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Analysis

Environment or food: Modeling future land use patterns of miscanthus for bioenergy using fine scale data☆

Lunyu Xie[a,*,1], Sarah L. MacDonald[b,2], Maximilian Auffhammer[c,3], Deepak Jaiswal[d,4], Peter Berck[e,5]

[a] Department of Energy Economics, School of Applied Economics, 939 Mingde Main Building, Renmin University of China, 59 Zhongguancun Ave., Haidian District, Beijing 100872, China
[b] Envision Geo LLC, P.O. Box 91, Oakville, CA 94562, United States of America
[c] Department of Agricultural and Resource Economics and Policy, 241 University Hall, University of California, Berkeley, CA 94720, United States of America
[d] Institute of Genomic Biology, University of Illinois at Urbana-Champaign, 1206 West Gregory Drive, Urbana, IL 61801, United States of America
[e] Department of Agricultural and Resource Economics and Policy, University of California, Berkeley, CA 94720, United States of America

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ABSTRACT

Using fine-scale panel data and an econometric model, we predict land use change in the Midwestern United States if a new bioenergy crop, *Miscanthus* × *Giganteus* (*miscanthus*), is introduced. To explain farmers' current crop choices, we use a local, limited dependent variable regression based on soil and weather characteristics. To this model, we add miscanthus as a new crop, based on its place dependent *BioCro* model-predicted yield. We find that the vast majority of land used to grow miscanthus will come from land now used for non-major crops, pasture, woodland, and other uses. This implies that miscanthus can help mitigate climate change by displacing oil usage without causing food conflict.

Concerns about energy security and climate change have led to a variety of U.S. federal and state-level regulatory interventions designed to reduce domestic consumption of liquid petroleum products in the United States. One main regulatory strategy to achieve this goal is to ramp up production of second generation biofuels via the renewable fuels standard (RFSII).[6] The RFS program, of which RFSII is the most recent standard, requires renewable fuel to be blended into transportation fuel in increasing amounts each year. The RFSII envisions annual production of 36 billion g .allons of cellulosic biofuel in the U.S. by 2022.[7] If this standard were met solely with *Miscanthus* × *Giganteus* (hereafter miscanthus), it would require, according to Scown et al. (2012), approximately 8 million ha of cropland, or 12.7 million ha of Conservation Reserve Program (CRP) land and 5 million ha of cropland. The potential use of large quantities of

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* Corresponding author.
E-mail addresses: lunyuxie@ruc.edu.cn (L. Xie), sarah@envisiongeo.com (S.L. MacDonald), auffhammer@berkeley.edu (M. Auffhammer), djaiswal@illinois.edu (D. Jaiswal).
[1] Xie is Associate Professor at the Department of Energy Economics, School of Applied Economics, Renmin University of China.
[2] MacDonald is President of Envision Geo, LLC.
[3] Auffhammer is George Pardee Professor of Sustainable Development, Professor at the Department of Agricultural and Resource Economics, University of California at Berkeley.
[4] Jaiswal is Postdoctoral researcher at University of Illinois at Urbana-Champaign.
[5] Berck was S.J. Hall Professor at the Department of Agricultural and Resource Economics, University of California at Berkeley, and passed away while this paper was under review.

[6] First-generation biofuels are crop-based, such as ethanol. Their production could raise the price of the crop and induce cropland expansion. Elshout et al. (2015) assessed the global warming performance of crop-based biofuels and found location of crop cultivation is the primary factor driving variation in such performance.

[7] Energy Independence and Security Act (EISA) of 2007, Title 2 Subtitle A, Section 202 (2) B (i) (III) sets the second Renewable Fuel Standard, known as RFSII. The standard extends through 2022. However, the standard has proven infeasible to enforce in the short term; see American Petroleum Institute v. EPA (*American Petroleum Institute v. EPA*, 2013). In addition, there are several state-level initiatives that promote the use of biofuels, such as California's Low Carbon Fuel Standard (LCSF).

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cropland for biofuels raises questions about the effects of this policy on food prices. Yet if large quantities of forest, scrub, and pasture are used to make biofuel, there will be an effect on biodiversity as well as direct greenhouse gas emissions from the land conversion and other natural production processes (Searchinger et al., 2008). Predicting whether food or environment will be more likely affected by the introduction of miscanthus is necessary for decision makers to weigh the benefits and social costs of growing miscanthus. This paper aims to provide evidence on the type and location of lands the market will allocate to miscanthus, based on farmers' past crop choices and projected miscanthus yields.

In the economics literature estimating land allocation to bioenergy crops under the RFSII, there are three main types of models: computable general equilibrium (CGE) models, programming models based on profits, and econometric models based on historical choices. The CGE approach (e.g. Taheripour et al. (2011)) considers the whole economy and makes all outputs and prices variable, treats land at a highly aggregated level, and allocates land to different uses based on profitability of use and a set of elasticities of substitution among land use classes. We do not use the CGE model in this paper, so the typical CGE questions about processor locations, by-product markets, agricultural technology, and machinery requirements and access are not the focus of the paper, and we assume them to be fixed as observed. We instead focus on the spatial distribution of miscanthus and how changes in its price affect its production, ceteris paribus.

Compared to CGE models, profits in programming models are deterministic and based on an engineering-economic model. This type of model assumes that the land allocation process depends largely on local conditions and expected profits. The underlying disaggregated approach is a model of the yield and profitability of miscanthus or other bioenergy crops.[8] This paper borrows miscanthus' average cost function from Khanna et al. (2008), but it differs in the following way. Using historical price, yield, and cost information, Khanna et al. (2008) calculated an opportunity cost of land for food crops. Then they parametrically varied the price of miscanthus and found the locations where miscanthus would be planted by comparing profitability of miscanthus and food crops. In this paper, we explain farmers' current crop choices first, and then simulate farmers' choices when miscanthus is added to their choice sets. That is, we make predictions based on farmers' revealed preferences instead of calculating farmers' profits.

Finally, there are models that are largely econometric. While a model of crop choices among existing crops could be entirely econometric, adding a new crop requires at least one piece of information outside of the estimating data set. The most common way to provide the additional information is the assumption that the new activity is very like one of the existing alternatives. In logit, this is the assumption that the alternative specific constant of the new activity is the same as that of an existing activity. This paper makes a very different type of assumption about the new crop, by borrowing from the programming models of crop choice.

Our work is most similar to Anderson et al. (2012), an econometric model based on historical choices. While some strong assumptions must be made about the response of crop coverage to crop characteristics, Anderson et al. (2012) provided a novel regression-based approach to land coverage when there is a new land use. Our paper differs in the method of adding the bioenergy crop miscanthus. In Anderson et al. (2012), a new crop's relative shares on the landscape (apart from a calibrated alternative specific constant) depended on crop characteristics, estimated coefficients, and land characteristics. We instead simulate miscanthus' yields with *BioCro* (a successor to the process-based model WIMOVAC) and predict the land use proportion based on varying functions of its profit.

The model developed in this paper is a new hybridization of deterministic and statistical modeling for the introduction of a new crop. The advantage of this model over a pure process model is that it is "normed" to hundreds of thousands of actual farm land use decisions rather than being calibrated to a few plots. The advantage over the usual ways of introducing a "new alternative" (see McFadden BART study (1977) for a famous example) is that a process model with initial calibration is an improvement over assuming that a calibrating constant (alternative specific constant in McFadden) is the same as the constant in an existing alternative.

This paper includes most relevant variables discussed in previous crop coverage literature but differs by using fixed effects to account for many unobservable variables. We use year fixed effects to account for prices, government programs, input prices,[9] and other variables that are common to all farmers; we use crop fixed effects to account for risk and other time-invariant variables; and we include an interaction term for heat and moisture to count for that higher temperature may reduce yield further when it is combined with less moisture (Lobell et al., 2011).

This paper also contributes to literature on biofuel crops in making use of direct observation of fine-scale crop coverage data. The paper utilizes the NASS Cropland Data Layer and matches this data to both soil and weather data at a resolution of 4×4 km, much finer than the county-level regressions common in agricultural land use studies. The crop coverage is defined as the land share covered by a crop in a 4×4 km grid cell. Both the average condition and the heterogeneity of soil in a cell are explored in a set of soil variables. The detailed information on temperature and precipitation are explored in a set of weather variables. These fine-scale data provide information critical for studying farmers' crop decisions. The data also make possible local moving regressions, which are used in this paper to address the spatial correlation in the model of land use shares for existing crops.

The logic of our crop share model is that crop choice is determined by profits; profits are determined by prices, yields, and costs; and these in turn are determined by soil, weather, and prices. So the reduced form model for crop choice is a regression of crop coverage (e.g., percent land in a crop) on a yearly indicator (accounting for prices), soil and weather, as well as lagged crop coverage as in Nerlove (1956). The model is used to explain historical crop coverage in six Midwestern states. The bioenergy crop miscanthus is then added to the model by creating its profit function from estimates of yield and cost. Finally, the model is calibrated to the production of 100 million t (Mt) of miscanthus within our study area, proportional to the scale of production mandated by the RFSII.

