Assessing the Opportunity Cost of Growing a Bioenergy Crop in California: a PMP Approach

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Abstract

A significant increase in demand for fuel ethanol in California should be expected if all gasoline sold in the state were to be blended with 10% ethanol, as envisaged in the State Alternative Fuels Plan. This paper assesses the potential of California agriculture to supply biofuel feedstock in the form of switchgrass. We construct a fully calibrated, multi-region, multi-input and multi-output model of agricultural supply for California's Central Valley based on the principles of Positive Mathematical Programming. We exploit the biogeochemical model DAYCENT to estimate production functions for switchgrass in each agricultural region. We then predict the extent and location of potential switchgrass production in the Central Valley. Our results suggest that adoption rates differ widely among regions, meaning that the location of processing plants may be an important issue. They also suggest that switchgrass adoption is not likely to displace specialty crops by much. From a purely methodological standpoint, this study illustrates the complementarity of agronomic and economic information for the calibration of economic optimization models meant to capture farmer behavior at the regional scale.

The State Alternative Fuels Plan (SAFP) approved by the California Energy Commission in 2007 predicts that if all gasoline sold in California were to be blended with 10% of ethanol, California would see an increased use of ethanol from 900 million gallons to approximately 1.5 billion gallons. In addition, the SAFP emphasizes the need for California to produce biofuels, establishing the goal that by 2020, 40% of the biofuels used in the state should be produced within the state. However, the economic feasibility of growing bioenergy crops in California has yet to be analyzed. Given the vast heterogeneity of California's agricultural landscape, assessing the potential of California agriculture to supply biofuel feedstock in sufficient quantity and at reasonable prices is a nontrivial question.

In this study, we propose to assess the opportunity cost of allocating farmland and water resources to the cultivation of biofuel crops in California's Central Valley.[1]

[1]Our focus on land and water as the main limiting resources for California agriculture seems

To this end, we construct a fully calibrated, multi-region, multi-input and multi-output model of agricultural supply based on the principles of Positive Mathematical Programming (PMP). Since their popularization by Howitt (1995b), PMP models of agricultural supply have been used extensively in policy analysis to predict the response of agricultural systems facing resource, technology and policy constraints to exogenous shocks. The models are typically calibrated against observed regional—e.g., in the U.S., county-level or state-level—cropping patterns and input allocations, under the maintained assumption of profit-maximizing behavior.

More recently, the literature on mathematical programming has developed methodologies to also force regional programming models to replicate an exogenous supply response pattern, through the use of prior information—typically in the form of econometric estimates—on supply elasticities (Heckelei, 2002; Heckelei and Wolff, 2003; Jansson and Heckelei, 2008; Mérel and Bucaram, 2010; Mérel et al., 2011a). The idea is to avoid constructing models that display unreasonable supply responses to price shocks. In practice, this additional demand on the part of PMP models is possible to satisfy, due to their typical under-determinacy. In the present study, we exploit these later developments in PMP calibration so as to control the model's responses to output price changes.

The U.S. Department of Energy believes that biofuels made from crops of native grasses could reduce the nation's dependence on foreign oil, curb emissions of greenhouse gases and strengthen America's farm economy (BFIN, 2009). Feedstocks differ in the amount of energy yielded per acre of land, the amount of inputs required in production and the extent to which they compete with existing agriculture for scarce resources. According to the above criteria, cellulosic ethanol feedstocks such as miscanthus and switchgrass can be expected to fare better than current biofuel feedstocks such as corn (Sexton et al., 2009).

Switchgrass, a perennial crop indigenous to Midwestern states, is one of the cellulosic ethanol feedstocks most commonly studied in the US (Schmer et al., 2008). Production conditions and expected yields under California's climate remain largely unknown. Recently, Lee et al. (2010) have used the biophysical process model DAYCENT, calibrated on experimental data collected by the University of California, Davis from various experimental plots, to simulate the yields of six different varieties of switchgrass in California's Central Valley. Their study provides spatially disag-

justified in light of the study by Johnston and McCalla (2004). Johnston and McCalla (2004) rank water shortages associated with global warming as the "number one future threat" to California agriculture. They further describe "relentless competition for resources" (land and water included) as California agriculture's "number two future threat".

gregated measures of expected yields under "optimal" production conditions, and we use this information to estimate regional production functions for switchgrass.

