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Spatial forecasting of switchgrass productivity under current and future climate change scenarios

Kathrine D. Behrman,[1,2,4] James R. Kiniry,[2] Michael Winchell,[3] Thomas E. Juenger,[1] and Timothy H. Keitt[1]

[1]*Section of Integrative Biology, University of Texas, 1 University Station C0930, Austin, Texas 78712 USA*
[2]*Grassland, Soil, and Water Research Laboratory, USDA-ARS, 808 East Blackland Road, Temple, Texas 76502 USA*
[3]*Stone Environmental Incorporated, 535 Stone Cutters Way, Montpelier, Vermont 05602 USA*

Abstract. Evaluating the potential of alternative energy crops across large geographic regions, as well as over time, is a necessary component to determining if biofuel production is feasible and sustainable in the face of growing production demands and climatic change. Switchgrass (*Panicum virgatum* L.), a native perennial herbaceous grass, is a promising candidate for cellulosic feedstock production. In this study, current and future (from 2080 to 2090) productivity is estimated across the central and eastern United States using ALMANAC, a mechanistic model that simulates plant growth over time. The ALMANAC model was parameterized for representative ecotypes of switchgrass. Our results indicate substantial variation in switchgrass productivity both within regions and over time. States along the Gulf Coast, southern Atlantic Coast, and in the East North Central Midwest have the highest current biomass potential. However, these areas also contain critical wetland habitat necessary for the maintenance of biodiversity and agricultural lands necessary for food production. The southern United States is predicted to have the largest decrease in future biomass production. The Great Plains are expected to experience large increases in productivity by 2080–2090 due to climate change. In general, regions where future temperature and precipitation are predicted to increase are also where larger future biomass production is expected. In contrast, regions that show a future decrease in precipitation are associated with smaller future biomass production. Switchgrass appears to be a promising biofuel crop for the central and eastern United States, with local biomass predicted to be high (>10 Mg/ha) for ~50% of the area studied for each climate scenario. In order to minimize land conversion and loss of biodiversity, areas that currently have and maintain high productivity under climate change should be targeted for their long-term growth potential.

Key words: ALMANAC model; biofuel; biomass; environmental change; Panicum virgatum; *precipitation; switchgrass; temperature; United States.*

Introduction

Increased production of renewable energy from biofuels will help reduce our national reliance on foreign fossil fuels and reduce greenhouse gas emissions. Approximately 1 billion megagrams (Mg) of biomass is needed to replace 30% of current fossil fuel demand with biofuel. Since food supplies and livestock feed are already competing with ethanol produced from corn (*Zea mays*), alternative energy crops need to be grown to meet biomass demands (Perlack et al. 2005). Large-scale biofuel production is expected to impact the economy as well as biodiversity, land use, greenhouse gas emissions, and biogeochemical cycling (Demirbas 2009, Dale et al. 2011, Robertson et al. 2011, Secchi et al. 2011, Wiens et al. 2011). The magnitude of potential changes will depend on the location and the amount of land needed to meet production demands. The quantity of biomass produced depends on many factors including: the species considered, climatic conditions, and management practices.

Switchgrass (*Panicum virgatum* L.), a native perennial herbaceous grass (see Plate 1), is a promising candidate species for cellulosic feedstock production (Schmer et al. 2008). Switchgrass can grow with low nutrients and little or no agrochemical inputs, but it also responds to nutrient additions and irrigation (Sanderson et al. 1996, McLaughlin et al. 2006). Reasonable biomass yields have been measured on many soil types and under drought stress conditions (Sanderson et al. 1996, McLaughlin et al. 2006, Sanderson et al. 2006). Harvesting of switchgrass instead of traditional row crops improves soil quality and water conservation by reducing runoff (Bransby et al. 1998, McLaughlin and Kszos 2005). High yield potential and the possibility of enhanced productivity through genetic breeding have also been reported (McLaughlin and Kszos 2005, McLaughlin et al. 2006). Field trials have advanced our understanding of the effects of management, soil type, soil properties (e.g., pH, nitrogen, moisture content), and genetic variation on switchgrass produc-

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[4] E-mail: kate.behrman@ars.usda.gov

tivity (Stout et al. 1988, Hopkins and Taliaferro 1997, Muir et al. 2001, Casler and Boe 2003, Fike et al. 2006).

Switchgrass yields are affected by spatial variation in temperature and precipitation (Casler and Boe 2003, Casler et al. 2004). Future climate change may similarly alter the capacity of biofuel production. Changes in climatic conditions over time, along with elevated atmospheric carbon dioxide concentrations, should be considered to ensure maintenance of high yields without supplemental nutrients and irrigation. Assessing future productivity has the potential added benefit of minimizing the amount of land conversion needed to meet production demands. Land-use change increases greenhouse gas emissions and is the primary factor responsible for the loss of biodiversity (Searchinger et al. 2008, Fletcher et al. 2011).

Large-scale geographic models can be used to evaluate the current potential of switchgrass for biofuel production. Previous studies have modeled yields or assessed the suitability of switchgrass across large geographic regions by using correlational approaches, such as generalized linear, generalized additive, and species distribution models (Barney and DiTomaso 2010, Evans et al. 2010, Jager et al. 2010, Wullschleger et al. 2010). This type of modeling provides initial insight into the factors affecting biomass. However, at a large spatial extent and resolution, these models take into account very little information about soil properties and crop management, both of which are known to have a sizeable effect on yield (Muir et al. 2001, Fike et al. 2006).

Alternatively, mechanistic models (e.g., ALMANAC, Agricultural Land Management and Numerical Assessment Criteria and EPIC, Erosion Productivity Impact Calculator) require detailed and fine-scale information on plant physiology and measured environmental variables, and can be used to simulate plant growth over time at a single field location (Williams et al. 1989, Kiniry et al. 1996). ALMANAC is a process-oriented model designed to simulate the growth and competition of plant communities (Kiniry et al. 1992). It has been extensively used to analyze plant community dynamics, phenology, water use efficiency, radiation use efficiency, and estimate crop yields (Kiniry et al. 2005, 2008*a*, 2011). For a mechanistic model to be capable of making realistic predictions over large geographic regions, it must be spatially parameterized and explicitly incorporate the factors that are known to affect productivity (i.e., management scheme, climate conditions, and soil attributes). Field management is explicitly defined within the ALMANAC model, and incorporates information on planting, harvesting, tilling, fertilizer application, and irrigation. Management strategies to maximize economic profits for switchgrass are aimed at eliminating irrigation and low levels of fertilizer application (Hill et al. 2006). Weather and wind databases are built into the ALMANAC interface, and county soil data from the USDA-NRCS web soil survey are easily imported and utilized by ALMANAC.

The productivity of switchgrass must be assessed over large geographic regions and over time to determine if biofuel production from this alternative energy crop is feasible and sustainable at a large scale (Hall 1997). For this study, the ALMANAC software interface was extended to predict switchgrass biomass potential across a large geographical range. This implementation of ALMANAC, called GeoALMANAC, is available on the USDA-ARS website.[5] The ALMANAC model was then parameterized across the central and eastern United States and used to predict switchgrass productivity for current climate conditions and two climate change scenarios. The relationship between changes in biomass and future temperature and precipitation was analyzed. These predictions were used to locate regions that should be targeted for biomass production to maximize current and future productivity.

Materials and Methods

General model description

The ALMANAC model contains detailed functions to simulate growth. These include light interception, competition for water and nutrients among plants, biomass production, and biomass partitioning (Kiniry et al. 1992). The model runs on a daily time step. Light interception is simulated by Beer's Law and depends on total leaf area and height of the canopy (Kiniry et al. 1992). The water and nutrient balance subroutines are from the Erosion Productivity Impact Calculator (EPIC) model (Williams et al. 1989). Biomass is partitioned into roots and leaves. The rates of leaf area accumulation and biomass partitioning are based on experimental data (Kiniry et al. 1996). In the case of switchgrass, leaf area increases from zero at planting to 95% of its potential leaf area index (LAI) when 20% of the degree-days to maturity (PHU) have accumulated. Leaf area then declines when 70% of the PHUs have accumulated for the season. Twenty percent of daily growth is partitioned to roots when growth is initiated and this decreases to 10% by flowering time.