We find that the simulation results heavily allocate land to miscanthus where miscanthus yields are high; increasing price, ceteris paribus, increases supply and high prices do lead to appreciable diversion of major amounts of cropland to biofuel uses. However, unless the miscanthus price is sufficiently high and the dependence of costs on yield is low, miscanthus is likely to compete for land more with forests and pastures, which are important to the environment, than with major food crops including corn, soy, and rice. This implies that growing miscanthus will likely bring environmental costs rather than an appreciable increase in food prices.

The remainder of the paper is organized as follows. We first

[8] A partial list of the previous relevant literature adopting profit-based models includes Khanna et al. (2008), Khanna et al. (2011), Rosburg and Miranowski (2011), National Academy of Sciences (2011), Chen et al. (2014), Elliot et al. (2014), and Scown et al. (2012).

[9] As we will present in the section on modeling, the year fixed effects are used in estimating farmers' choice on existing crops only. We would not be able to find the effect of a change in support policies or prices of existing crops. But the goal of paper is to analyze the effect of government policies on miscanthus and this goal can still be reached, because we simulate miscanthus' land shares based on the estimated choice function and a profit function of miscanthus, rather than by a fixed effect. When miscanthus price increases (for example, due to government's subsidy on miscanthus), the value of the profit function changes, and the simulated land shares change accordingly.

Table 1
Summary statistics.

Variable	North				South			
	Mean	St. dev.	Min	Max	Mean	St. dev.	Min	Max
Dependent variable: Area shares (%, from 2001 to 2010)	(Obs = 256,575 cell year)				(Obs = 142,830 cell year)			
Corn	27.5	19.6	0.0	98.3	2.0	5.6	0.0	82.8
Soy	20.9	16.2	0.0	100.0	9.9	16.7	0.0	95.5
Rice	–	–	–	–	3.2	8.7	0.0	100.0
Cotton	–	–	–	–	3.8	10.9	0.0	98.2
Land use (ha, from 2001 to 2010)	(Obs =257,965 cell year)				(Obs = 154,275 cell year)			
Corn	402.4	300.6	0.0	1479.3	29.7	87.4	0.0	1447.6
Soy	307.3	248.6	0.0	1407.8	148.4	266.2	0.0	1641.6
Rice	–	–	–	–	49.2	138.9	0.0	1368.8
Cotton	–	–	–	–	57.4	172.1	0.0	1690.0
Agricultural	1416.8	261.5	0.0	1711.3	1502.2	479.5	0.0	1845.9
Crop yield	(Obs = 27,333 cell)				(Obs = 15,493 cell)			
Miscanthus (t/ha, average from 2001 to 2010)	22.61	4.13	6.87	30.36	24.03	3.62	8.89	34.28
Weather variables								
Planting season (April through June from 2002 to 2010)	(Obs = 711,873 cell month)				(Obs = 416,307 cell month)			
Temperature (daily average, Celsius)	15.18	5.04	2.64	27.59	21.09	3.81	11.73	28.93
Precipitation (monthly average, CM)	10.26	3.91	1.45	37.16	12.14	3.61	2.09	28.54
Growing season (April through November from 2001 to 2009)	(Obs = 1,844,784 cell month)				(Obs = 1,110,248 cell month)			
Temperature (daily average, Celsius)	15.19	6.55	−2.39	28.92	21.00	5.29	5.67	30.41
Precipitation (monthly average, CM)	9.00	4.15	0.15	33.31	10.89	3.66	0.50	28.61
Soil condition	(Obs = 27,418 cell)				(Obs = 15,506 cell)			
Percent of land in Class 1 (%)	0.5	5.2	0.0	100.0	0.9	7.5	0.0	100.0
Percent of land in Class 2	61.8	42.8	0.0	100.0	24.9	35.8	0.0	100.0
Percent of land in Class 3	21.8	34.3	0.0	100.0	28.1	38.6	0.0	100.0
Percent of land in Class 4	4.9	18.4	0.0	100.0	6.4	20.9	0.0	100.0
Percent of land in Class 5	5.6	19.7	0.0	100.0	4.0	17.5	0.0	100.0
Percent of land in Class 6	5.1	18.9	0.0	100.0	28.6	40.3	0.0	100.0
Percent of land in Class 7	0.2	3.1	0.0	100.0	7.0	19.9	0.0	100.0
Percent of land in Class 8	0.1	2.7	0.0	100.0	0.1	2.7	0.0	99.2
Percent clay (%)	23.1	9.0	0.0	57.7	29.1	10.3	0.4	62.9
Percent sand (%)	31.4	22.5	0.1	95.3	28.6	13.6	0.1	84.6
Percent silt (%)	44.5	15.7	0.0	73.6	41.7	12.8	0.5	73.6
Water-holding capacity	0.17	0.03	0.00	0.45	0.15	0.03	0.00	0.25
pH value	6.31	0.63	0.02	7.70	5.45	0.68	0.06	8.00
Slope	4.60	5.00	0.01	48.00	8.82	7.53	0.05	25.40
Electrical conductivity	0.01	0.07	0.00	1.00	0.01	0.23	0.00	9.80
Frost-free days	151.03	29.13	0.00	213.75	206.32	58.18	0.00	302.70
Depth to water table	71.32	43.72	0.00	201.00	69.66	32.77	0.68	201.00
Depth to restrictive layer	172.43	48.87	3.30	201.00	165.40	53.71	18.00	201.00

Notes: North includes the three northern states (Wisconsin, Iowa, and Illinois) and South includes the three southern states (Missouri, Arkansas, and Mississippi). We distinguish them because they have very different major crops. Corn and soy are the major crops in the North, while rice and cotton are the major crops in the South.

summarize the data on land use, soil conditions, weather, and miscanthus yield for the states along the Mississippi-Missouri River corridor, in Section 1. Next we describe estimation issues and establish the econometric system, in Section 2. Then we present the estimation results in Section 3, describe how miscanthus is added to the system, and simulate the spatial distribution of miscanthus in Section 4. Finally, we conclude in Section 5.

1. Data

This paper uses four major data sets on land use, soil characteristics, weather, and miscanthus yield simulated from the *BioCro* model. The primary data set is created by matching these four fine-scale geospatially-explicit data sets on a 4 km by 4 km grid. The states included in this analysis are those along the Mississippi-Missouri River corridor for which there are land cover data from 2000 through 2010: Wisconsin, Iowa, Illinois, Missouri, Arkansas, and part of Mississippi. The first three data sets are similar to those analyzed in Xie et al. (2018), with the difference that only parts of Missouri and Arkansas were included in the previous study, because complete data for those states became available later. Summary statistics are provided in Table 1. Each variable in the table is described in detail below.

1.1. Land use

Land use data is derived from the Cropland Data Layer, provided by the USDA NASS. We define the share of major crops as the area of major crops divided by the area of agricultural land. Agricultural land is defined broadly as crop, pasture, idle, forest, etc., including all land except bodies of water and urban areas. We assume that the water and urban coverages are constant and do not discuss them further in this paper. Within the broad agricultural category, we explicitly model major croplands, which include lands growing corn and soybean for Wisconsin, Iowa, and Illinois, and corn, soybean, rice, and cotton for Missouri, Arkansas, and Mississippi. The remaining category is "other" land, which includes wild land, pasture, forest, etc.[10] Fig. 1 shows the shares of major crops and the "other" land in our study area.

1.2. Soil characteristics

Soil data are derived from the USDA's U.S. General Soil Map

[10] We originally intended to explicitly model some of the other land uses; however, the underlying data have large standard errors in classification, which would make such modeling very speculative.