These production functions are used to construct a net revenue function for switchgrass which is then included in the PMP objective function. The regionalized supply pattern for switchgrass is derived by iterating the economic optimization algorithm over switchgrass price levels. Our model fully captures the opportunity cost of allocating scarce resources—land and water—to switchgrass production at the regional level, defined as the forgone net revenue from other cropping activities. Our analysis provides information about the extent and location of potential switchgrass production in California and has direct policy implications regarding the economic viability of switchgrass-based biofuel production and the optimal location of processing plants.

The paper is organized as follows. First, we review recent developments in the field of PMP calibration, with a focus on the incorporation of prior information on own-price supply elasticities in calibrated models. This provides the methodological basis for calibrating a regionalized model of California agriculture with land and water constraints. Second, we explain how information obtained through simulation of crop cycles within the biogeochemical model DAYCENT (Del Grosso et al., 2008) can be used to introduce a new crop into the calibrated PMP model. Third, we present the results from an application of this approach to switchgrass adoption in California. In the conclusion, we discuss limitations and extensions.

1 First- and second-order PMP calibration

By construction, PMP models permit first-order calibration, that is, the exact replication of an observed allocation of inputs and scarce resources among activities. They can also be calibrated to replicate exogenous supply response patterns, and we refer to this property as second-order calibration.

1.1 Calibration against observed acreage

Calibration of a PMP model to observed input allocations and output levels is standard and described in Howitt (1995b) and Howitt (1995a). Model parameters are chosen so that the first-order conditions to the economic optimization program are satisfied at the observed base-year allocation. This is made possible by specifying a non-linear objective function, to avoid overspecialization. In Howitt (1995b), a quadratic term is added to the net revenue of profitable activities so that yields are linearly decreasing in acreage, but other specification rules may be used (Heckelei and Britz, 2005; Heckelei and Wolff, 2003). The profit-maximizing assumption allows the analyst to model the outcome of the production decisions of atomized farmers, facing the same input and output prices, as the result of the optimization of aggregate farm returns subject to regional resource and/or technical constraints. As such, the calibrated production functions obtained from PMP reflect technology and resource limitations at the regional level.

The allocation data typically consists of a single observation on market conditions (prices of outputs and inputs, resource availabilities) and observed economic behavior (input allocations and output levels). In applications, the reference year allocation may be obtained as the average of a small number of observations. This is particularly useful when the data comes from different sources, as with models of explicit input allocation such as constant-elasticity-of-substitution (CES) models, because input allocation data typically comes from accounting surveys that are conducted at different dates and/or frequencies than available data on prices, acreage and yields. In our application, data on acreage, output prices and yields comes from the California Department of Water Resources, while input use data comes principally from the University of California Cost and Return Studies.

1.2 Calibration against own-price elasticities

The use of prior information on supply elasticities to calibrate PMP models of agricultural supply has been advocated repeatedly in the recent literature (Heckelei and Britz, 2005; Mérel and Bucaram, 2010). The reason is two-fold: first, PMP models are typically underdetermined, that is, the information on the observed cropping pattern and input allocation is not sufficient to recover the entire set of model parameters. The literature has dealt with this underdeterminacy problem by either imposing *a priori* restrictions—in quadratic models for instance, setting off-diagonal elements to zero is a popular modeling choice—or, more recently, by using generalized maximum entropy algorithms to recover the entire set of model parameters (Paris and Howitt, 1998). The use of prior information on crop supply elasticities as a second source of information to recover model parameters has the ability to mitigate the under-determinacy problem.