The ALMANAC model accounts for increased growth with elevated CO_2 directly via increased radiation use efficiency (RUE) and indirectly via increased water use efficiency (WUE). The positive relationship between increased CO_2 concentrations and RUE is based on experimental data for C_4 grasses (Kimball 1983). This defines the potential growth per unit of intercepted photosynthetically active radiation. Thus as plant dry matter production increases with increased CO_2 concentration, the WUE (based on biomass produced per unit water transpired) also increases. Therefore, simulated RUE and WUE increase with increased CO_2 concentration.

[5] http://www.ars.usda.gov/Main/docs.htm?docid=16601

TABLE 1. Leaf area index (LAI) parameter values by state for locally adapted ecotypes of switchgrass (*Panicum virgatum*).

LAI	Ecotype	States	Reference
3.3	upland	Maine, North Dakota, Nebraska, South Dakota	Kiniry et al. (2008*b*)
2.5	upland	Michigan, Minnesota, Wisconsin	Kiniry et al. (2008*a*)
4.5	upland	Connecticut, District of Columbia, Delaware, Iowa, Illinois, Indiana, Massachusetts, Maryland, New Hampshire, New Jersey, New York, Ohio, Pennsylvania, Rhodel Island, Vermont	Kiniry (*unpublished data*)
5.8	lowland	Alabama, Arkansas, Florida, Georgia, Kansas, Kentucky, Louisiana, Missouri, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, West Virginia	McLaughlin et al. (2006), Kiniry (*unpublished data*)

Crop parameters and management

In this study, the growth of two regionally adapted ecotypes of switchgrass (*Panicum virgatum*), upland and lowland, were modeled. Upland and lowland ecotypes are differentiated based on their phenotypic and genetic variation (Casler 2005). Upland ecotypes are adapted to northern regions and capable of surviving harsh winters and freezing temperatures. Lowland ecotypes thrive in warmer climate, are generally taller, have a longer growing season, and later heading date. Generally, upland ecotypes have higher productivity in the north and lower productivity in the south, and the converse is true for the lowland ecotypes. The ALMANAC model has previously been parameterized for these adapted ecotypes of switchgrass and used to realistically simulate switchgrass in 11 states across the Great Plains of the United States (Kiniry et al. 1996, 2005, 2008*a*, *b*, McLaughlin et al. 2006).

We locally parameterized the lowland and upland ecotypes by state (Table 1). The division between upland ecotypes in the northern United States and the lowland ecotypes in the southern United States was based on the recent genetic analysis of wild switchgrass populations by Zhang et al. (2011). The model assumes establishment and overwintering survival of the adapted ecotype in each region. The ALMANAC model requires crop parameters and management schedules to be specified for each location.

The ecotypes were parameterized by adjusting two crop parameters, the potential leaf area index (LAI), and degree-days to maturity (PHU). LAI values were assigned by state based on field trials. The LAI was calculated as mean leaf area of an ecotype measured for at least two years in the region of interest. The LAI parameters were validated by comparing the ALMANAC simulation output with measured yields (McLaughlin et al. 2006, Kiniry et al. 2008*a*, *b*). The PHU values were calculated based on the latitude of each site. Local daily maximum and minimum temperature were used to determine the accumulation of degrees greater than the baseline temperature of 12°C (Kiniry et al. 2008*a*). The maximum PHU used to establish maturity was set to 2300. Degree-days were set to zero at planting and each year after maturity was reached. The PHU values used are well within the range of those calculated by replicated field trails at similar locations (McLaughlin et al. 2006, Kiniry et al. 2008*a*, *b*). All other plant parameter values remained the same as those presented in Kiniry et al. (1996).

A unified management scheme was applied to all areas in order to emphasize the effect of changes in the environment across space. Switchgrass was planted the first year on 1 March. Each subsequent year on 1 February, 100 kg/ha of nitrogen and 50 kg/ha of phosphorus were applied. Switchgrass was harvested once a year on 30 September. Growth and harvesting was simulated for 13 years. Post-establishment and development results were reported as the average over the final 10 years of the simulations.

Environmental variables

ALMANAC contains a database of the average monthly conditions from 1960 to 1990 for 975 weather and wind stations in the United States from the National Climate Data Center (containing 158 derived weather variables and 182 derived wind variables) and a daily weather generator (Williams et al. 1989, NCDC 1993). The closest weather and wind station to each location was used as a proxy for the current conditions, and weather was simulated daily. ALMANAC relies on USDA-NRCS Soil Survey Geographic database (SSURGO) spatial and tabular data, which can be downloaded by county from Soil Data Mart (*available online*).[6] The soil component (or type) at each location was used to parameterize the model. A number of soil properties in the SSURGO data files were used in ALMANAC, including depth, water holding capacity, texture, pH, slope, and available nutrients.

Local variation in soil type and soil properties was taken into account by dividing the central and eastern United States into 0.25-degree^2 ($\sim$27.5-km^2) cells and randomly distributing fields in each cell. Five grid cells were tested by distributing 5, 10, 20, 30, and 40 random locations in each. Owing to the trade-off between computation time and accuracy, the minimum number of fields needed to decrease the relative standard error

[6] http://soildatamart.nrcs.usda.gov

(RSE) of the average cell yield by <1% was chosen. As a result, the value of each grid cell is the average of 20 ALMANAC simulations run at randomly distributed locations with an estimated average RSE of 2.7% (Appendix B). The resulting grid cell values are estimates of the "local biomass potential" (LBP) for each 0.25-degree^2 cell.

Model evaluation

Ideally, our spatial predictions could be validated using field data collected throughout the study region with consistent measurements taken for a long time period, and on many different soil types. However, there are many differences between our LBP estimates for switchgrass and yield measures available from recent field trials. First, the LBP value is an average value across the different soil types present in each 27.5-km^2 grid cell. Field trials tend to be at relatively small scales (meters or acres [1 acre = 0.4 ha]) and on one soil type. Second, the long-term average (30 years) weather data are used to drive the ALMANAC model. The weather generator used in ALMANAC can accurately predict the long-term mean at a particular location, but it does not accurately predict the weather experienced in any given year or a small subset of years. Third, modern field trials often consist of many upland and lowland cultivars grown at each field location. The crop parameters for ALMANAC have not been refined to account for genotype by environment interaction for each genetically diverse cultivar. Instead, we have simply split switchgrass into two main ecotypes: upland and lowland. Averaging and comparing across diverse plant material is problematic when cultivars not previously studied are included in field trials at a different location. Fourth, one unified management scheme is used for all locations (i.e., same date of planting, harvesting, fertilizing). There is variation in management for each field trial that affects yield. Therefore, our LBP of switchgrass is not easily comparable to other measured yields. Instead, we performed two analyses: the first is designed to evaluate the range of yield estimates across the study region, and the second assesses the relationship between variation in LBP, measured yields, and climate.

First, our modeled yield estimates, for a single field, were compared to independently collected representative alfalfa, *Medicago sativa*, yields on the same soil type and within the same soil survey area. The alfalfa yields from the USDA-NRCS nonirrigated crops database were controlled for soil properties and climate, but may vary in management practices other than irrigation. They are "representative" yields, which are comparable to a long-term average and are widely distributed throughout the study region. We compared the relationship between our yield estimates and representative alfalfa yields to the linear relationship reported by Johnson et al. (2010) between USDA-NRCS representative alfalfa yields and measured yields from switchgrass field trials in Oklahoma, Kansas, and Nebraska. This was a post hoc comparison and does not affect our yield estimates. However, this comparison does provide additional confidence in our range of spatial switchgrass yield estimates.