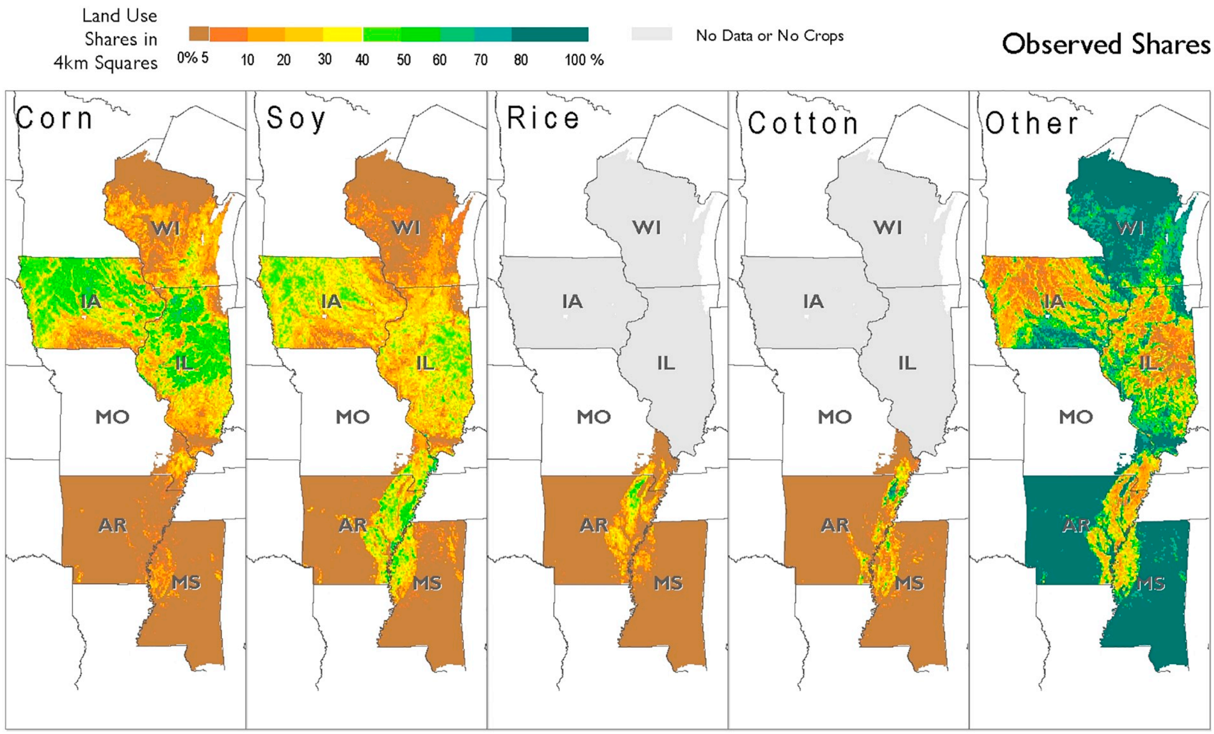


Fig. 1. Land use along the Mississippi-Missouri River system.
Notes: The land use shares displayed are average shares of corn, soy, rice, cotton, and "other" land over 2001 through 2010. The north half part of this graph is the same as Fig. 1 in Xie et al. (2018), because of the same data source.

(STATSGO2). According to the official website, the approximate minimum area delineated is 625 ha (1544 acres) and the data was mapped at a 1: 250,000 scale. Soil variable averages are spatially weighted from irregular polygons for each grid cell. The irregular polygons allow for flexibility for data that varies continuously across a landscape but is represented by discrete boundaries that are intersected by our regular grid. The spatial averaging of the irregular polygons allows for a better representation of the soil statistics within the fixed grid in which we work in this paper.

We focus on two types of soil variables. One is underlying soil data, and the other is Land Capability Class (LCC), a classification system generated by the USDA. Underlying soil data, including percent clay, sand, and silt, water-holding capacity, pH value, electrical conductivity, slope, frost-free days, depth to water table, and depth to restrictive layer. The LCC integer scores increase from one to eight, with higher LCC classifications signifying more limitations on the land for agricultural production.

The distribution of LCC levels is shown in Fig. 2. Reviewing this together with Fig. 1, we see that fertile soils spread in Iowa and Illinoi and hug the river in Missouri and Arkansas, and so do the major crops.

1.3. Weather variables

Weather variables include temperature and precipitation at daily level, which are processed by Schlenker and Roberts (2009) from the PRISM data sets and provided at a 4 km by 4 km spatial resolution.

Given that farmers make crop choice in planting season based on the observed weather condition in the planting season and also the expected weather condition in the following growing season, we include two time periods for each crop year. The first period data is for the planting season, which we define as the time-period from April to June. The second period data is for the past growing season, used as a proxy for expected weather. Past growing season is defined as the time period from April to November[11] in the last year.

Fig. 3 shows the observed weather during the planting seasons from 2002 through 2010 and growing seasons from 2001 through 2009, which is one year before the planting season, because we use past growing season in the regressions.

Instead of directly putting the temperature variable in the regressions, we use the degree day bins of each month in the planting season and the past growing season. Degree days are used to approximate the amount of heat is in a certain bin, and calculated by a fitted sine curve (Baskerville and Emin, 1969). We limit the number of classifications of temperature to those at critical thresholds identified in Schlenker and Roberts (2009).

1.4. Simulated miscanthus yield

The miscanthus yields that we use in this paper are produced using the R package *BioCro*, a semi-mechanistic dynamic crop growth and production model. The model and its calibration, described in Miguez et al. (2009, 2012), are based on levels of solar radiation received by the discrete layers of plant canopy, taking into consideration leaf photosynthesis capacity, phenology, and partitioning of dry biomass into different plant organs. The model is run at hourly time steps using a 4 km square gridded soil database. For each 4 km square, soil variables include field capacity, wilting point, available depth, and initial soil

[11] The planting season and the growing season are not the same across states. The start of a growing season is earlier in southern states than in northern states. We use April as the start of the growing season even though planting starts later in some of the states studied in this paper, so that we can cover the early growing season to avoid an omitted variable problem, at the potential cost of lower efficiency caused by including irrelevant variables for the northern states.

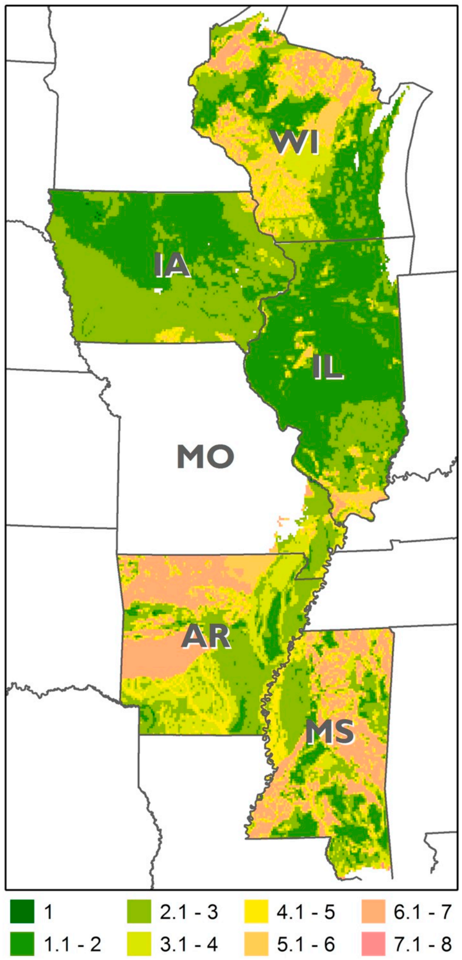


Fig. 2. Geographical distribution of Land Capability Classification levels.
Notes: The Land Capability Class score increases as the soil quality decreases. Because of the same data source, the north half part of this graph is the same as Fig. 2 in Xie et al. (2018).

moisture; weather variables include precipitation, solar radiation, wind speed, temperature, and relative humidity, derived from the corresponding North American Regional Reanalysis (NARR) grid. The simulated yield is the rain-fed[12] end-of-growth-season harvestable biomass.[13]

Fig. 4 shows the simulated miscanthus yield[14] along the corridor. Compared with Figs. 1 and 2, we see that most of the places with high miscanthus yield are where the soil is good and corn share is high. Southern Mississippi is the obvious exception, with high miscanthus yield and low corn shares.

2. Econometric model

In this section, we model farmers' crop choices, and then add miscanthus as a new crop into their choice sets.

Assume that there are M major crops, and farmers make crop choices for each hectare with the rule that the crop i with the highest profit (π_{int}) will be chosen. π_{int} can be decomposed as $V_{int} + d_{int}$, where V_{int} is a function of variables that affect profit and are observable to the researcher, and the parameters of the function can be estimated statistically; d_{int} is a function of the factors that affect profit but are not included in V_{int}. Within each of the 4 km squares, n, we observe the fraction of land in year t that was allocated to a crop i: S_{int}. The fraction of land in year t that was allocated to "other" use (e.g., minor crops, forest, pasture, etc.) is the alternative zero, denoted as S_{0nt}, and therefore $S_{0nt} + \sum_{i=1}^{M} S_{int} = 1$. We model the fraction of the crop chosen in a square using a proportion type model:

$$S_{int} = \phi_i((V_{1nt} + d_{1nt}),...,(V_{Mnt} + d_{Mnt})) \tag{1}$$

where $\phi_i()$ is a suitable transformation with its domain on the unit interval. All crops' profits are in the function, because farmers make choices by comparing across profits of all crops. Following Xie et al. (2018), we use a ratio transformation to simultaneously deal with the additive constraint and a great number of zero shares, and we get:

$$\frac{S_{int}}{S_{0nt}} = V_{int} + d_{int} \tag{2}$$

Eq. (2) is the form of our estimating equations. We estimate the crop coverage shares described in Eq. (2) by a limited dependent variable regression, a generalization of Nerlove's (1956) classic estimating equations. Based on the estimation, we predict V_{int}. We will discuss the regression specification in detail in the next section.