Second, whether arbitrary restrictions or GME algorithms are used, traditional PMP algorithms are not always geared towards ensuring consistency of the model's implied supply responses with econometric priors regarding the value of supply elasticities. Although any PMP model exactly replicates the observed cropping pattern, different calibration rules imply different—and sometimes unrealistic—supply response patterns (Heckelei and Britz, 2005).

An early solution to this problem has been to use "myopic" calibration rules. Such rules ignore the change in the shadow prices of constrained resources (in particular, land) that are induced by the change in crop prices, and therefore allow each activity to be calibrated separately from all others. However, they provide an acceptable calibration rule only when changes in shadow prices are negligible. Mérel and Bucaram (2010) recently provided an *ex ante* test to determine, within quadratic models of acreage allocation, whether the use of a myopic calibration rule is defendable in practice. In essence, the base-year allocation must have a sufficiently large number of positive activities, and no activity can have a desired acreage response that dominates all others.

When the use of "myopic" calibration rules cannot be justified, one must take account of the fact that the implied supply elasticity of each crop depends on all model parameters. Thus, it is no longer possible to calibrate each activity independently. The analyst needs to solve a system of nonlinear equations that is not guaranteed to have an acceptable solution, that is, a solution that preserves the concavity properties of the economic optimization program. Recent research in the area of *exact* calibration of PMP models has focused on the following questions: (i) How to recover the supply elasticities implied by a given model specification, as a function of the model parameters to be calibrated? (ii) Given a system of nonlinear calibrating equations, under which conditions can the analyst recover an acceptable solution? and (iii) Under which conditions is the solution to the calibrating system unique?

Mérel and Bucaram (2010) have provided a general answer to question (i). Questions (ii) and (iii) cannot be answered generally and instead are model-specific. This is because the general form of the calibration system depends upon the form of the objective function. In the present study, we use the specification proposed in Mérel et al. (2011a). These authors have derived an explicit criterion for second-order calibration of a generalized CES model specification, and here we build on their findings to generate regional variability in supply elasticities.