Second, we analyzed the linear relationship between important climate variables to simulated LBP estimates and measured yields from field trials. This analysis determines if climatic variation impacts modeled yields the same as measured yields. Current climate variables (average annual precipitation, maximum temperature, and minimum temperature) from the ALMANAC weather database were compared to the LBP at the 558 weather station locations. The measured yields used were compiled by Wullschleger et al. (2010) from 39 switchgrass field trials performed between 1992 and 2001. Only 16 of these trials were established for more than three years and applied a comparable amount of nitrogen fertilizer each year (80–120 kg/ha). The first three years of field data during which plants become established were excluded from analysis. The annual average precipitation, maximum temperature, and minimum temperature for the time period at the location of each field trial were calculated from annual 4-km^2 resolution PRISM grids (PRISM Climate Group 2011). The relationship between measured yields and each environmental variable was compared to the relationship between modeled LBP estimates and the environment.

Predictions using future climate change scenarios

To make projections for climate change scenarios using ALMANAC, "future weather" databases were created and added to the GeoALMANAC interface. In this study, two climate change scenarios were analyzed for the 10-year interval from 2080 to 2090. The A2 scenario was chosen to represent an extremely pessimistic future assuming large population increases, slow economic advancement, and very little technological change (Kumar 2007). The A2 scenario predicts a large increase in atmospheric carbon dioxide and large increases in temperature. The B2 scenario was chosen as a "middle of the road" scenario that predicts intermediate population size and economic growth created to portray local efforts in order to enhance environmental sustainability. The B2 scenario corresponds to a moderate increase in carbon dioxide levels and a smaller increase in temperature. We used the statistically downscaled climate predictions for the Canadian Climate Change Modeling and Analysis CGCM2 (CCCMA-CGCM2) model for the IPCC Fourth Assessment B2 and A2 SRES scenarios from Worldclim (Ramirez and Jarvis 2008).

Modeling climate change in ALMANAC required the adjustment of the several environmental and crop variables. Average monthly precipitation, maximum monthly temperature, and minimum monthly temperature were updated for all weather stations to reflect the predicted 10-year average from 2080 to 2090 for both scenarios. In addition, the atmospheric carbon dioxide concentrations were adjusted to 550 and 690 ppm for

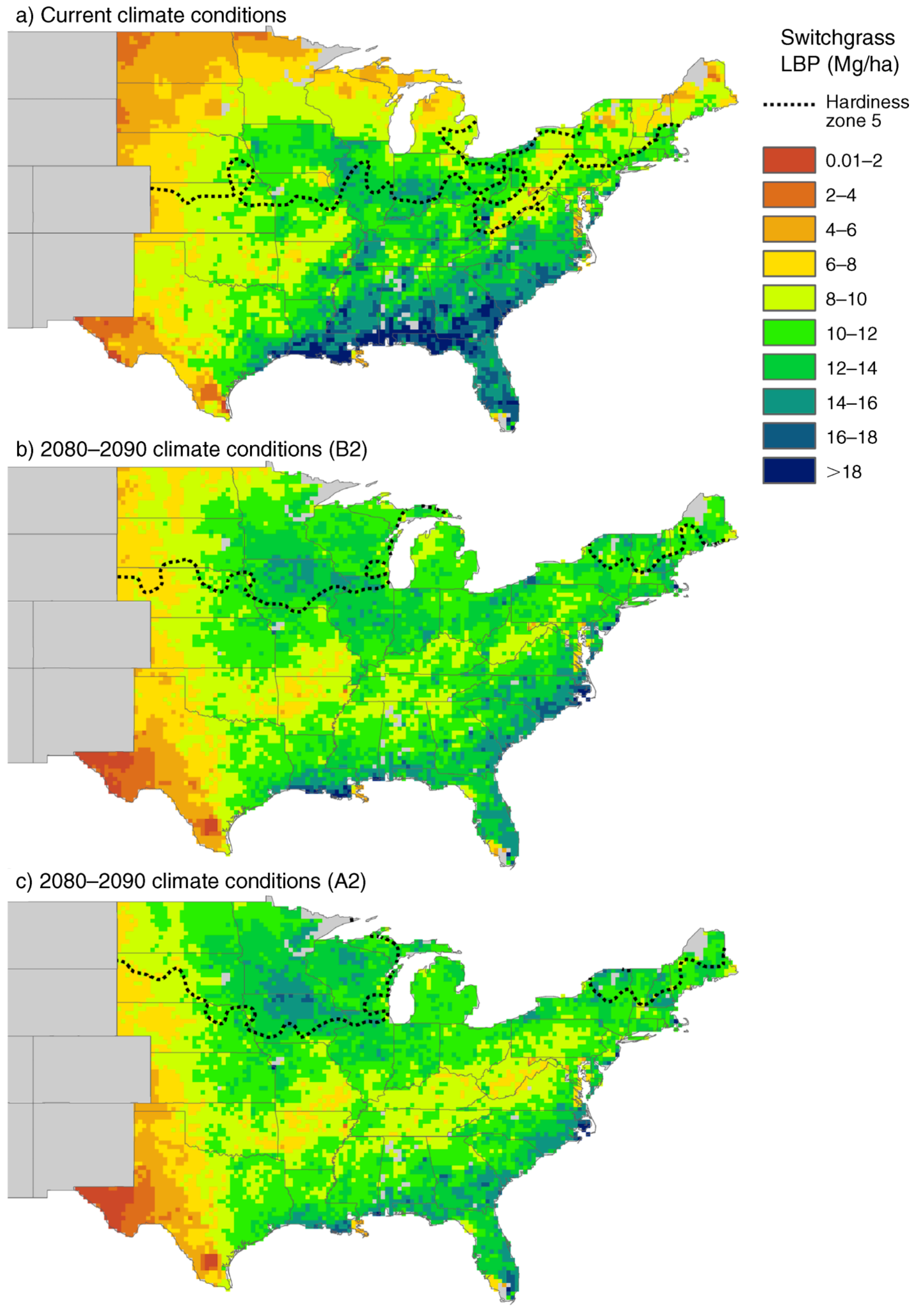

FIG. 1. ALMANAC estimates for average yearly local biomass potential (LBP) of switchgrass (*Panicum virgatum*) over 10 years for the central and eastern United States for (a) current climate conditions, and for future climate predictions from the CCCMA-CGCM2 and IPCC Fourth Assessment SRES: (b) scenario B2; (c) scenario A2 for 2080–2090. Each 27.5-km^2 grid cell is an average of 20 randomly distributed yield estimates.

the B2 and A2 scenarios, respectively (Kumar 2007). All other weather and wind variables remained unchanged. The crop parameters were adjusted for future projections by recalculating the PHU, number of degree-days to maturity, to reflect these changes in temperature for the B2 and A2 scenarios for 2080–2090. The geographic extent of the lowland and upland ecotypes were assumed to remain constant; therefore no other crop parameters were changed. Management and soil remained the same.