To find the implied shares as a function of the independent variables, we sum the share ratio S_{int} over i and solve for S_{0nt} and S_{int}:

$$S_{0nt} = \frac{1}{1 + \sum_{j=1}^{M} V_{jnt} + d_{\mathrm{jnt}}} \tag{3}$$

$$S_{int} = \frac{V_{int} + d_{int}}{1 + \sum_{j=1}^{M} V_{jnt} + d_{jnt}} \tag{4}$$

To add a new alternative (b) to the choice set, the share of a crop

[12] We assume in the *BioCro* model that miscanthus will be grown only under rain-fed conditions, because miscanthus is a very robust crop which does not need many inputs such as fertilizer, pesticides, irrigation etc. (e.g., Dwivedi et al., 2015; Christian et al., 2008; Heaton et al., 2008; Khanna et al., 2008). Besides, food crops generally have higher priority for irrigation in comparison to energy crops, and therefore irrigation resources would be diverted to land used for the production of food, rather than energy crops.

[13] This is significantly less than maximum biomass and accounts for losses while waiting for harvest. In addition, given that miscanthus is perennial, a rotation period of 15 years is typically considered to have little effect on the yield, but rotation length would be eventually determined by improvement in technology and agronomy practices (Hudiburg et al., 2015).

[14] As with all experimental crop data, there are caveats. Experimental fields are more carefully managed and controlled than farmers' actual fields, but these conditions are not necessarily profit-maximizing. Experimental fields do not show the full extent of potential insect and disease problems. On the other hand, experimental results could understate the results for full-scale producers, because farmers eventually will find unforeseen ways of increasing yields and profits. The role of nutrients and fertilization is not explicitly modeled in the *BioCro* model, because there are conflicting findings in experimental studies on

(*footnote continued*)
miscanthus' yield response to N fertilizers (e.g., Himken et al., 1997; Clifton-Brown et al., 2007; Christian et al., 2008; Arundale et al., 2014), and there is insufficient data to provide an optimal nitrogen application recommendation (Cadoux et al., 2011). The calibration of the *BioCro* model uses observations from experimental fields where the same type and the same level of inputs (e.g., fertilizer, pesticides etc.) are provided. As a consequence, when we simulate miscanthus shares in a later section, we implicitly assume that farmers input the same amount of fertilizer, pesticides, etc. This assumption is acceptable for our research purpose, because we focus on how the spatial variation in soil and weather will affect the spatial distribution of miscanthus, holding other factors (e.g., farmers' characteristics) the same across location. In addition, the role of atmospheric N deposition is not explicitly modeled. Atmospheric N deposition rates of 4 to 25 kg per ha per year are reported for grassland across multiple sites globally (Gomez-Casanovas et al., 2016). Keymer and Kent (2014) reported that about 16% of new plant nitrogen in the first year of miscanthus' plantation was derived from nitrogen fixation. The long-term productivity of miscanthus is likely to be maintained without N fertilization because N supplied by atmospheric deposition and free-living N fixation can keep pace with N removed with biomass harvest.

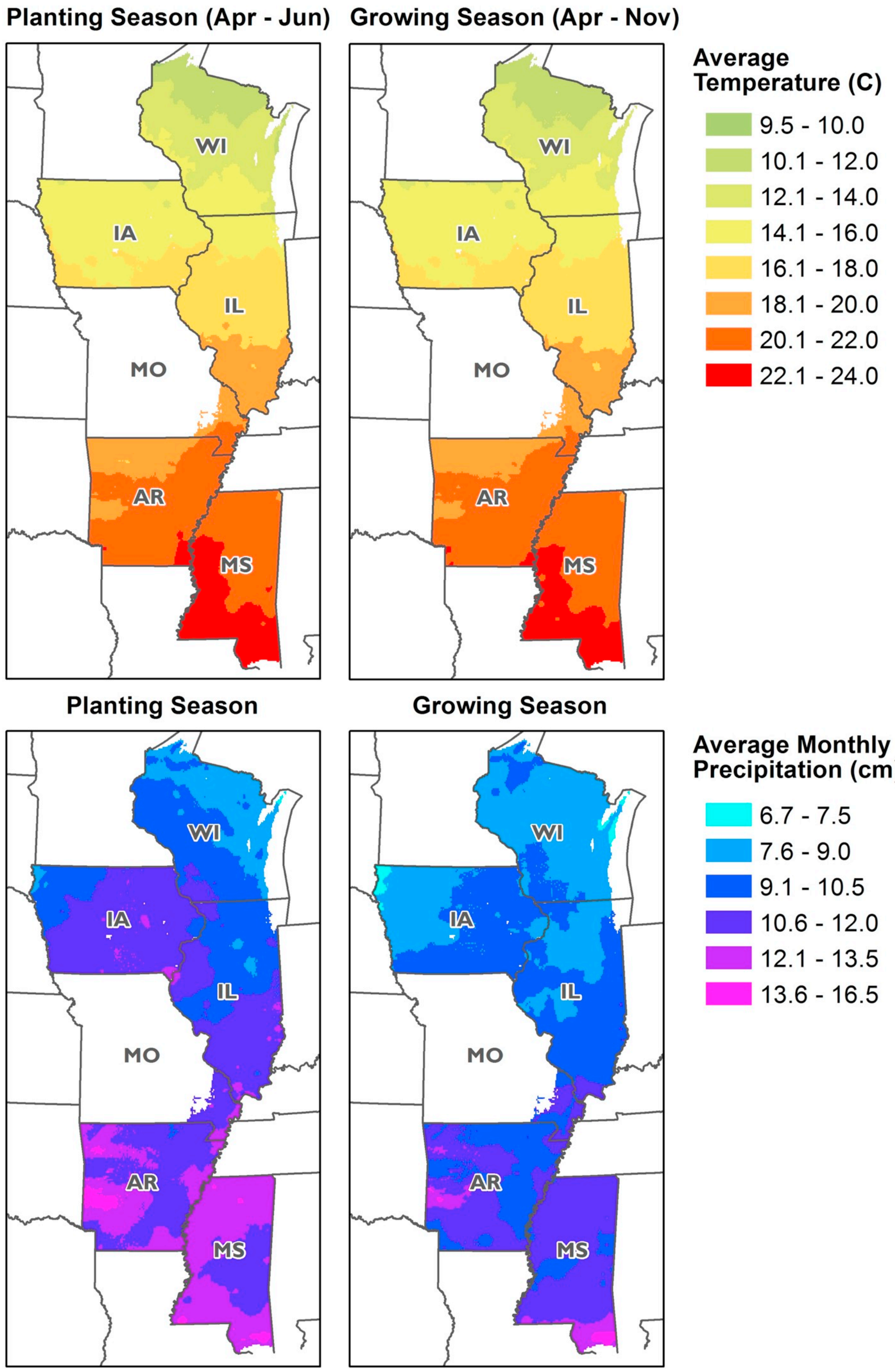


Fig. 3. Weather conditions.

Notes: The value of average temperature in a season is obtained by taking the average of daily temperature of all days in that season; and the value of average monthly precipitation in a season is obtained by summing up daily precipitation in a month, and then taking the average of monthly precipitation of all months in that season. The north half part of this graph is the same as Fig. 3 in Xie et al. (2018), because of the same data source.

becomes

$$S_{bnt} = \frac{V_{bnt} + d_{bnt}}{1 + V_{bnt} + d_{bnt} + \sum_{j=1}^{M} V_{jnt} + d_{jnt}} \tag{5}$$

and

$$S_{int} = \frac{V_{int} + d_{int}}{1 + V_{bnt} + d_{bnt} + \sum_{j=1}^{M} V_{jnt} + d_{jnt}} \tag{6}$$

In our case, the variance of the profits could be different for existing crops and the new crop. To normalize the scale of profit, we normalize the variance of the error terms (Train, 2009).

