Response of switchgrass yield to future climate change

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Received 3 September 2012
Accepted for publication 16 October 2012
Published 6 November 2012
Online at stacks.iop.org/ERL/7/045903

Abstract
A climate envelope approach was used to model the response of switchgrass, a model bioenergy species in the United States, to future climate change. The model was built using general additive models (GAMs), and switchgrass yields collected at 45 field trial locations as the response variable. The model incorporated variables previously shown to be the main determinants of switchgrass yield, and utilized current and predicted 1 km climate data from WorldClim. The models were run with current WorldClim data and compared with results of predicted yield obtained using two climate change scenarios across three global change models for three time steps.

Results did not predict an increase in maximum switchgrass yield but showed an overall shift in areas of high switchgrass productivity for both cytotypes. For upland cytotypes, the shift in high yields was concentrated in northern and north-eastern areas where there were increases in average growing season temperature, whereas for lowland cultivars the areas where yields were projected to increase were associated with increases in average early growing season precipitation.

These results highlight the fact that the influences of climate change on switchgrass yield are spatially heterogeneous and vary depending on cytotype. Knowledge of spatial distribution of suitable areas for switchgrass production under climate change should be incorporated into planning of current and future biofuel production. Understanding how switchgrass yields will be affected by future changes in climate is important for achieving a sustainable biofuels economy.

Keywords: switchgrass, biofuels, climate change, spatial variability, climate envelope

1. Introduction

‘Second generation biofuels’ have long been proposed as a sustainable alternative over crop feedstocks (Lynd et al 1991). Although the potential negative indirect effects of biofuels on biodiversity, water use, and indirect land use changes have been documented (Cook et al 1991, Searchinger et al 2008, US Congress 2007), 80 billion litres of non-corn starch based biofuels will be produced in the United States by 2022. However, second generation biofuels that utilize perennial native plants such as switchgrass (Panicum virgatum L.) are thought to have a lower impact on biodiversity than crops (Fletcher et al 2011) especially when considerations such as reduced chemical inputs, increased heterogeneity in the fields
and delayed harvest until bird breeding has ceased are taken into account. Switchgrass has been highlighted as the model herbaceous feedstock in North America not only for its high productivity and ability to tolerate a vast range of conditions and to grow well on marginal environments, but also for its environmental benefits such as carbon sequestration and erosion control (McLaughlin and Walsh 1998).

Despite the potential for developing advanced biofuel technologies, there is evidence that climate change might alter the geography of suitable habitat for feedstock crops. Climate envelope models (CEMs) are typically used to predict how species ranges change given a future climate and are commonly used in biogeography studies to predict changes in species distribution. CEMs use the current distribution of a species to infer its environmental requirements, and then predict its future distribution based on these requirements given changes in climate (Araujo et al. 2005, Nunes et al. 2007, Williams and Jackson 2007). For example, Barney and DiTomaso (2010) used bioclimatic envelope models and historical switchgrass presence/absence data to predict that there will be an overall increase in suitable habitat for switchgrass cultivation in the coming century under both the CCCMA and HADCM3 climate models and A2 and B2 emission scenarios. The desired traits of an ideal biofuel feedstock species (e.g., high biomass, ability to grow under marginal conditions, drought, salinity and low-fertility soil tolerance) are typically similar to traits of invasive plants (Cousens 2008, Mack 2008). Thus, despite the attraction of increased yields, there is also concern that feedstock species, including switchgrass, have the potential of becoming invasive under future climates (Barney and DiTomaso 2008, Simberloff 2008).

Understanding how switchgrass yields will respond to projected future climate change is of fundamental importance for planning, implementation, and operational management of future biofuel production systems. A recent study by Tulbure et al. (2012) showed that switchgrass yields are sensitive to climatic variability in space and time, with different cytotypes exhibiting different responses. Utilizing switchgrass yield data in bioclimatic envelope models provides improved insights into how future changes in climate will affect switchgrass productivity compared to models based on presence–absence data. Therefore the aim of our research was to apply our modelling approach to project how future changes in climate will influence changes in switchgrass yields.