RESULTS

Under current climate conditions, the LBP of switchgrass exhibits significant spatial variation across the central and eastern United States (Fig. 1a). The current LBP ranges from 1.3 Mg/ha to 24.9 Mg/ha with

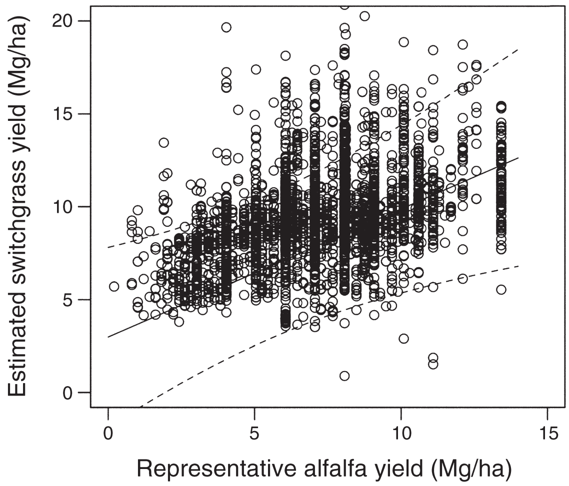

FIG. 2. The current ALMANAC switchgrass yield estimates compared to measures of nonirrigated alfalfa yields from the USDA-NRCS "non-irrigated crops" database across the central and eastern United States. The solid line is the relationship between field trials comparing measured switchgrass yields to nonirrigated alfalfa yields from Johnson et al. (2010) in Oklahoma, Kansas, and Nebraska. The dashed lines are 95% prediction intervals.

an average of 10.48 Mg/ha. In the central and eastern United States, 47% of the area is predicted to have a high LBP of >10 Mg/ha. Only 2.2% of the area had the highest biomass potential (>18 Mg/ha) and those regions are located in Florida and along the Gulf Coast. The regions with the lowest potential (<4 Mg/ha) are predicted along the Great Plains (in North Dakota, South Dakota, Kansas, Minnesota, and western Texas). The dashed line shows the upper bound of USDA Hardiness Zone 5 created for each time interval and above which lowland ecotypes are susceptible to winter freezes (Fig. 1).

The ALMANAC model was evaluated by comparing 2851 of the current modeled switchgrass yields for a single field location to independently collected USDA-NRCS nonirrigated alfalfa yields in the same county and on the same soil type (Fig. 2). The spatial distribution of these locations is shown in Appendix C. The USDA-NRCS alfalfa yield estimates were not controlled for management other than irrigation. Nonetheless, nearly all of the switchgrass estimates fall within the 95% prediction interval for the linear relationship reported between switchgrass field trials and USDA-NRCS alfalfa yields in Oklahoma, Kansas, and Nebraska by Johnson et al. (2010).

In addition, the ALMANAC model was further evaluated by comparing the relationship between measured yields and climate (Fig. 3, red points and lines) to the relationship between modeled LBP and climate (Fig. 3, black points and line). All three climatic variables (average yearly precipitation, maximum temperature, and minimum temperature) have a positive linear relationship with measured yield and modeled LBP. For all climate variables, the correlation between LBP and climate (precipitation, $R^2 = 0.61$; maximum temperature, $R^2 = 0.18$; minimum temperature, $R^2 = 0.33$) is higher than the correlation between measured yields and climate (precipitation, $R^2 = 0.15$; maximum temperature, $R^2 = 0.14$; minimum temperature, $R^2 = 0.17$). The correlations for measured yields are smaller because of the same factors confounding the direct comparison between modeled and measured yields, such as variation in management and soil type. The effect of change in precipitation, maximum temperature, and minimum temperature on measured yields (precipitation, $B = 0.07$; maximum temperature, $B = 0.28$; minimum temperature, $B = 0.40$) and modeled LBP (precipitation, $B = 0.09$; maximum temperature, $B = 0.39$; minimum temperature, $B = 0.41$) are similar. The consistency of these relationships provides further evidence that the ALMANAC model incorporates the effect of spatial climate variation on LBP in a similar manner as field trials. Variation in modeled LBP increases as average annual precipitation, maximum temperature, and minimum temperature increase. This is likely because at high values these climate variables may no longer be governing growth.

The amount of spatial variation attributed to climatic (weather) vs. environmental (soil) variation across space was quantified by analyzing the relationship between current switchgrass LBP and 32 of the weather variables, 14 soil textures, seven soil orders, and three soil characteristics. The weather variables are correlated; therefore a principal components analysis of the average minimum temperature, maximum temperature, and precipitation for each month was performed. The first two axes explain 86% of the spatial variation in these 32 climate variables. Therefore, these two orthogonal climate axes are used in the subsequent regression analysis. The first weather principal component (WPC1) is a linear combination of monthly minimum and maximum temperature (Appendix D). The second axis (WPC2) reflects differences in monthly average precipitation. Simultaneous spatial autoregressive linear models were fit for six subsets of the 26 climatic and environmental variables (Table 2). The models were compared using the Akaike Information Criteria (AIC), a measure of goodness of fit that is penalized for increasing the number of independent parameters (Akaike 1974). The model with the lowest AIC contains all 26 variables but only six of these independent variables are statistically significant (Table 2, Appendix A). The weather model containing just the two PC-axes explained ~64% of the variation in current switchgrass LBP. The model containing all soil variables (14 textures, seven orders, three characteristics) explained ~60% of the variation in current switchgrass LBP. A decrease in WPC1 (variation in temperature) and slope is expected to increase LBP, whereas an increase in WPC2 (variation in precipitation) and water availability of the soil is expected to increase LBP (Appendix A). All

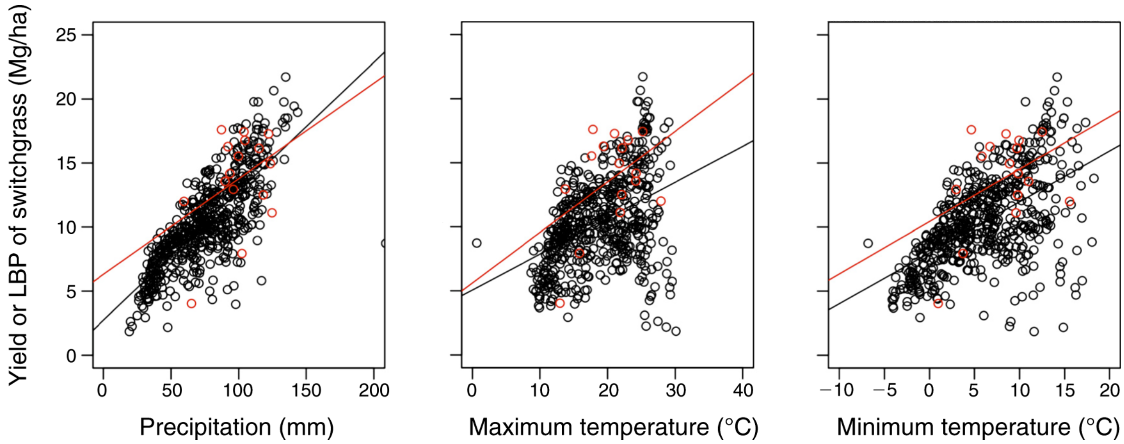

FIG. 3. The relationship between measured yields from 16 field trials and spatial variation in mean annual precipitation (left panel), maximum temperature (middle panel), and minimum temperature (right panel) is shown by the red points and lines. The black points and lines show the relationship between modeled local biomass potential (LBP) and spatial variation in climate at the 558 weather stations.

analysis of model results was performed in R using spdep (R Development Core Team 2011).

The predicted LBP of switchgrass from 2080 to 2090 for the CCCMA-CGCM2 global climate model for the IPCC Fourth Assessment B2 and A2 SRES scenarios is shown in Fig. 1b, c. Future LBP for the B2 and A2 scenarios ranges from 0.8 to 24.4 Mg/ha and 0.7 to 25.5 Mg/ha, and has an average of 10.48 Mg/ha and 10.47 Mg/ha, respectively. The percentage of the central and eastern United States expected to produce >10 Mg/ha of switchgrass increased to 59% for both the B2 and A2 scenarios (Fig. 1b, c). Most of this increase comes from the midwestern states, particularly in North Dakota, South Dakota, Kansas, Minnesota, and Wisconsin. For both scenarios, the percentage area with the highest potential (>18 Mg/ha) decreased to 0.3% and 0.1% for the B2 and A2 models; however these areas remained in Florida and in states along the Gulf Coast. As temperature increases for both the B2 and A2 scenarios, the upper limit of the USDA Hardiness Zone 5 moves farther north (Fig. 1, dashed line).