We denote the ratio of variances as k (known as a scale parameter, Train, 2009), then the model is rewritten as

$$S_{bnt} = \frac{k(V_{bnt} + d_{bnt})}{1 + k(V_{bnt} + d_{bnt}) + \sum_{j=1}^{M} V_{jnt} + d_{jnt}} \tag{7}$$

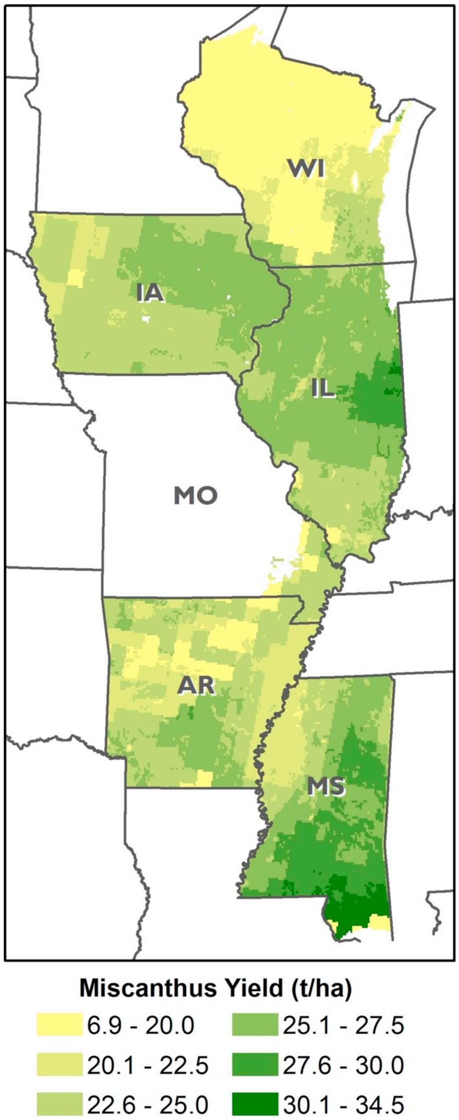


Fig. 4. Simulated miscanthus yield.
Notes: Miscanthus yield is predicted using the R package *BioCro*. The model predictions are matched to the 4 km square grid used for the rest of the data.

$$S_{int} = \frac{V_{int} + d_{int}}{1 + k(V_{bnt} + d_{bnt}) + \sum_{j=1}^{M} V_{jnt} + d_{jnt}} \tag{8}$$

As described in Eqs. (7) and (8), the simulation of coverage shares after adding the new crop depends on the estimation of V_{int}, V_{bnt}, and the scale parameter k. For the existing crops, we observe the crop shares, So V_{int} can be estimated from Eq. (2). For the new crop, we do not observe its share of the market, but we observe its yields on experiment fields. Therefore, we use a process model for yield and an engineering economic model of cost and price to construct the profitability of the new crop, π_{bnt}, which is $V_{bnt} + d_{bnt}$. In this way, k also takes care of the scale issue caused by the fact that the profits of existing crops and the new crop are estimated in different systems. We will discuss the construction of π_{bnt} and the calibration of k in the section on simulation.

3. Estimation for existing crops

In this section, we estimate Eq. (2), which states that crop choice depends on the profitability of growing crops.

First, we consider which explanatory variables V_{int} can depend on. To follow the literature,[15] we include as explanatory variables lagged crop shares, lagged substitute crop shares, weather in the current planting season and the last growing season, and soil conditions. In addition, we include the interaction term of heat and moisture, year fixed effects, and crop fixed effects. As in Xie et al. (2018), the regression specification is as follows:

$$\frac{S_{int}}{S_{0nt}} = \alpha_i + \beta_i S_{int-1} + \boldsymbol{\gamma_i}'\boldsymbol{SS}_{int-1} + \boldsymbol{\varphi}_i'\boldsymbol{Soil}_n + \boldsymbol{\theta}_{1i}'\boldsymbol{GDD}_{nt-1} + \boldsymbol{\theta}_{2i}'\boldsymbol{PDD}_{nt} + \boldsymbol{\theta}_{3i}'\boldsymbol{GP}_{nt-1} + \boldsymbol{\theta}_{4i}'\boldsymbol{PP}_{nt} + +\boldsymbol{\theta}_{5i}'\boldsymbol{PreDD}_{nt-1} + \mu_t + d_{int} \tag{9}$$

where $\boldsymbol{SS}_{int-1}$ is a vector of substitute crop shares planted in year $t-1$; $\boldsymbol{Soil}_n$ is a vector of soil conditions, including all the soil characteristics described in the data section; $\boldsymbol{GDD}_{nt-1}$ is a vector of degree days by month in the last growing season, and the critical temperatures are 10 °C and 15 °C (10 °C is the base temperature limit of rice, corn, and soybean development, while 15 °C is the base temperature limit of cotton development); $\boldsymbol{PDD}_{nt}$ is a vector of degree days by month in the current planting season, and the critical temperatures include 10 °C, 15 °C, 20 °C, 25 °C, 29 °C, and 32 °C (temperatures higher than 29 °C are harmful to corn, 30 °C to soybean, and 32 °C to rice and cotton (Schlenker and Roberts, 2009)); $\boldsymbol{GP}_{nt-1}$ is a vector of precipitation by month in the last growing season; $\boldsymbol{PP}_{nt}$ is a vector of precipitation by month in the current planting season; $\boldsymbol{PreDD}_{nt-1}$ is a vector of interactions of degree days above 30 °C and the inverse of precipitation levels in the same month; μ_t is year fixed effects; α_i is crop i's fixed effects, and d_{int} is the error term.

Second, we consider which econometric model to use. Following Xie et al. (2018), we adopt a Tobit model to deal with a great number of zero shares, and estimate Eq. (2) by moving local regressions to deal with the spatial correlation problem in the estimation. The spatial correlation can be addressed by a moving local regression, because the coefficients, including the constant, are free to vary across the landscape. In addition, by the local moving regression, yearly dummies vary across counties and therefore, geographic price variation is accounted for.

At last, we run separate regressions (Eq. (5)) for each crop and each county. One separate regression is estimated for one county, using data from squares in this county and its neighboring counties. Following Xie et al. (2018), we define neighbors of a county to be counties whose centroids are within 70 km of the centroid of this county. Therefore, each regression has about 900 squares (one county for itself, and eight county neighbors) for nine years. In sum, we have 1112 sets of estimates (445 counties; two main crops for the northern states and four main crops for the southern states).

The results of the F-tests on the significance of soil, precipitation, and degree days are shown in Table 2. Temperature is significant at the 1% level for 89% or more of the regressions in all crops. Soil is significant at the 1% level for proportions ranging from 76% of the regressions for rice and 93% for corn. Precipitation has the lowest percent of regressions that are significant, from 62% for rice to 77% for soy. Rice covers only about 4% of the land in the southern states, while the “other” category (land for other use) covers about 80% of the land. It is not surprising that the coefficients for rice are not statistically significant as often, given that the dependent variable is the ratio of rice share to the share of other land use. In a linear probability model, using only rice share, all coefficient groups are significant, so the lack of significance is likely because of the inability to predict the category of “other” land use. Cotton covers a small portion of land as well; however, cotton responds more strongly than rice to weather. Therefore, the coefficients are significant in the regressions for cotton while they are not in the regressions for rice.

[15] A short list of the related literature includes Askari and Cummings (1977), Braulke (1982), Choi and Helmberger (1993), Nerlove and Bessler (2001), Huang and Khanna (2010), Hausman (2012).

Table 2
F-tests for soil, precipitation and temperature.

	Corn	Soy	Rice	Cotton
Regressions with 1% significance level				
Soil	93%	88%	76%	84%
Precipitation	76%	77%	62%	74%
Temperature	92%	89%	89%	97%
Regressions with 5% significance level				
Soil	94%	91%	81%	91%
Precipitation	83%	84%	75%	82%
Temperature	93%	92%	89%	97%
Regressions with 10% significance level				
Soil	94%	92%	87%	91%
Precipitation	87%	88%	78%	87%
Temperature	94%	92%	89%	97%
Number of regressions in total	413	408	134	159

Notes: Separate regressions are run for each crop and each county. Corn and soy regressions are for counties in the six states along the Mississippi-Missouri River corridor (445 counties), while rice and cotton are for counties in the three southern states (172 counties). Some counties do not grow a certain crop in all years and neither do their neighbors. The regression of that crop is not run for those counties. This leads to 413 regressions for corn, 408 regressions for soy, 134 regressions for rice, and 159 regressions for cotton. Soil includes the LCC and the raw soil characteristics. Precipitation and temperature include precipitation and weather variables, respectively, in the current planting season and the last growing season.

4. Simulation for the new crop: miscanthus

In this section, we first construct the profitability of the new crop miscanthus (π_{bnt}), by using a process model for yield and an engineering economic model of cost and price. Together with the value of V_{int}, predicted after the estimation in the last section, we calibrate the model by finding the value of k. Then, we simulate the spatial distributions of miscanthus and the existing crops with the calibrated model (Eqs. (7) and (8)).

To construct π_{bnt}, we follow Khanna et al. (2008) and assume the average cost of growing miscanthus $ac = a - b * yield$, so profit of growing miscanthus $\pi_{bnt} = yield * (p - a + b * yield)$, which is quadratic in *yield*.[16] The parameter b in the cost function arises because the cost per ton falls when there are more tons per hectare. This is a usual feature of farming, as many operations depend on how much ground is cultivated with implements rather than how much yield is ultimately produced. Different crops, however, have different cost sensitivities to output. Miscanthus, having high bulk relative to its value and therefore high costs of collection, should have a particularly high b. As a result, its profits quickly increase in yield and, if it is grown at all, it is likely grown where its yields are high and other crops' yields are low. This will be borne out in the simulations below. Based on Table 6 in Khanna et al. (2008), the average cost of producing miscanthus dry matter is $54.72 - 0.35 * yield + 0.049 * 192.76$, where 192.76 is the average opportunity cost of land. Therefore $k\Pi_{bn2010}$ in Eqs. (6) and (7) is $k * yield * (p - a + b * yield)$, where $a = 54.72 - 0.049 * 192.76$, $b = 0.35$ and from the same source $p = 50$.[17] We call this the baseline scenario.