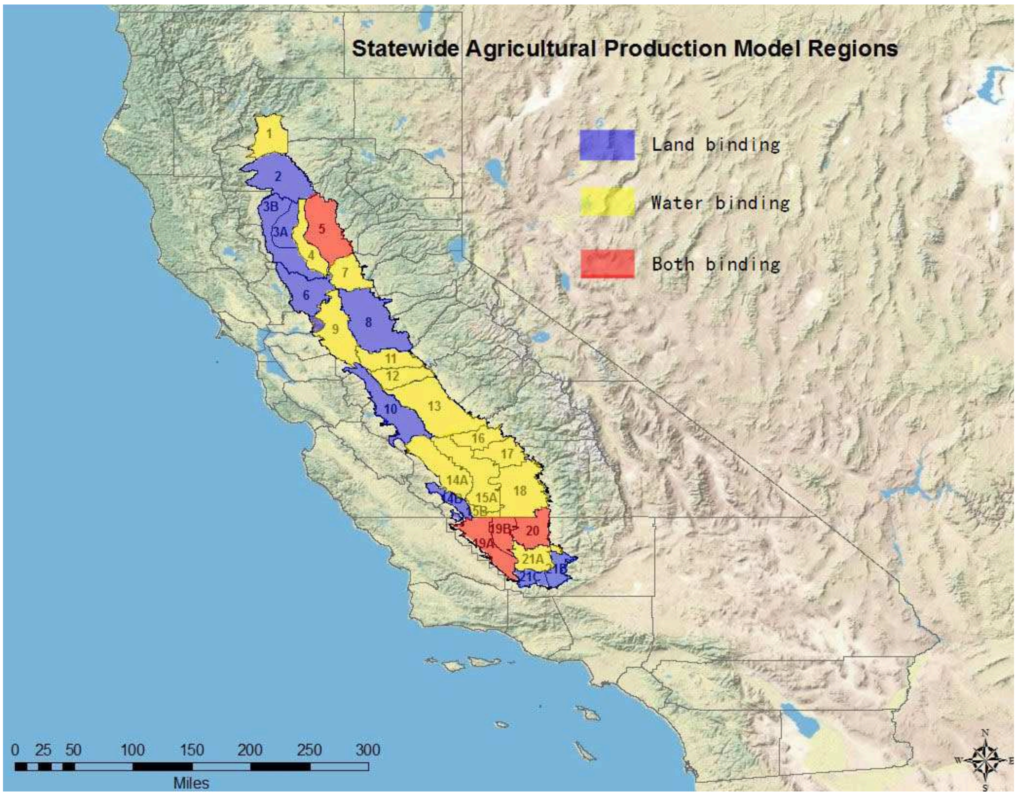

Figure 1: The SWAP agricultural regions

2 An application to California agriculture

2.1 The SWAP model

Our model of California agriculture is built as an extension to the existing statewide agricultural production (SWAP) model developed by R. Howitt (Jenkins et al., 2001). The SWAP model divides the California Central Valley into $G = 27$ regions based mostly on water transferability. These regions are shown in Figure 1 and described in Table 1.

There are four water sources in California: the Central Valley Project (CVP), the State Water Project (SWP), local surface water and ground water. Water use from these sources is either based on long-term contracts (e.g., CVP and SWP), or water cannot be transferred between regions because of existing law (e.g., ground water). In addition, local water agencies only provide water to specific regions. As a result, each of the 27 SWAP regions can be considered to be independent in terms of water allocation. Thus, there are two constrained resources in each SWAP region: land and water. (Both constraints need not be binding, see Figure 1.)

The statewide economic optimization model maximizes net farm returns under regional land and water constraints. The generalized CES model, first proposed by Heckelei and Wolff (2003) and further analyzed by Mérel et al. (2011a), assumes crop-specific production functions of the CES form, allowing for decreasing returns to scale at the crop level. The optimization program is defined as follows:

$$
\begin{array}{l}
\max\limits_{q_{gi}\geq 0, x_{gij}\geq 0} \sum_g \sum_i \{p_{gi}q_{gi} - [(c_{gi1}+\lambda_{gi1})x_{gi1} + (c_{g2}+\lambda_{gi2})x_{gi2} + (c_{g3}+\lambda_{gi3})x_{gi3}]\} \\
\text{subject to} \\
\left\{\begin{array}{ll}
\sum_{i=1}^{I} x_{gi1} \leq b_{g1} & \forall g \in [|1, G|] \\
\sum_{i=1}^{I} x_{gi2} \leq b_{g2} & \forall g \in [|1, G|] \\
q_{gi} = \mu_{gi} \left[\sum_{j=1}^{3} \beta_{gij} x_{gij}^{\rho_{gi}}\right]^{\frac{\delta_{gi}}{\rho_{gi}}} & \forall (g,i) \in [|1, G|] \times [|1, I|]
\end{array}\right.
\end{array}
\tag{1}
$$

where p_{gi} is the price of crop i in region g and c_{gj} is the price of input j ($j = 1, 2, 3$) in region g. The choice variables x_{gij} represent the amount of input j used in the production of crop i in region g, and q_{gi} the output level, related to the input employments in a generalized CES production function with parameters μ_{gi}, β_{gij} and δ_{gi}, satisfying $\mu_{gi} > 0$, $\beta_{gij} > 0$, $\sum_j \beta_{gij} = 1$ and $\delta_{gi} \in (0, 1)$. There are three explicit inputs in our model. The indices $j = 1$ and $j = 2$ denote land and water, respectively. The third explicit input is fertilizer, assumed to be supplied in a