Changes in average yearly precipitation, minimum temperature, and maximum temperature from current conditions to the A2 scenario tend to have the greatest impact on switchgrass LBP in the northern central United States (Fig. 4). By 2080–2090, the midwestern states (particularly in North Dakota, South Dakota, Kansas, Minnesota, and Wisconsin) are predicted to experience the largest regional increase (+8 Mg/ha) in LBP and the western half of Texas and southeastern United States (Louisiana, Alabama, Arkansas, Georgia, Florida, North Carolina, South Carolina, Tennessee, Kentucky) the largest regional decrease (–6 Mg/ha) in LBP. This regional increase corresponds to an increase in average growing season precipitation, April–August (Appendix E) and average yearly precipitation of up to 10 mm per year (Fig. 4a). Regions where there is little change (0 to +2 Mg/ha) or a decrease in LBP (0 to –6 Mg/ha) correspond to a decrease in the average growing season (Appendix E) and annual precipitation (Fig. 4a). The average growing season precipitation decreases by as much or more than the average yearly precipitation (Appendix E: Fig. E1a vs. Fig. 4a). Average minimum

TABLE 2. Comparison of six simultaneous spatial autoregressive models that predict switchgrass yield.

Model	df	Likelihood	AIC	R^2
All variables	29	−936.7	1931.5	0.72
Soil texture	17	−1024.5	2084.9	0.50
Soil orders	10	−1023.5	2067.1	0.51
Soil characteristics	6	−1014.7	2041.3	0.53
Soil all variables	27	−983.1	2020.2	0.60
Weather	5	−989.0	1987.9	0.64

Notes: The "All variables" model contains 26 independent variables: 14 categorical soil textures, seven categorical soil orders, three soil characteristics (slope, water availability, and restriction depth), and the two weather variables (WPC1 and WPC2). All other models are subsets of these variables. R^2 is the pseudo-R^2 defined by Nagelkerke (1991), which is the ratio of 1 minus the likelihood of the null model to the likelihood of the estimated model to the power of 2 divided by the sample size.

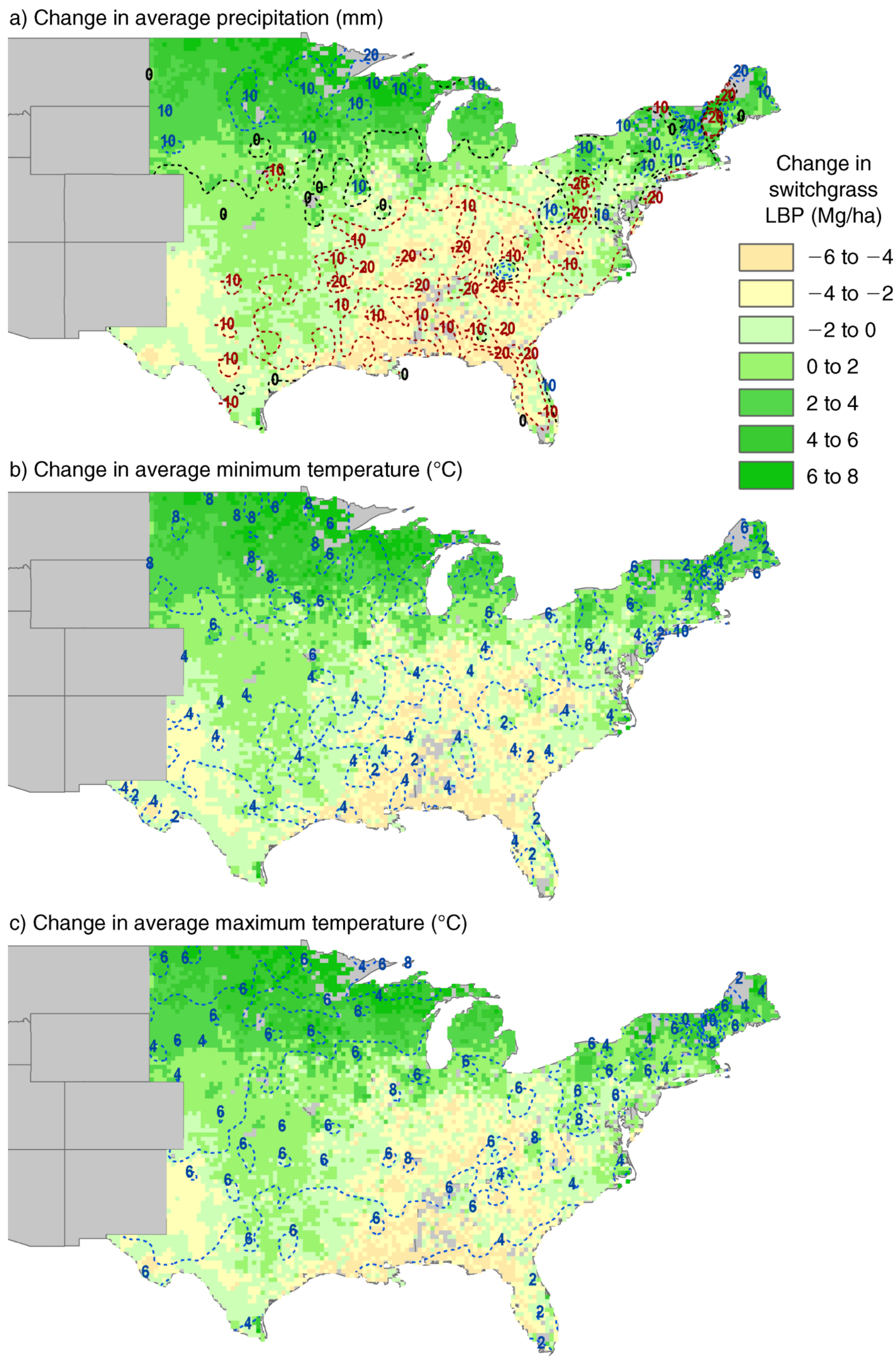

FIG. 4. The change in local biomass potential (LBP) expected from current climate to 2080-2090 under the A2 scenario from 2080 to 2090. The contour lines illustrate a change in expected (a) average yearly precipitation, (b) minimum temperature, and (c) maximum temperature by 2080–2090 expected from the CCCMA-CGCM2 and IPCC Fourth Assessment SRES A2. Blue contour lines and labels indicate an increase in precipitation (mm) and temperature (°C). Black lines represent no change, and red contour lines show a decrease in precipitation (mm).

growing season and yearly temperature increases the most (+8°C) in the northern midwestern states (North Dakota, South Dakota, Minnesota, Wisconsin), where the largest increase in LBP is expected (Appendix E: Fig. E1b; Fig. 4b). The change in average growing season maximum/minimum temperature and average yearly maximum/minimum temperature is fairly consistent (Appendix E: Fig. E1b, c and Fig. 4b, c). In western Texas and the southeastern United States, average yearly maximum temperature increased (Fig. 4c) and

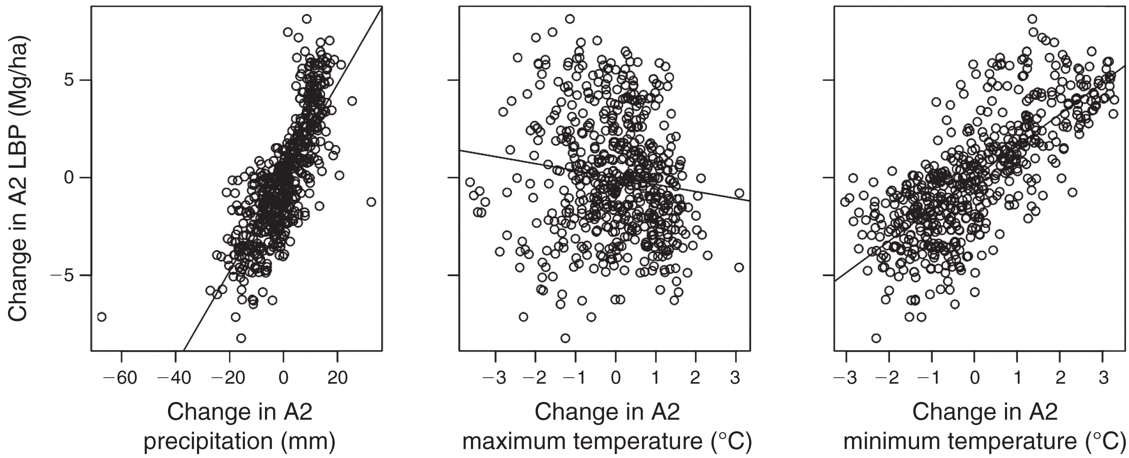

FIG. 5. The mean deviates of change in annual precipitation (left panel), maximum temperature (middle panel), and minimum temperature (right panel) from the current to the A2 climate scenario plotted against the mean deviates of change in LBP from the current to A2 scenario. The solid line shows the linear regression for each relationship.

yearly precipitation decreased (Fig. 4a) resulting in decreased LBP.

