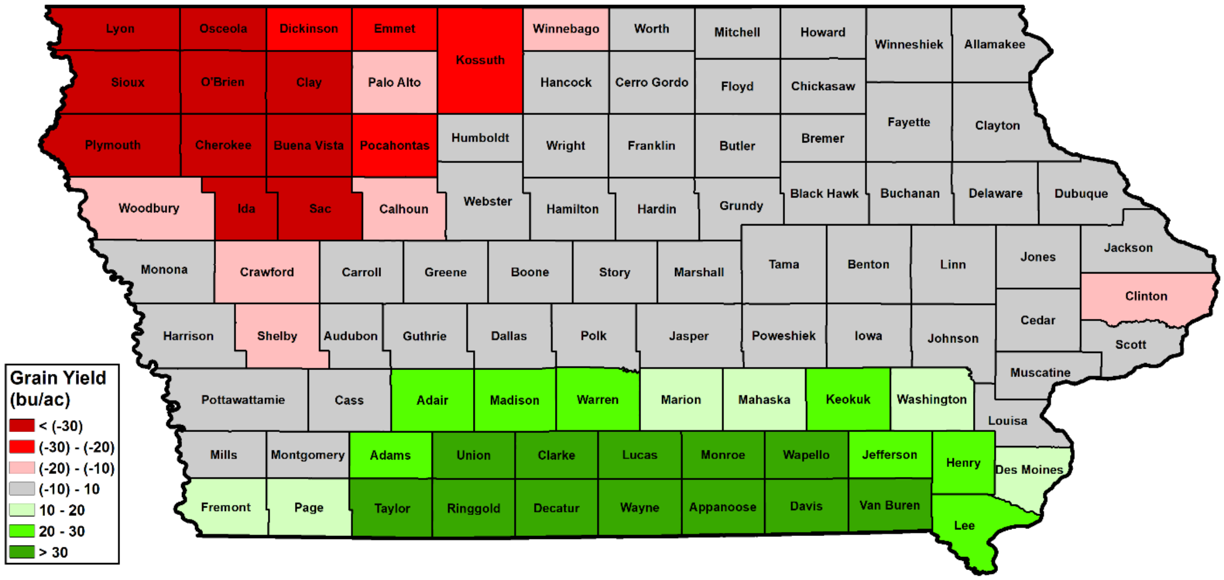

Figure S9: Difference in Agro-IBIS county-averaged simulated corn grain yield (1998-2007) & USDA NASS county-level average corn grain yield (2010-2019).