With the cost function and the price for miscanthus, we then calibrate the scale parameter k. The method is to find miscanthus' share in each 4 km square and add these shares together to get a production of 100 Mt under the price of \$50/t, using the formula for new crop shares, Eq. (8). 100 Mt production and a price of \$50 are used in the calibration, because according to Khanna et al. (2008), with the same cost function, the production in our study area is about 100 Mt when the price is \$50.[18]

Besides the profitability of the existing crops (V_{jnt}), which has been projected from the estimation of Eq. (9), and the profitability of miscanthus (π_{bnt}, which is described as $V_{bnt} + d_{bnt}$ in Eq. (8), and has been calculated from $\pi_{bnt} = yield * (p - a + b * yield)$), Eq. (8) also depends on the error terms from the regressions, d_{jnt}. In order to get shares averaged over these regression residuals, we simulate d_{jnt} ($j = 1, \dots, M$) by drawing from a left truncated normal distribution with mean 0, the regression estimated standard deviation σ_{jnt}, and truncation point at $-\boldsymbol{\beta_j}'\boldsymbol{X_{jnt}}$, where $\boldsymbol{\beta_j}'\boldsymbol{X_{jnt}}$ is the deterministic part of Eq. (9): $\alpha_j + \beta_j S_{jnt-1} + \gamma_j{}'\boldsymbol{SS}_{jnt-1} + \boldsymbol{\varphi_j}'\boldsymbol{Soil}_n + \boldsymbol{\theta_{1j}}'\boldsymbol{GDD}_{nt-1} + \boldsymbol{\theta_{2j}}'\boldsymbol{PDD}_{nt} + \boldsymbol{\theta_{3j}}'\boldsymbol{GP}_{nt-1} + \boldsymbol{\theta_{4j}}'\boldsymbol{PP}_{nt} + + \boldsymbol{\theta_{5j}}'\boldsymbol{PreDD}_{nt-1} + \mu_t$. Given a value of k, we calculate S_{jnt} and S_{bnt} for each draw from the distribution and take the average over the draws. The average of the shares over draws is the reported share. The number of hectares in the square planted in miscanthus is then multiplied by the predicted yield of miscanthus for that square given by the *BioCro* model to get the tons of miscanthus by square. Those are then summed over squares to get the total tons. The process is repeated for different k, by trial and error, until the total tons were equal to 100 Mt. The parameter k is found to be 0.00214.

Once the scale parameter k is calibrated, the model is calibrated, and therefore the choice rule is identified. With the revealed choice rule, we finally simulate the spatial distribution of miscanthus and the existing crops, using Eqs. (7) and (8).

We make the simulation in several scenarios. In the baseline scenario, the cost function follows Khanna et al. (2008) and the price of miscanthus is \$50 dollars. In the scenarios with different cost functions, k holds unchanged because the revealed choice rule is unchanged, and price is adjusted to keep total output at 100 Mt in order to exclude the output enhancing effect of the quadratic form in the cost function.

4.1. Baseline scenario

Fig. 5 shows the land use change caused by adding miscanthus to the landscape for the base case. The first panel of Fig. 5 shows where miscanthus is grown. In the north, it is patchy: these areas include southern Wisconsin and the adjacent part of Illinois, and the areas of southern Iowa and southern Illinois, south of the better soil types. In the south, the areas for growing miscanthus are away from the Mississippi River, again not on the better soil types, and it is heavily grown in the

[16] In the miscanthus yield model (*BioCro* model), the yield is projected for the condition that the input cost is held constant across space. Therefore, the relation between the projected yield and profit is constant across space. The quality of land is reflected in the projected yield, instead of in the cost. For low-quality land, with the same cost, the yield will be low, therefore the profit will be low as well.

Results from experiment fields with the same input cost can be applied to actual farming because, as we mentioned in the data section, miscanthus is a very robust crop that has low input requirements. Miscanthus is able to recycle nitrogen by sending nitrogen from the above-ground to the below-ground part of the rhizome at the time of harvest, and the same nitrogen is utilized for the next growing season (Somerville et al., 2010). The low (or no) nitrogen fertilizer requirement is the reason why it is so attractive as a biofuel feedstock.

As for irrigation, since the yield simulation results are only for rain-fed conditions, there is no cost associated with irrigation. Therefore, the simulated land share of miscanthus on irrigated area will be the same as that on non-irrigated areas if the two areas have the same soil characteristics and weather conditions. Even if regular irrigation improves the quality of the land (e.g., soil moisture), the effect of irrigation on land allocation is implicitly reflected in the land share simulation, since the simulation explicitly models the role of land quality.

[17] Khanna et al. (2011) estimated about 100Mt miscanthus production in the Midwest at a price of \$50/t (2007 value. US dollars in this paper are all in 2007 values). This price falls within the range of farm-gate breakeven price estimated in Khanna et al. (2008) for Illinois counties, which is \$41 to \$58/t.

[18] According to Khanna et al.'s (2011) simulation results, when the cost of cellulosic feedstock production is low (their scenario 1), at a price of \$50/t, 27% of the total miscanthus produced (352 Mt) will be in the Midwest (12 states). Here we assume all miscanthus is produced in the six states studied in this paper.

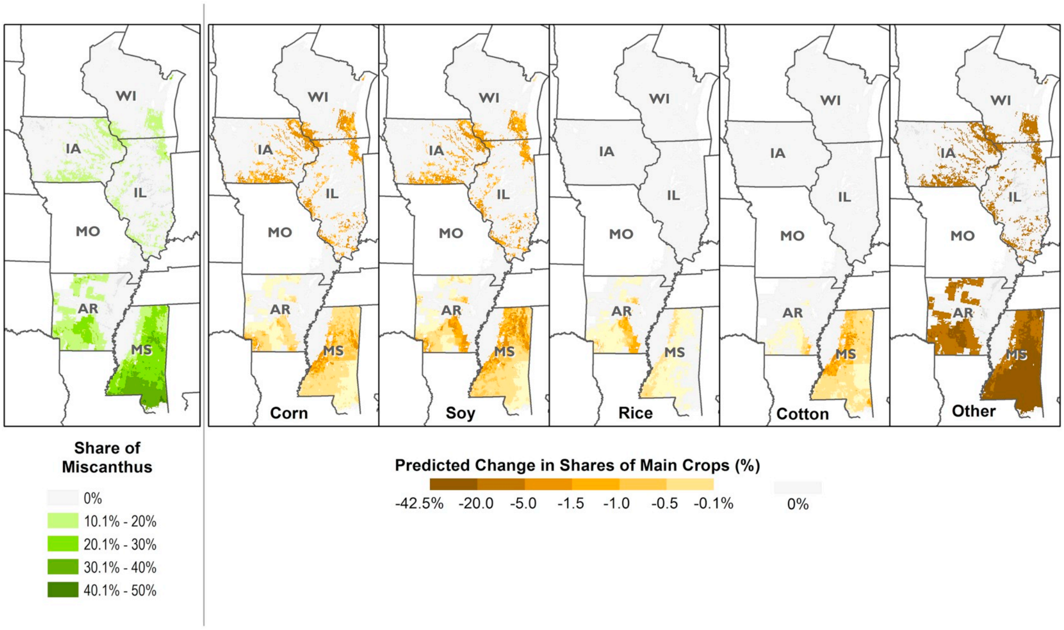
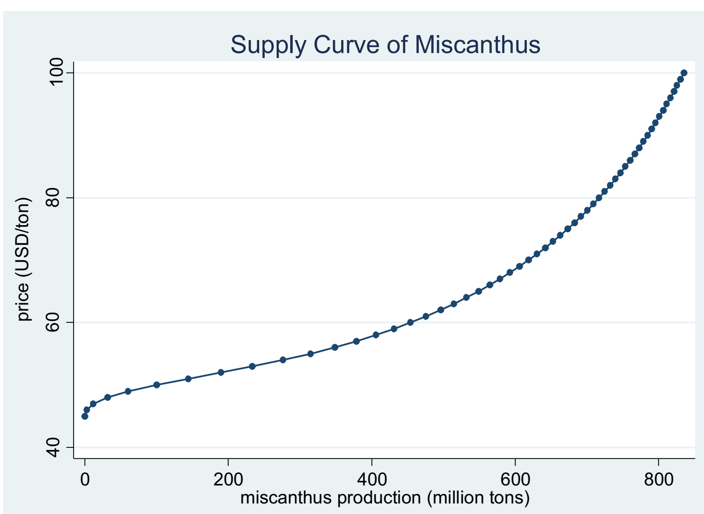


Fig. 5. Spatial distributions of predicted miscanthus shares and changes of crop shares under the baseline scenario.
Notes: At the baseline scenario, the sensitivity of average cost to yield b is 0.35, price is \$50/t, and the scale parameter k is calibrated to produce 100 Mt miscanthus. A −20% change reported here means corn share (for example) decreases from a to $a - 0.2$.