The sensitivity of the ALMANAC model to future changes in climate was analyzed by plotting the mean deviates of change in future LBP from the current to the A2 scenario vs. change in future annual precipitation, maximum temperature, and minimum temperature (Fig. 5). Change in LBP at a given location is most strongly correlated to change in annual precipitation ($R^2 = 0.62$). There is a significant positive relationship between change in precipitation and change in LBP ($B = 0.24$, $P < 0.001$). Change in minimum temperature and change in LBP are moderately correlated ($R^2 = 0.56$), and there is a significant positive linear relationship ($B = 0.16$, $P < 0.001$). There is no relationship between change in maximum temperature and LBP ($R^2 = 0.02$). The results for change in growing season climate are not presented here because they are nearly identical to the results for annual climate.

DISCUSSION

Future climatic change will have a substantial impact on the spatial distribution and the productivity of switchgrass. The percentage of the study area able to produce the most biomass (>18 Mg/ha) is expected to decrease with climate change but the average biomass per unit area remains fairly constant across all climate conditions studied. This is due to a large increase in local biomass potential (up to 8 Mg/ha) expected by 2080–2090 for part of the Great Plains region of the Midwest (particularly in North Dakota, South Dakota, Kansas, Minnesota) where local biomass potential was low (<4 Mg/ha) under current conditions. This increase in biomass potential corresponds to locations where minimum temperature and precipitation are expected to increase the most. A similar relationship between increased precipitation and current productivity has been observed for other nonirrigated grasslands (Sala et al. 1988, Epstein et al. 1997). Large decreases in LBP (up to −6 Mg/ha) in the eastern half of Texas and southeastern states (in Louisiana, Alabama, Arkansas, Georgia, Florida, North Carolina, South Carolina, Tennessee, Kentucky) are predicted in 2080–2090, where both yearly and growing season precipitation decreases and temperature increases. Grassland productivity is also observed to be negatively correlated to temperature when precipitation decreases or remains constant (Epstein et al. 1997). Our results for simulated switchgrass monocultures are similar to those observed for diverse native grassland communities.

The areas that currently have and are expected to maintain high LBP under both future climate scenarios are obvious targets for the long-term growth of switchgrass. Considering current and future potential when establishing fields for cellulosic feedstock production will reduce the amount of land conversion necessary to meet and maintain biomass demands. Several regions that contain both high current and future potential are urban areas or prime agricultural lands used for food and fiber production. In addition, some of these regions contain wetlands and marsh habitat critical for conservation of biodiversity and endangered species. Careful decisions will need to be made to maximize production of crops for both food and fuel while maintaining biodiversity (Fletcher et al. 2011). The regions in this study most likely to satisfy these conditions are in eastern Texas, northern Louisiana, and Kansas. However, a rigorous study of these trade-offs is needed to assess the risk of land conversion.

This is the first study to use a mechanistic model for large-scale spatial predictions of biomass while including variation in soil type and properties within the unit area of analysis. Brown et al. (2000) used EPIC, another mechanistic model, to predict the potential of switch-

PLATE 1. Lowland switchgrass stand in Fayetteville, Arkansas, USA. Photo credit: K. D. Behrman.

grass for 50-km^2 cells in Missouri, Indiana, Nebraska, and Kansas by placing one representative field in the center of each cell, and variation in soil properties within the cell was not accounted for. Thomson et al. (2009) used EPIC to estimate switchgrass potential for large hydrologic units across the United States. Only major agricultural soils within each hydrologic unit were included in the model. Davis et al. (2011) used DAYCENT to simulate switchgrass yield by choosing the dominant agricultural soil in each major corn-producing county throughout the central United States. These approaches may result in under- or overestimated yields if a sparse low-quality soil is located in the cell center, or if there is a low proportion of agricultural soil in the unit area.

Previous efforts to estimate future potential or future presence of switchgrass have been limited. The future yield of switchgrass was predicted using EPIC across four states (Missouri, Indiana, Nebraska, Kansas) by Brown et al. (2000). Their results similarly predict switchgrass yields in this region to increase by >8 Mg/ha. Barney and DiTomaso (2010) used a climate envelope model to estimate the species range (as presence or absence) for switchgrass under future climate scenarios. It is difficult to directly compare a range map to continuous estimates of biomass. However, they forecast the future species range to encompass all of the central and eastern United States and be absent to the south in Texas and in states along the Gulf Coast. Whereas, our results predict a decrease in local biomass potential in this region but productivity still remains relatively high.

Modeling of future climate change scenarios predicts warmer minimum temperatures that shift the USDA Hardiness Zones northward and influence the susceptibility of the lowland ecotype to freezing winter temperatures. Increases in productivity over time when precipitation remains constant is due to an increase in the number of degree-days that expands the growing season allowing for higher biomass production. Our analysis for future climate change holds the geographic extent of the lowland and upland ecotypes constant. However, increases in temperature may make conditions suitable for lowland switchgrass types to thrive farther north in upland regions. Thus productivity may be expected to increase more than we predict in these regions.

An alternative form of model evaluation was used to verify our spatial and future productivity estimates. We compared the relationships between climate factors governing changes in modeled output and measured values (Schimel et al. 1997). The dominant relationship between modeled and measured yields to climate is identical. The consistency of these spatial relationships indicates that the ALMANAC model is accurately incorporating the effect of variation in climate on spatial yields. This also provides additional confidence in our future predictions. Because switchgrass is a managed perennial species, temporal changes in climate will impact yield production in a similar manner as spatial changes.

The CCCMA-CGCM2 model was chosen to simulate both the B2 and A2 climate change scenarios. One model was chosen to emphasize how the intensification of greenhouse gas emissions impact switchgrass yields, as opposed to how predictions may vary depending on the climate model selected. The CGCM2 model was chosen because it performs well in North America and only has known biases in air temperature during the winter (December, January, February), a time period that is not critical for warm season grass growth (Flato et al. 2000). Despite the variation in climate change predictions across models, all models consistently predict that there will be increased intensification of air warming toward northern latitudes and increased precipitation toward northern latitudes (Cubasch et al. 2001). The degree of warming in eastern North America is relatively certain across many models while the magnitude of warming in central North America is more unpredictable (Tebaldi et al. 2005). In this study, our results depict how spatially explicit changes in temperature and precipitation are related to yield and may allow for inferences to be made if future climate is different than that predicted.

For this study, management was held constant across the geographic range and for all time periods studied to highlight the effect of climate. Variation in management may have a profound effect on yield estimates. For example, nitrogen may be limiting growth at locations with poor quality soils and additional nitrogen fertilizer may be added to increase productivity (Muir et al. 2001). However, fertilizer is costly, decreases profits, and may have negative environmental impacts (i.e., eutrophication, soil acidification). The time of planting and harvesting may also affect productivity estimates. In our model, harvesting was done once a year late in the growing season. Increasing harvesting to twice a year may allow for further increases in biomass production (McLaughlin and Kszos 2005). Alternative management schemes may be studied to enhance regional productivity.