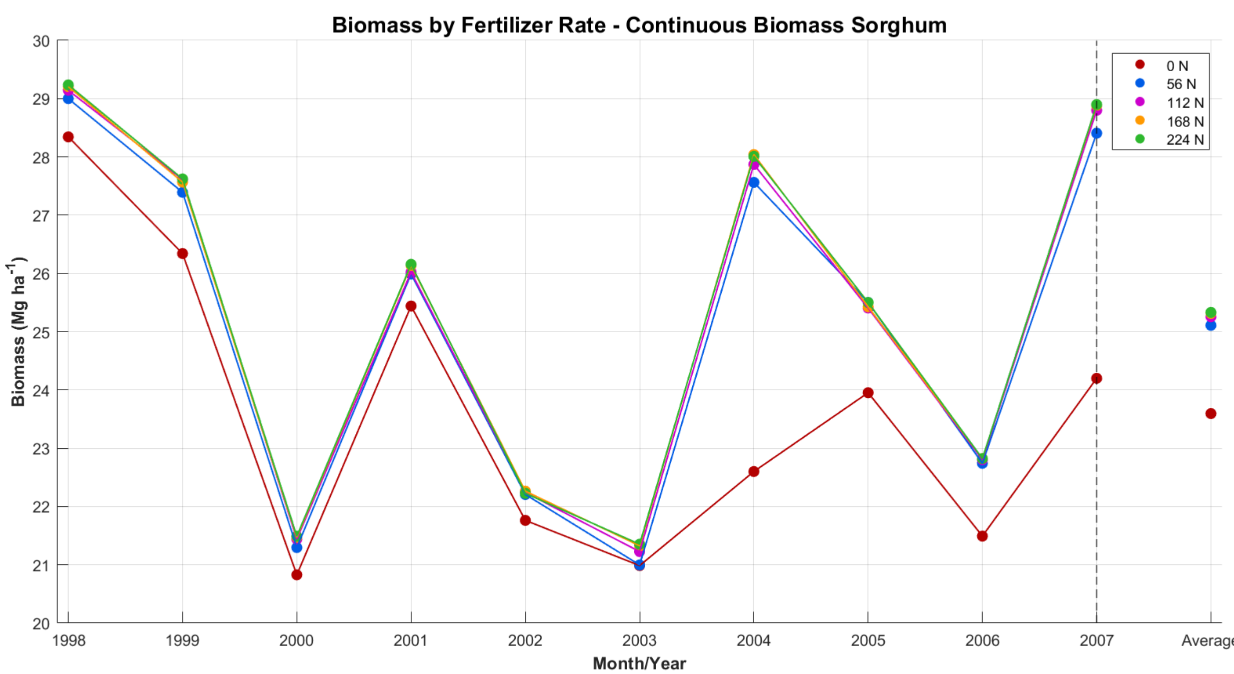

Figure S10: Agro-IBIS biomass sorghum nitrogen fertilizer rate sensitivity analysis for Ames, IA (1998-2007).

Table S1: SABR field site management details from the 2019 & 2020 growing seasons

Operation	2019		2020	
	Date	Details	Date	Details
Planting	1 June		3 June	
Fertilizer Applied	1 June	Liquid UAN 32% (80 lbs/ac)	3 June	Liquid UAN 32% (80 lbs/ac)
Spraying	*N/A*	*N/A*	27 June	Basagran (1 pt/ac); Atrazine (0.5 lb/ac)
	N/A	*N/A*	30 June	Bucktril (20 oz/ac)
Harvest	18 October	Chopped & baled	18-22 September	Chopped
Tillage	7 November	Chisel Plow	21 November	Chisel Plow

Table S2: SABR biomass sorghum measurement dates - 2019 & 2020 field seasons

Sorghum Sampling Dates - 2019 & 2020 Growing Seasons						
Year	**Parameter**	**June**	**July**	**August**	**September**	**October**
2019	**Biomass**		198	219, 241	261	274
	LAI (2200)		182, 191, 196, 204, 210	218, 226, 231, 239		
	LAI (Dest.)		198	219, 241	261	274
	C/N		198	241		274
	Height		189, 196, 206	213, 217, 232	247	
2020	**Biomass**	178	204	238	259	
	LAI (2200)	180	189, 195, 210	215		
	LAI (Dest.)	178	204	238		
	Height	177	183, 192, 198, 202, 213	218, 231	259	

Table S3: SABR biomass sorghum carbon (C) and nitrogen (N) concentrations (%)

DOY	Leaf C	Stem C	Leaf N	Stem N	Plant C	Plant N
198	44.0 (1.9)	35.2 (1.6)	4.0 (0.2)	3.7 (0.3)	40.4 (1.6)	3.8 (0.1)
241	43.8 (0.5)	42.5 (0.9)	2.1 (0.2)	1.0 (0.2)	42.9 (0.7)	1.4 (0.2)
274	44.7 (0.6	44.9 (1.9)	1.9 (0.4)	0.5 (0.2)	44.9 (1.5)	0.9 (0.2)
Average	44.2 (1.2)	40.9 (4.4)	2.7 (1.0)	1.7 (1.4)	42.7 (2.3)	2.0 (1.3)

Table S4: Energy budget over the SABR biomass sorghum plot (1 September - 15 October 2019) - GPP (gross primary productivity), R_n (net radiation), H (sensible heat flux), LE (latent heat flux)

Crop	GPP (μmol CO_2/m^2*s)	R_n (W/m^2)	H (W/m^2)	LE (W/m^2)	Residual (W/m^2)
Corn	6.2	79.7	12.9	55.9	10.9
Sorghum	9.8	80.6	-1.5	71.9	10.2