Price ($ / ton)	Quantity (Mt)
45	0.08
48	31.54
50	100.15
60	454.43
70	618.52
80	717.08
90	784.58
100	834.86

Fig. 6. Supply curve of miscanthus under the baseline scenario.
Notes: As we increase the price of miscanthus and keep unchanged the relationship between average cost and yield (coefficient b in the average cost function of growing miscanthus) and the scale parameter k (see Eq. (7)), profit of growing miscanthus increases in each square and so does the share of miscanthus.

south of Mississippi. The latter area is characterized by conifers, grass, pasture, and woody wetlands. Much of it also has good soils. The first two columns of Table 3 show the change in land use incident to the growing of miscanthus. There is a much bigger allocation of land to miscanthus in the southern states, the displacement of major crops is minimal, and the displacement mostly comes from the “other” land category, including trees. To summarize, the biofuel crop competes primarily with extensive rather than intensive land uses, including fiber production and uncultivated areas in the base case.

Next, we find the supply curve of miscanthus under the baseline scenario by simulating production with different prices. As we increase price p, profit π increases in each square and so does the share of miscanthus. Fig. 6 shows the supply curve in terms of millions of tons of miscanthus produced at prices between \$45/t and \$100/t. At \$45/t, output is near zero. From \$50/t to \$60/t, output increases quickly. The arc elasticity of supply is 7. As price increases further, the supply curve becomes steeper. From \$80/t to \$90/t, output increases more slowly and the arc elasticity of supply is 0.8. The decrease in elasticity comes from the modeling of land shares of miscanthus. As shown in Eq. (7), when profit of growing miscanthus increases, land share of miscanthus increases at a decreasing rate. As for the type of land converted to miscanthus, Table 3 shows that, as price increases, miscanthus takes more land from corn and soy in the north as well as land currently occupied by non-major crops, pasture, forest, etc., in both north and south. At a price of \$100/t, more than 10% of land is converted from corn to miscanthus in the north.

4.2. Scenarios with different cost functions

The profitability of growing miscanthus varies with changing cost

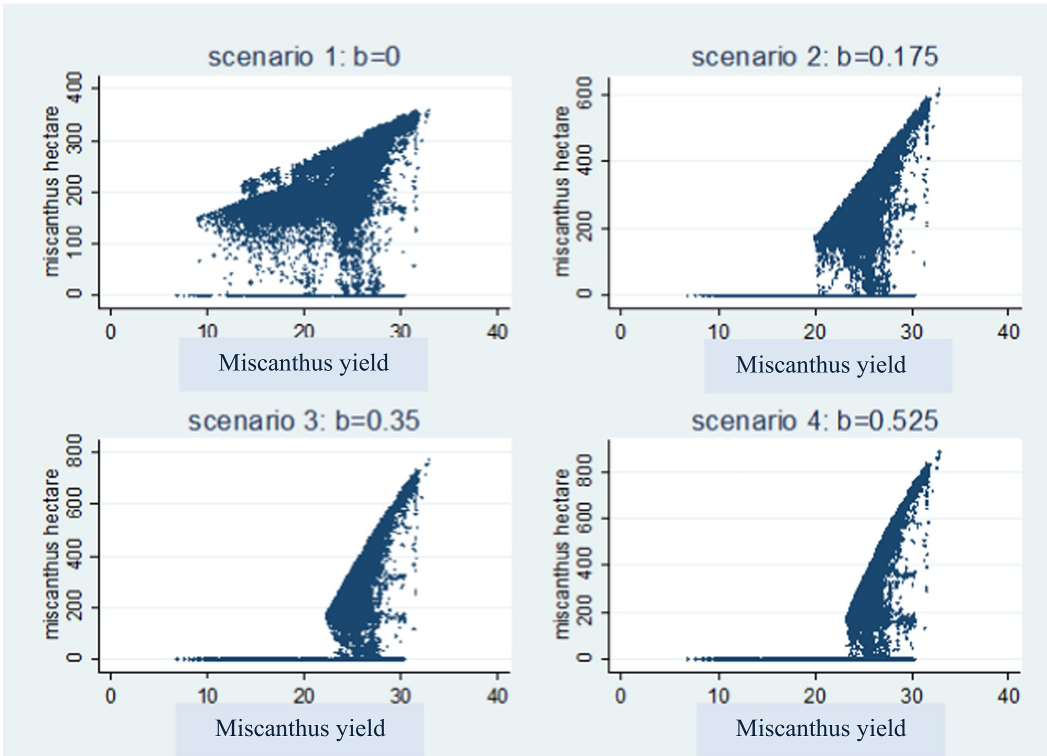


Fig. 7. Scatter plots of miscanthus hectares by yield in 4 km squares for four scenarios each producing 100 Mt of miscanthus.
Notes: As the coefficient b in the average cost function increases, the average cost of growing miscanthus decreases, profit increases, and hence the total quantity of miscanthus grown increases. So, to keep the quantity of miscanthus constant at 100 Mt, it must be that an increase in b leads to a decrease in price. The prices in each scenario are \$66.2, \$58.3, \$50, and \$41.6/t, respectively.

functions. To examine how important the quadratic term is in the cost function, we parametrically vary b. If all that were changed were b, then as b increases so would the shares in all squares and so would the total amount of miscanthus. To see just the locational and not the output enhancing effect of b, we create scenarios where p has been adjusted to keep total output at 100 Mt. That is, in this section, we investigate the land use change if 100 Mt of miscanthus is produced in three other scenarios with cost not reacting to yield ($b = 0$), cost less sensitive to yield ($b = 0.5 * 0.35 = 0.175$), and cost more sensitive to yield ($b = 1.5 * 0.35 = 0.525$).

Table 4 shows the results for the four scenarios, with scenario 3 being the base case, which is listed again for comparison. Panel A of Table 4 shows the results in terms of land use change in thousands of hectares. The first scenario, where $b = 0$, results in a total of 4306 thousand ha of miscanthus, which displace 179 thousand ha of corn and 153 thousand ha of soy, 42 thousand ha of rice and cotton, and 3932 thousand ha of land in other uses. The vast majority of all land used to newly grow miscanthus comes from land previously used for non-major crops, pasture, woodland, etc. in both north and south. For scenarios in which b is greater than zero, land used for miscanthus decreases from 3816 thousand ha to 3710 thousand ha, as b increases from 0.175 to 0.525. With a higher b, higher yield land is selected, and so less land is used to make the same 100 Mt. There is also a distinct shift of miscanthus hectares to the south when b increases.

Panel B of Table 4 shows the results in terms of land use shares. Starting with the first column, when b is zero, the results are that miscanthus occupies 4.49 and 11.12% of the land in the north and south, respectively. The decreases in corn and soy are 0.59 and 0.46% of total land use in the north and south, respectively. The decrease in rice and cotton in the south is 0.18%. The decrease in land in other uses is 3.90 and 10.48% in the north and south, respectively. In this scenario, the miscanthus hectares come primarily from the other uses and have a slightly greater impact in terms of shares in the south. As b increases, we see that (1) miscanthus occupies smaller shares of land in the north and larger shares of land in the south; (2) smaller shares of corn and soy land are diverted; (3) a nearly unchanged share of rice is diverted; (4) a larger share of cotton land is diverted; and (5) less "other" land is used for miscanthus and southern land is increasingly used.

The reason for the selection of different land in the scenarios is the relative weighting of price and cost. The model chooses land with the desirability of miscanthus dependent on $\pi = k * yield * (p - a + b * yield)$. An increase in b leads to an increase in π on every 4 km square and hence to an increase in the total quantity of miscanthus grown. So, to keep the quantity of miscanthus constant at 100 Mt, it must be that an increase in b leads to a decrease in p. A decrease in price makes π more dependent on the cost per ton of miscanthus, which is less on better yielding ground. Therefore, more ground with a high yield will be chosen. Fig. 7 shows this effect in terms of yield. Each dot on the figure represents one of the 4 km squares. When $b = 0$, land is chosen at all yields above 10 t/ha, while with $b = 0.525$, nearly all the chosen land has 25 t/ha or more. Moreover, there is a steep upward pattern in the graph showing that, as yield increases, more and more of the square with higher yield is used for miscanthus.

Finally, we plot supply curves for the four cases of b. As expected, an increase in b shifts the supply curve outward. The second curve from the bottom is the baseline case and it goes through the point where $p = \$50$, production $= 100$ Mt. To get an output of 100 Mt in the $b = 0.525$ scenario, the figure shows that the price would only need to be \$41.6. Overall, Fig. 8 shows that the supply curve is sensitive to the estimation of b.