SWAP Region			Counties
Name	Farming acres	Water (ac-ft)	
1	22,100	77,722	Tehema, Shasta
2	171,700	561,944	Butte, Glenn, Tehema
3A	270,053	1,083,484	Colusa, Glenn, Yolo
3B	90,267	286,157	Colusa, Glenn, Yolo
4	256,010	962,542	Butte, Colusa, Glenn, Sutter, Yolo
5	358,140	1,516,316	Butte, Glenn, Sutter, Yuba
6	230,140	728,973	Solano, Yolo
7	95,560	423,454	El Dorado, Placer, Sacramento, Sutter
8	309,360	775,195	Amador, Claveras, Sacramento, San Joaquin, Stanislaus
9	394,050	1,165,949	Alameda, Contra Costa, Sacramento, San Joaquin, Solano, Yolo
10	426,980	1,448,857	Fresno, Merced, San Benito, San Joaquin, Stanislaus
11	237,130	837,133	San Joaquin, Stanislaus
12	252,200	836,296	Merced, Stanislaus
13	561,500	171,327	Madera, Mariposa, Merced
14A	485,700	1,267,819	Fresno, Kings
14B	38,100	60,553	Fresno, Kern, Kings
15A	624,300	1,735,226	Fresno, Kings, Tulare
15B	19,000	69,505	Kings
16	150,900	333,408	Fresno
17	260,800	651,771	Fresno, Kings, Tulare
18	712,700	2,074,069	Kings, Tulare
19A	84,200	297,197	Kern
19B	168,300	565,844	Kern
20	209,800	626,275	Kern, Tulare
21A	194,100	603,833	Kern
21B	102,200	219,558	Kern
21C	68,000	158,836	Kern

Table 1: Description of the SWAP regions

perfectly elastic fashion to the farm sector. For the purpose of this study, all other inputs (such as pesticides, labor, custom operations etc.) are assumed to be employed in fixed proportion with land, and therefore their respective cost is included in the price of land, c_{gi1}.[2] The parameters b_{g1} and b_{g2} represent the limited land and water resources in each region.

Following common PMP practice, calibration parameters λ_{gi1}, λ_{gi2} or λ_{gi3} are added to the land, water and fertilizer cost terms to allow for calibration against the reference allocation (otherwise, the model does not have enough parameters to calibrate). For each crop, at most one of these parameters is nonzero, so that the calibration problem is not under-determined. The choice of whether $\lambda_{gi1} = 0$, $\lambda_{gi2} = 0$ or $\lambda_{gi3} = 0$ is driven by ease of calibration against the supply elasticity. The analysis by Mérel et al. (2011a) suggests that larger sets of supply elasticities will be replicable if the cost adjustment parameter is added to the input with the largest cost share in the reference allocation. Therefore, we choose to add the cost adjustment to whichever input has the largest cost share, here either land, water or fertilizer.[3]

The calibration phase consists of recovering the set of unknown parameters (μ_{gi}, β_{gi}, $\delta_{gi}, \lambda_{gi1}, \lambda_{gi2}, \lambda_{gi3}$), given the reference allocation and a set of supply elasticities. The parameter ρ_{gi} is a pure substitution parameter and is given by $\rho_{gi} = \frac{\sigma_{gi}-1}{\sigma_{gi}}$, where σ_{gi} is the elasticity of substitution between any two inputs. As suggested by McFadden (1963), we keep partial elasticities of substitution constant between any pair of factors.[4]

2.2 Data

For crop acreages in each region, we rely on the latest available version of the SWAP model, which uses crop acreages for the year 2005 assembled by the California Department of Water Resources (DWR). We follow the DWR crop classification, which includes twenty crops or groups of crops. For grouped crops, we choose to define a "representative" crop within the group, and attribute the information on price, yield,

[2]Since different activities require different proportions of these other inputs, the "cost" of land is therefore crop-specific in our model. Note that this cost represents the cost of these inputs and does not reflect the scarcity of land, which is embedded in the shadow value of the land constraint.

[3]Mérel et al. (2011a)'s analysis applies for regions with one binding constraint only. In regions where two of the constraints are binding we apply the increment to the land cost systematically ($\lambda_{gi2} = 0$ and $\lambda_{gi3} = 0$).