Source: SABR Rshiny App, https://sabr.shinyapps.io/appSABR/

APPENDIX B. ENDURING UNDERSTANDINGS

1. Science is characterized by the formulation, testing, and revision of hypotheses.

Before we began our investigation, we hypothesized that if biomass sorghum would produce a greater amount of biomass than corn in Iowa, that difference would be greatest in the southern counties. This hypothesis was derived based on prior literature, which suggested that biomass sorghum produces higher biomass yields at lower latitudes, coinciding with a longer growing season. Using the biomass sorghum plant functional type developed in Agro-IBIS, we were able to test this hypothesis and discover that in fact, simulated biomass sorghum aboveground biomass was highest in southern Iowa. However, not all of the aboveground biomass will be harvested for biofuels, and the different plant component (grain vs. leaves and stems) will have different ethanol conversion factors. Therefore, we revised our hypothesis to "biomass sorghum will produce the highest amount of biomass in Southern Iowa, but corn will have the higher energy ethanol yield", due in part to the higher conversion factor of grain biomass to biofuel.

2. Conservation laws govern the fluxes of mass and energy among the soil, vegetation, and atmosphere.

The energy balance equation (Campbell & Norman, 1998) is given by the following equation:

$$R_n + M - H - LE - G = 0 \tag{2}$$

R_n is the net radiation absorbed by the surface, M is the energy absorbed by photosynthesis, H is the sensible heat flux, LE is the latent heat flux, and G is heat storage in soil and vegetation. Biomass sorghum has a longer period compared to corn in that it will continue to stay in the vegetative stage in the middle/late fall after corn has reached physiological maturity.

An example of this is shown in Table S4, from eddy covariance data from the SABR farm (https://sabr.shinyapps.io/appSABR/). Between 1 September and 15 October 2019, biomass sorghum had a higher average gross primary productivity (GPP) compared to corn. The amount of R_n over both plots was near equal during these weeks, but biomass sorghum had a higher LE as it was still actively growing and transpiring water during this time. To balance the higher LE, H was lower over the sorghum canopy versus corn. The residual energy over both plots (~10 W m^{-2}) could be accounted for by M and G, but these quantities were not directly measured at SABR.

3. Feedbacks exist between agricultural ecosystems and the atmosphere.

Large amounts of aboveground biomass (~90%) are removed with biomass sorghum harvest, or similarly when corn stover is harvested for cellulosic biofuels. As a result, the amount of residue left on the soil surface to decompose into soil organic carbon is minimal. The removal of stover also makes the soil more vulnerable to erosion, which can act to degrade the soil and make it less productive for future crops. A reduction in subsequent crop productivity coincides with a reduction in carbon uptake through photosynthesis and thus even lesser amounts of carbon (in residues and roots) being left in the system. Therefore, this is an example of a negative feedback loop as the more crop biomass is removed from the cropping system at harvest, the less organic carbon will be accumulated in those soils.

4. "Essentially, all models are wrong, but some are useful." Box and Draper (1987).

The Agro-IBIS model is a prime example of a model that is wrong but quite useful. For example, the model parameterization assumes that carbon and nitrogen concentration during the vegetative period is at a constant value, but our field measurements reveal that the concertation were changing over the growth period. This may be why the LAI is being over- and underestimated throughout the growing season (Figure S6). The model assumes a constant fraction of biomass allocated to leaves during the vegetative period, but our field measurements reveal that the crops are "leafier" earlier in the season with a higher fraction of total above-ground biomass as leaves (data not shown). Likewise, other parameters that we measured (height, LAI, specific leaf area) varied both with space and time in our plots, but the model assumes a constant value. Gridded model output from Agro-IBIS suggests common crop parameter values (such as biomass) over a domain, such as the ~8 km grid cells of the ZedX input data, but measurements for SABR suggest that biomass sorghum parameter values vary substantially over a several-acre plot. Such simplifications of reality make accurate model predictions quite difficult to obtain, as was shown in our calibration and validation processes. Despite these limitations, the output from our well-evaluated biomass sorghum model provides estimates of potential biomass sorghum production that can be used in future analyses and inform farmer decision-making. Such experimentation can act to further develop the Agro-IBIS model and increase output accuracy.