2. Methods

2.1. Yield data used and data analysis

Switchgrass yield data collected from 1167 observations at 45 field trials across the native range of switchgrass were used. Ten variables previously shown to influence switchgrass yields were used as explanatory variables (Tulbure et al. 2012). Explanatory variables included early and late growing season precipitation, average growing season temperature, cultivar, germplasm origin, month of harvest, soil texture (percent sand and clay), stand age, and amount of nitrogen fertilizer applied. Given that the relationship between several explanatory variables and the dependent variable showed non-linear trends, we used general additive models (GAMs) to model switchgrass as a non-linear function of explanatory variables. GAMs allow for non-linear relationships between the dependent and explanatory variables thus revealing structure in the data that might otherwise be missed with linear models (Faraway 2004, Hastie and Tibshirani 1990). For a description of the sources of switchgrass yield data, their location and explanatory variables please refer to (Tulbure et al. 2012). The models previously developed were refitted using the WorldClim dataset. We used the mgcv package (Wood 2006, 2010) in the statistical software R (R Development Core Team 2012). The degree of smoothness for each covariate in the model was estimated as part of model fitting using generalized cross validation for parameter selection in mgcv (Wood 2006). In order to limit the amount of smoothing and avoid overfitting the models we set the k parameter to 4, thereby allowing only three degrees of freedom for each covariate in the model and producing ecologically defensible results (Wood 2006).

2.2. Climate data

We used interpolated climate surfaces of high resolution monthly maximum (tmax), minimum (tmin), and mean temperatures (tmean), and monthly precipitation (prec). For both current and future conditions we used WorldClim data (www.worldclim.org/) of approximately 1 km spatial resolution (Hijmans et al. 2005). Data were created by interpolation using a thin-plate smoothing spline of observed climate at weather stations, with latitude, longitude, and elevation as independent variables (Hijmans et al. 2005). Current conditions are interpolations of observed data, representative of 1950–2000. Downscaled projected future climate included three global climate models (GCM) based on the International Panel on Climate Change 3rd assessment data (Randall et al. 2007). The three GCMs included the Canadian Centre for Climate Modelling and Analysis (CCMCA), the Hadley Centre Coupled Model (HADCM3), and the Commonwealth Scientific and Industrial Research Organization (CSIRO). Coupled with each GCM, there were two emission scenarios (A2 and B2) based on differences in demographic, technological and economic advances (Nakicenovic et al. 2000) and three time frames (2020, 2050 and 2080), yielding a total of eighteen combinations (Hijmans et al. 2005). The A2 scenario family describes a heterogeneous world and assumes a high increase in population up to 15 billion in 2100, a CO2 emission rate of 30 Gt Cy−1, and a CO2 concentration of ~850 ppm by 2100. In contrast, the B2 scenario family emphasizes local solutions to economic and environmental sustainability and assumes an increase in population of up to 10 billion in 2100, a CO2 emission rate of 12 Gt Cy−1 and a total CO2 concentration of ~600 ppm by 2100.

For modelling the response of switchgrass yields to climate predictions, we used the predict.gam function, which
uses a fitted gam object (the result of our GAM modelling) and produces predictions with a new set of values for the model covariates (R Development Core Team 2012). Here, the only functions and the only variables allowed to vary over time were the climate variables (April–May precipitation, June–September precipitation, and average growing season temperature), whereas the other variables were set to mean values or the mode. We worked at the spatial resolution of the climate data sets and summarized switchgrass yield under current climate and predicted yields per scenario (A2 and B2) averaged over the three global climate models per time step.

3. Results

Predicted switchgrass yields are shown in figures 1 and 2 for upland and lowland cytotypes, respectively. For both upland and lowland cytotypes, the maximum switchgrass yields under climate change were projected to stay relatively similar to current values with a maximum of 15 Mg ha$^{-1}$ for upland and 42 Mg ha$^{-1}$ for lowland cytotypes. The spatial distribution of high yields shifted for both cytotypes towards northern areas of the switchgrass range, but the patterns were heterogeneous and cytotype specific (figures 1 and 2).

For upland cytotypes, the highest yields under current climate conditions occurred in Iowa, Wisconsin, and Pennsylvania. Predicted yields under both A2 and B2 scenarios showed similar patterns for the three time steps (figures 1(b) and (e), (c) and (f), and (d) and (g)) with yields generally decreasing over time within the current range of switchgrass. A shift in the locations of the highest predicted yields towards the north and the northeast also occurred (figures 1(b)–(g)).

For lowland cytotypes the area of highest yields currently includes most of Iowa, north-western Missouri along with parts of north-eastern Kansas, Illinois, Indiana, Kentucky, Tennessee and West Virginia (figure 2(a)). In 2020 the areas of highest yield shifted northward (figures 2(b) and (e)). In 2050 higher yields shifted northwest into much of South Dakota and...
Figure 2. Mean predicted switchgrass yield (Mg ha$^{-1}$) for lowland cytotypes for the (a) baseline period and under the A2 scenario for (b) 2020, (c) 2050, and (d) 2080 and under the B2 scenario for (e) 2020, (f) 2050, and (g) 2080. Areas shown in grey fell outside the ranges of precipitation and temperature conditions used to parameterize our GAM models. The analysis was conducted at 1 km resolution of the WorldClim data.