5. Conclusion

Growing a bioenergy crop can compete directly for land with crops

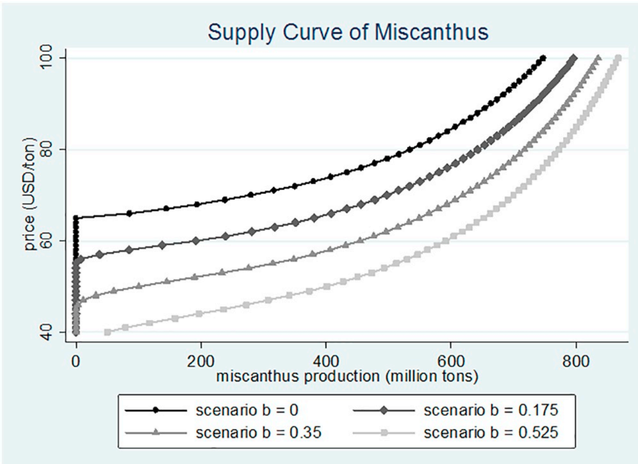


Fig. 8. Supply curves for miscanthus from the four scenarios.
Notes: Parameter b is the coefficient of yield in the average cost function of growing miscanthus. Parameter k (the scale parameter, see Eq. (7)) is unchanged across scenarios.

grown for food, as is the case when corn is used for ethanol (Hausman et al., 2012). One possible advantage of miscanthus over corn-based ethanol is that farmers may choose to grow it on land not currently used for food crops. Using fine-scale data on weather, soil, and farmers' land use decisions in the past, this paper shows the likely geographical distribution of miscanthus, taking into account competition with existing crops.

The predictions of miscanthus land use are based on yield from the *BioCro* model adapted to miscanthus and the assumption that the desirability of growing miscanthus will be proportional to profit. For existing crops, we use actual land coverage, which represent farmers' past decisions, to find predicted crop coverage desirability as a function of weather and soil. We then combine these two sources of information on likely land coverage into one model and use it to simulate miscanthus crop coverage, assuming the production of miscanthus in the six states along the Mississippi-Missouri River corridor will be 100 Mt.

The results show that, in our base case, miscanthus largely occupies non-food land, and this is true even for miscanthus grown within the corn states of Illinois and Iowa. For Iowa and Arkansas particularly, variation in soil quality is the defining characteristic for where miscanthus is grown: primarily in lower quality soils. The use of the lower Mississippi region for miscanthus production is likely a function of the temperature and moisture environments that are not suitable for the main crops in this study. In the base case, while we find that miscanthus potentially has a low requirement for land currently used for corn, soy, cotton, and rice, we also find that it has a high requirement for land that is currently in the "other" category: pasture, forest, and grassland. Use of this land will likely bring environmental costs rather than an increase in food prices. However, the simulations are quite sensitive to the quadratic term in yield, which has the interpretation of sensitivity of cost to yield. As costs decrease more strongly in yield, miscanthus becomes more concentrated on the land where it yields most. That land is largely in the far south.

Returning to the other studies, Khanna et al. (2011), in their Fig. 2, show that, within our landscape, areas near the Mississippi River are an important region for growing miscanthus, while the northern part of Wisconsin is an area where miscanthus is not likely to be grown. Our results (our Fig. 5) generally agree with their findings. The only difference is that our paper indicates Mississippi to be the most important region within our landscape, while Khanna et al. (2011) show little difference among the states along the Mississippi River. Detailed quantitative comparison of the results of the two papers is available upon request. Since our paper and Khanna et al. (2011) share many parameters, we think that the difference in findings may be due to the following differences in methodologies. One is that we use a regression-based approach, in contrast with their use of a process-based approach for the food crops. The second is that we assume the demand for biofuel to be met solely by miscanthus, while they assume it to be met by miscanthus, switchgrass, and crop residual. Specifically, spatial difference in switchgrass yield plays a role in the miscanthus production simulation in Khanna et al. (2011), while it does not in this study. The third difference is that to simulate the yield of miscanthus we use a semi-mechanistic dynamic crop growth and production model, the R package *BioCro*, while they use a crop productivity model, MISCANMOD. Comparing Fig. 2a in Khanna et al. (2008) to our Fig. 4, we do see different simulation results for miscanthus yield from the two models.

Anderson et al. (2012) predicts a generally northern location for miscanthus. Since this paper and Anderson et al. (2012) are similar in the econometric modeling, we think that the difference in results may come from the difference in the prediction methodology. Anderson et al. (2012) predict crop shares based on characteristics of crop and land, and the estimated coefficients in a choice model, while we predict land use proportion based on simulated yield of miscanthus and its profit function.

Elliot et al.'s (2014) results share with ours the prediction of southern concentration of miscanthus, but do not agree on eastern Iowa as an important growing region. We suspect the difference here also comes from our regression results as opposed to their land allocation model.

The other models are all equilibrium models, taking account of how land use change leads to price changes, which in turn lead to more land use change. The equilibrium effects from growing miscanthus depend on where it is grown. In our baseline scenario with minimal changes in major crop coverage, our estimates and equilibrium estimates should be quite close. If anything, putting our land use model into an equilibrium model would accentuate the concentration of miscanthus on non-major cropland because the little bit of cropland taken by miscanthus would raise crop prices and push miscanthus more off the cropland.

In conclusion, farmers are likely to grow miscanthus on land that is not currently used for food crops. However, grasslands, pastures, and forests contain substantial natural values that would be endangered with a switch to a cultivated crop. In the case of forests, the conversion process would also entail substantial releases of carbon. This returns us to the concerns first elucidated in Searchinger et al. (2008) and most recently evaluated by Elliot et al. (2014), that advanced biofuels will require carbon-releasing land use change. However, miscanthus biofuels have demonstrated significant potential to mitigate carbon emission by displacing oil usage (Dwivedi et al., 2015), with potential to grow even on marginal land (Xue et al., 2016). If room for miscanthus expansion can be made on land of marginal productivity (Cai et al., 2010), it can be a potent tool to mitigate climate change. Therefore, quantifying the environmental costs of miscanthus (or other advanced biofuels) will be the direction of our future research.

Table 3
Percent change in land use for various prices.

	Price = $50/t		Price = $70/t		Price = $100/t	
	North	South	North	South	North	South
	(Obs: 26,579)	(Obs: 14,355)	(Obs: 26,579)	(Obs: 143,55)	(Obs: 26,579)	(Obs: 143,55)
Miscanthus	1.68	13.10	38.27	51.58	54.95	65.32
Corn	−0.21	−0.22	−6.56	−1.41	−10.79	−2.05
Soy	−0.18	−0.36	−5.16	−2.39	−8.54	−3.61
Rice	0.00	−0.06	0.00	−0.85	0.00	−1.41
Cotton	0.00	−0.17	0.00	−0.99	0.00	−1.50
Other	−1.29	−12.29	−26.55	−45.95	−35.61	−56.74

Notes: Price = $50/t is the baseline scenario. Land use changes at price of $70/t and $100/t are simulated by changing price only.

Table 4
Land use change for four scenarios each producing 100 Mt of miscanthus.

Panel A	Scenario 1: b = 0		Scenario 2: b = 0.175		Scenario 3: b = 0.35		Scenario 4: b = 0.525	
Thousand ha	North	South	North	South	North	South	North	South
Miscanthus	1647.84	2658.65	709.17	3106.64	593.92	3152.33	521.60	3188.22
Corn	−139.53	−39.72	−90.84	−50.34	−75.62	−51.48	−64.18	−51.80
Soy	−83.66	−69.14	−75.18	−84.69	−64.77	−85.60	−55.31	−85.19
Rice	0.00	−12.80	0.00	−14.66	0.00	−13.98	0.00	−13.53
Cotton	0.00	−29.18	0.00	−38.36	0.00	−39.95	0.00	−40.02
Out	−1424.65	−2507.81	−543.15	−2918.59	−453.53	−2961.33	−402.11	−2997.68

Panel B:	Scenario 1: b = 0		Scenario 2: b = 0.175		Scenario 3: b = 0.35		Scenario 4: b = 0.525	
Shares (%)	North	South	North	South	North	South	North	South
Miscanthus	4.49	11.12	1.98	12.94	1.68	13.10	1.50	13.22
Corn	−0.37	−0.17	−0.25	−0.21	−0.21	−0.22	−0.18	−0.22
Soy	−0.22	−0.29	−0.21	−0.36	−0.18	−0.36	−0.16	−0.36
Rice	0.00	−0.06	0.00	−0.06	0.00	−0.06	0.00	−0.06
Cotton	0.00	−0.12	0.00	−0.16	0.00	−0.17	0.00	−0.17
Out	−3.90	−10.48	−1.53	−12.15	−1.29	−12.29	−1.16	−12.42

Notes: Scenarios are calibrated to produce 100 Mt miscanthus by reducing price as *b* (the relationship parameter between yield and average cost in the cost function of producing miscanthus) is increased.

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