The ALMANAC model assumes that the stands of adapted ecotypes establish and persist over the sampling period. In addition, each adapted ecotype is assumed to exhibit consistent growth attributes (e.g., LAI) across each planting region and over the entire timescale modeled. A key improvement for future studies will be to directly incorporate genotype × environment interaction on biomass potentials across the spatial and temporal scales studied. Although our approach incorporates some notion of genetic diversity in evaluating biomass potential, additional studies including more cultivars are needed. Switchgrass is known to exhibit genotype × environment interactions for biomass production across years and sites (Hopkins et al. 1995*a*, *b*, Casler and Boe 2003, Casler et al. 2004, 2007). These complex interactions are important to consider for plant breeding, utilization of diverse germplasm, and accuracy of agronomic modeling used to predict biomass.

The results in this study may provide future insights into several aspects of biofuel research. First, the spatial biomass estimates presented in this study can be used to guide empirical projects. Ongoing field trials may be used to validate local estimates of biomass or to determine additional factors limiting the growth of switchgrass. Second, ALMANAC also can be used to direct the genetic breeding of switchgrass by running a range of crop parameters within measured genetic variation (i.e., LAI). Third, ALMANAC local biomass potential can be used to guide land conversion to maintain adequate production of food and biodiversity levels.

Growing energy demands and concerns for climate change have pushed forward the timeline for biofuel based energies. Despite more than two decades of research, there are still large gaps in the understanding of switchgrass biology. The collection of vital empirical data and plant breeding will take considerable time. As such, modeling is an important tool for filling the existing knowledge gap. In this study, it is demonstrated that spatially explicit modeling can help assess spatial variation in current and future biofuel crop productivity and may help ensure long-term sustainability of biofuel production.

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Literature Cited

Akaike, H. 1974. A new look at the statistical model identification. IEEE Transactions on Automatic Control 19:716–723.

Barney, J. N., and J. M. DiTomaso. 2010. Bioclimatic predictions of habitat suitability for the biofuel switchgrass in North America under current and future climate scenarios. Biomass and Bioenergy 34:124–133.

Bransby, D. I., S. B. McLaughlin, and D. J. Parrish. 1998. A review of carbon and nitrogen balances in switchgrass grown for energy. Biomass and Bioenergy 14:379–384.

Brown, R. A., N. J. Rosenberg, C. J. Hays, W. E. Easterling, and L. O. Mearns. 2000. Potential production and environmental effects of switchgrass and traditional crops under current and greenhouse-altered climate in the central United States: a simulation study. Agriculture, Ecosystems and Environment 78:31–47.

Casler, M. D. 2005. Ecotypic variation among switchgrass populations from the northern USA. Crop Science 45:388–398.

Casler, M. D., and A. R. Boe. 2003. Cultivar x environment interactions in switchgrass. Crop Science 43:2226–2233.

Casler, M. D., K. P. Vogel, C. M. Taliaferro, N. J. Ehlke, J. D. Berdahl, E. C. Brummer, R. L. Kallenbach, C. P. West, and R. B. Mitchell. 2007. Latitudinal and longitudinal adaptation of switchgrass populations. Crop Science 47:2249–2260.

Casler, M. D., K. P. Vogel, C. M. Taliaferro, and R. L. Wynia. 2004. Latitudinal adaptation of switchgrass populations. Crop Science 44:293–303.

Cubasch, U., G. A. Meehl, G. J. Boer, R. J. Stouffer, M. Dix, A. Noda, C. A. Senior, S. Raper, and K. S. Yap. 2001. Projections of future climate change. Pages 526–582 *in* J. T. Houghton, Y. Ding, D. J. Griggs, M. Noguer, P. J. Van der Linden, X. Dai, K. Maskell, and C. A. Johnson, editors. Climate Change 2001: The Scientific Basis. Contribution of

Working Group I to the Third Assessment Report of the Intergovernmental Panel, Cambridge, UK.

Dale, V. H., K. L. Kline, L. L. Wright, R. D. Perlack, M. Downing, and R. L. Graham. 2011. Interactions among bioenergy feedstock choices, landscape dynamics, and land use. Ecological Applications 21:1039–1054.

Davis, S. C., W. J. Parton, S. J. Del Grosso, C. Keough, E. Marx, P. R. Adler, and E. H. DeLucia. 2011. Impact of second-generation biofuel agriculture on greenhouse-gas emissions in the corn-growing regions of the US. Frontiers in Ecology and the Environment 10:69–74.

Demirbas, A. 2009. Political, economic and environmental impacts of biofuels: a review. Applied Energy 86:108–117.

Epstein, H. E., W. K. Lauenroth, and I. C. Burke. 1997. Effects of temperature and soil texture on ANPP in the U.S. Great Plains. Ecology 78:2628–2631.

Evans, J. M., R. J. Fletcher, Jr., and J. Alavalapati. 2010. Using species distribution models to identify suitable areas for biofuel feedstock production. GCB Bioenergy 2:63–78.

Fike, J. H., D. J. Parrish, D. D. Wolf, J. A. Balasko, J. T. Green Jr., M. Rasnake, and J. H. Reynolds. 2006. Switchgrass production for the upper southeastern USA: influence of cultivar and cutting frequency on biomass yields. Biomass and Bioenergy 30:207–213.

Flato, G. M., G. J. Boer, W. G. Lee, N. A. McFarlane, D. Ramsden, M. C. Reader, and A. J. Weaver. 2000. The Canadian Centre for Climate Modelling and Analysis global coupled model and its climate. Climate Dynamics 16:451–467.

Fletcher, R. J., B. A. Robertson, J. Evans, P. J. Doran, J. R. Alavalapati, and D. W. Schemske. 2011. Biodiversity conservation in the era of biofuels: risks and opportunities. Frontiers in Ecology and the Environment 9:161–168.

Hall, D. O. 1997. Biomass energy in industrialised countries—a view of the future. Forest Ecology and Management 91:17–45.

Hill, J., E. Nelson, D. Tilman, S. Polasky, and D. Tiffany. 2006. Environmental, economic, and energetic costs and benefits of biodiesel and ethanol biofuels. Proceedings of the National Academy of Sciences USA103:11206–11210.

Hopkins, A. A., and C. M. Taliaferro. 1997. Genetic variation within switchgrass populations for acid soil tolerance. Crop Science 37:1719–1722.

Hopkins, A. A., K. P. Vogel, K. J. Moore, K. D. Johnson, and I. T. Carlson. 1995*a*. Genotype effects and genotype by environment interactions for traits of elite switchgrass populations. Crop Science 35:125–132.

Hopkins, A. A., K. P. Vogel, K. J. Moore, K. D. Johnson, and I. T. Carlson. 1995*b*. Genotypic variability and genotype × environment interactions among switchgrass accessions from the midwestern USA. Crop Science 35:565–571.

Jager, H. I., L. M. Baskaran, C. C. Brandt, E. B. Davis, C. A. Gunderson, and S. D. Wullschleger. 2010. Empirical geographic modeling of switchgrass yields in the United States. GCB Bioenergy 2:248–257.

Johnson, M. V., J. R. Kiniry, H. Sanchez, H. W. Polley, and P. A. Fay. 2010. Comparing biomass yields of low-input high-diversity communities with managed monocultures across the central United States. BioEnergy Research 3:353–361.

Kimball, B. A. 1983. Carbon dioxide and agricultural yield: an assemblage and analysis of 430 prior observations. Agronomy Journal 75:779–788.