In 2080 for the A2 scenario the highest switchgrass yields were projected to occur in most of North Dakota, Eastern South Dakota, south eastern Nebraska, Iowa and southern Minnesota (figure 2(d)) and the pattern was fairly similar to the B2 scenario for the areas where we could predict the yield based on our models (figure 2(g)).

For both current and projected climate conditions, areas shown in grey (e.g., Texas, Louisiana) fell at the extremes or outside of the ranges of precipitation and temperature data used to parameterize our GAM models. We masked these areas in the results because of our low confidence about our ability to extrapolate yield estimates outside the range of the parameterization dataset (figures 1 and 2). The models thus only included pixels with early and late growing season precipitation between 50 and 150 mm of and with an average growing season temperature between 15 and 25 $^\circ$C. This masking highlighted the areas that lay outside the range of our parameterization dataset under the different climate change scenarios.

4. Discussion

Understanding how switchgrass yields will be affected by future changes in climate is important for achieving a sustainable biofuel economy (Glaser and Glick 2012). Here we provide results of how switchgrass yields are predicted to change under different climate change scenarios at the highest available spatial resolution using 1 km WorldClim global climate data and employing CEMs. CEMs have been previously used to predict distribution of birds in the UK (Araujo et al 2005), butterflies in Australia (Thomas et al 2004) and vascular plants in the Americas (Hijmans and Graham 2006) under different climate change scenarios. CEMs are typically based on presence–absence data. However, in the context of biofuels where productivity is important, models can be improved by using biomass data as a measure of performance rather than using presence/absence data which is only a rough proxy for potential productivity. Our analysis thus improves on the work of Barney and DiTomaso (2010) by using switchgrass yield data as opposed to presence/absence.
For both cytotypes the spatial distribution of maximum switchgrass yield is predicted to shift considerably. For upland cytotypes, the shift in distribution is more towards northern and north-eastern areas following an increase in average growing season temperature, whereas for lowland cultivars the areas where yields are projected to increase follow an increase in average early growing season (April–May) precipitation, which is the highest for 2050 (figures 2(c) and (f)). It should be noted that for areas where field trials are located (black dots in figures 1 and 2) which fell outside or were at the extremes of the precipitation and temperature conditions used to parameterize our GAM models, we cannot claim that yields will not change in the future, but rather that based on our current data and models we cannot make an informed prediction. In the future, it would be valuable to conduct switchgrass field trials in more extreme climates that reflect the future predictions projected under climate change scenarios.

It should also be noted that CEMs are empirical models therefore do not necessarily describe cause and effect relationships between the explanatory variables and the dependent variable (Kearney and Porter 2004) and thus may not reflect how a different set of conditions in the future might affect the variable of interest (e.g., higher temperature combined with higher precipitation that extend beyond the values observed at present). An alternative to CEMs is mechanistic models (MM), which use physiological requirements of species to parameterize the models and have the potential to give more realistic predictions under future climates that have no current analogue, but do not account for non-climatic influences (e.g., biotic interactions, dispersal limitations) (Pearson et al 2006). The use of MMs to model switchgrass yields is expected to increase as more switchgrass physiological data become available. As both MM and CEMs have pros and cons, a comparison of results produced by both approaches should be conducted to assess their performance and ultimately integrate the two modelling approaches (Midgley and Thuiller 2005, Thuiller et al 2005).

This study helps improve our understanding of how switchgrass yield will be affected by future changes in climate. The study by Barney and DiTomaso (2010) predicted an overall increase in suitable habitat for switchgrass cultivation in the coming century under both the CCCMA and HadCM3 climate models and A2 and B2 emission scenarios, whereas our findings project that the influences of climate change on yield will be spatially heterogeneous and will vary depending on cytotype. The continued development of bioclimatic envelope models using data on switchgrass yields can provide improved insights into how future changes in climate will affect switchgrass biomass yields. Given that switchgrass for biofuel production will likely be planted on marginal cropland, future work should map marginal cropland and integrate the maps thus created with the switchgrass yield maps provided here to assist planners with information on where it is more feasible to plant switchgrass. Projections of the geographic distribution of suitable areas for switchgrass production under climate change should be incorporated into planning of current and future locations for biofuel cultivation and therefore help maximize production while minimizing negative effects on biodiversity and losses of perennial land cover.

Acknowledgments

This research was supported by the US Department of Energy through the Sun Grant Initiative’s Regional Biomass Feedstock Partnership. We thank two anonymous reviewers for comments which improved the manuscript.

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