Kiniry, J. R., K. A. Cassida, M. A. Hussey, J. P. Muir, W. R. Ocumpaugh, J. C. Read, R. L. Reed, M. A. Sanderson, B. C. Venuto, and J. R. Williams. 2005. Switchgrass simulation by the ALMANAC model at diverse sites in the southern US. Biomass and Bioenergy 29:419–425.

Kiniry, J. R., M. V. Johnson, S. B. Bruckerhoff, J. U. Kaiser, R. L. Cordsiemon, and R. D. Harmel. 2011. Clash of the titans: comparing productivity via radiation use efficiency for two grass giants of the biofuel field. BioEnergy Research 5:41–48.

Kiniry, J. R., L. Lynd, N. Greene, M. V. Johnson, M. Casler, and M. S. Laser. 2008*a*. Biofuels and water use: comparison of maize and switchgrass and general perspectives. Pages 17–30 *in* J. H. Wright and D. A. Evans, editors. New research on biofuels. Nova Science, New York, New York, USA.

Kiniry, J. R., M. A. Sanderson, J. R. Williams, C. R. Tischler, M. A. Hussey, W. R. Ocumpaugh, J. C. Read, G. Van Esbroeck, and R. L. Reed. 1996. Simulating Alamo switchgrass with the ALMANAC model. Agronomy Journal 88:602–606.

Kiniry, J. R., M. R. Schmer, K. P. Vogel, and R. B. Mitchell. 2008*b*. Switchgrass biomass simulation at diverse sites in the northern Great Plains of the US. BioEnergy Research 1:259–264.

Kiniry, J. R., J. R. Williams, P. W. Gassmann, and P. Debaeke. 1992. General, process-oriented model for two competing plant species. Transactions of the ASAE 35:801–810.

Kumar, S. 2007. Fourth assessment report of the Intergovernmental Panel on Climate Change: important observations and conclusions. Current Science 92:1034.

McLaughlin, S. B., J. R. Kiniry, C. M. Taliaferro, D. De La, Torre Ugarte, and D. L. Sparks. 2006. Projecting yield and utilization potential of switchgrass as an energy crop. Advances in Agronomy 90:267–297.

McLaughlin, S. B., and L. A. Kszos. 2005. Development of switchgrass (*Panicum virgatum*) as a bioenergy feedstock in the United States. Biomass and Bioenergy 28:515–535.

Muir, J. P., M. A. Sanderson, W. R. Ocumpaugh, R. M. Jones, and R. L. Reed. 2001. Biomass production of Alamo switchgrass in response to nitrogen, phosphorus, and row spacing. Agronomy Journal 93:896–901.

Nagelkerke, N. J. D. 1991. A note on a general definition of the coefficient of determination. Biometrika 78:691–692.

NCDC. 1993. Solar and Meteorological Surface Observation Network, 1961–1990, Version 1.0, September 1993. National Climatic Data Center, U.S. Department of Commerce, Asheville, North Carolina, USA.

Perlack, R. D., L. L. Wright, A. F. Turhollow, R. L. Graham, B. J. Stokes, and D. C. Erbach. 2005. Biomass as feedstock for a bioenergy and bioproducts industry: the technical feasibility of a billion-ton annual supply. Technical Report ORNL/TM 2006/66. Oak Ridge National Laboratory, Oak Ridge, Tennessee, USA.

PRISM Climate Group. 2011. "PRISM Climate Group." Oregon State University. http://prism.oregonstate.edu

R Development Core Team. 2011. R: a language and environment for statistical computing. R Foundation for Statistical Computing. http://www.r-project.org

Ramirez, J., and A. Jarvis. 2008. High resolution statistically downscaled future climate surfaces. Centre for Tropical Agriculture, CIAT, Cali, Colombia.

Robertson, G., S. Hamilton, S. Del Grosso, and W. Parton. 2011. The biogeochemistry of bioenergy landscapes: carbon, nitrogen, and water considerations. Ecological Applications 21:1055–1067.

Sala, O. E., W. J. Parton, L. A. Joyce, and W. K. Lauenroth. 1988. Primary production of the central grassland region of the United States. Ecology 69:40–45.

Sanderson, M. A., P. R. Adler, A. A. Boateng, M. D. Casler, and G. Sarath. 2006. Switchgrass as a biofuels feedstock in the USA. Canadian Journal of Plant Science 86:1315–1325.

Sanderson, M. A., et al. 1996. Switchgrass as a sustainable bioenergy crop. Bioresource Technology 56:83–93.

Schimel, D. S., VEMAP Participants, and B. H. Braswell. 1997. Continental scale variability in ecosystem processes: models, data, and the role of disturbance. Ecological Monographs 67:251–271.

Schmer, M. R., K. P. Vogel, R. B. Mitchell, and R. K. Perrin. 2008. Net energy of cellulosic ethanol from switchgrass. Proceedings of the National Academy of Sciences USA 105:464–469.

Searchinger, T., R. Heimlich, R. A. Houghton, F. Dong, A. Elobeid, J. Fabiosa, S. Tokgoz, D. Hayes, and T.-H. Yu. 2008. Use of U.S. croplands for biofuels increases greenhouse gases through emissions from land-use change. Science 319:1238–1240.

Secchi, S., P. W. Gassman, M. Jha, L. Kurkalova, and C. L. Kling. 2011. Potential water quality changes due to corn expansion in the Upper Mississippi River Basin. Ecological Applications 21:1068–1084.

Stout, W. L., J. A. Shaffer, G. A. Jung, T. E. Staley, and R. R. Hill. 1988. Nitrogen effects on soil water extraction by tall fescue in northern Appalachia. Journal of Soil and Water Conservation 46:150–153.

Tebaldi, C., R. L. Smith, D. Nychka, and L. O. Mearns. 2005. Quantifying uncertainty in projections of regional climate change: a Bayesian approach to the analysis of multimodel ensembles. Journal of Climate 18:1524–1540.

Thomson, A. M., R. C. Izarrualde, T. O. West, D. J. Parrish, D. D. Tyler, and J. R. Williams. 2009. Simulating potential switchgrass production in the United States. Pacific Northwest National Laboratory PNNL-19072, Richland, Washington, USA.

Wiens, J., J. Fargione, and J. Hill. 2011. Biofuels and biodiversity. Ecological Applications 21:1085–1095.

Williams, J. R., C. A. Jones, J. R. Kiniry, and D. A. Spanel. 1989. The EPIC crop growth model. Transactions of the American Society of Agricultural Engineers 32:497–511.

Wullschleger, S. D., E. B. Davis, M. E. Borsuk, C. A. Gunderson, and L. R. Lynd. 2010. Biomass production in switchgrass across the United States: database description and determinants of yield. Agronomy Journal 102:1158–1168.

Zhang, Y., J. E. Zalapa, A. R. Jakubowski, D. L. Price, A. Acharya, Y. Wei, E. C. Brummer, S. M. Kaeppler, and M. D. Casler. 2011. Post-glacial evolution of *Panicum virgatum*: centers of diversity and gene pools revealed by SSR markers and cpDNA sequences. Genetica 139:1–16.

Supplemental Material

Appendix A

Table with parameter estimates for the best-fit multiple simultaneous spatial autoregressive linear model (*Ecological Archives* A023-006-A1).

Appendix B

Figure showing the relative standard error (RSE) of mean switchgrass yield as a function of the number of random points distributed in each 27.5-km^2 cell (*Ecological Archives* A023-006-A2).

Appendix C

The spatial distribution of the 2851 USDA-NRCS nonirrigated alfalfa yields across the north central and eastern United States used in Fig. 2 (*Ecological Archives* A023-006-A3).

Appendix D

The first and second principal component scores for each weather station id and the loading for each variable (*Ecological Archives* A023-006-A4).

Appendix E

The change in switchgrass LBP expected from current climate by 2080–2090 under the A2 scenario in relation to changes in growing-season precipitation, maximum temperature, and minimum temperature (*Ecological Archives* A023-006-A5).