[4]In the absence of reliable prior information on the value of substitution elasticities, we choose to set $\sigma_{gi} = 0.21$.

Crop	Prior elasticity	Calibrated elasticity	Regional variation
Almond and Pistachio	0.19	0.19	No
Alfalfa	0.44	0.46	Yes
Corn	0.21	0.79	Yes
Cotton	0.50	0.50	No
Melons, Squash and Cucumbers	0.05	0.06	Yes
Dried Bean	0.13	0.23	Yes
Fresh Tomato	0.27	0.27	No
Wheat	0.36	0.86	Yes
Onion and Garlic	0.11	0.13	Yes
Other deciduous fruits and nuts	0.19	0.19	Yes
Other field crops	0.63	0.63	Yes
Other truck crops	0.11	0.11	No
Pasture	0.24	0.25	Yes
Potato	0.11	0.15	Yes
Processing tomato	0.55	0.55	Yes
Rice	0.48	0.48	Yes
Safflower	0.34	0.35	Yes
Sugar Beet	0.11	0.25	Yes
Citrus	0.03	0.04	Yes
Grape Vine	0.05	0.06	Yes

Table 2: Statewide supply elasticities

input intensities per acre and per acre variable costs for that crop to the entire group.[5]

The water price for each agricultural region comes from DWR. DWR water prices are weighted average prices, computed based on usage of the three main sources of water: canal water, local surface water and groundwater.

For each crop/crop group, county-level agricultural commissioner reports provide information on yield and price.[6] We exploit GIS data to infer the area of each county present in each SWAP region and then convert the county-level information into SWAP-level data.

Most of the state supply elasticities come from the initial SWAP model. However, supply elasticities for almond and pistachio, alfalfa, cotton, rice, processing tomato and fresh tomato are updated using the recent study by Russo et al. (2008).

[5]The main reason for this approach is that we do not have the regional acreage for each individual crop, but only for the group. In addition, the input intensity and per acre cost data, which comes from the Cost and return studies published by the Department of Agriculture and Resource Economics at UC Davis, are typically available only for a subset of the crops included in a given group.

[6]They also provide information on acreage, but we do not use this information.

We calibrate model (1) against the observed cropping pattern and supply elasticities using the latest PMP methodology developed by Mérel et al. (2011a).[7] The starting point is a set of exogenous statewide elasticity priors (see Table 2). Mérel et al. (2011a) have derived the necessary and sufficient conditions for calibration of the generalized CES model. These conditions are often violated when the available statewide elasticities are used at the regional level, even once the cost increment parameters are chosen optimally to allow for maximum flexibility.

Our approach is therefore to construct region-specific supply elasticities using a generalized maximum entropy algorithm that disaggregates the statewide elasticity prior by minimizing the information cost from deviating, in each region *and* at the state level, from the statewide elasticity prior, while allowing for exact calibration based on the calibration criterion of Mérel et al. (2011a). State-level elasticities are calculated as weighted averages of the regional supply elasticities, using output shares as the weights. To reflect the fact that available elasticity priors are statewide and not region-specific, we specify wider support intervals for regional elasticities than for state-level elasticities. This implies that the information cost of deviating from the elasticity prior is larger at the state level than at the regional level. This algorithm enables us to recover region-specific elasticities while allowing for calibration of the model against a set of elasticities that departs from the prior minimally—in a maximum entropy sense. The resulting regional variation in supply elasticities, certainly desirable from a modeling perspective, is driven by observed input and output allocation patterns, the choice of functional form for the crop-specific production functions, and the necessity to calibrate as closely as technically feasible to the initial prior.

In our application, a majority of 16 crops (out of 20) display regional variation in their supply elasticities. The resulting statewide elasticities are reported in Table 2. While a small number of elasticities seem to differ widely from the initial prior (notably, corn and wheat), our choice of regional and state elasticities is optimal in the sense that the resulting statewide elasticities are as close as possible to the prior values while allowing the model to exactly calibrate against regional elasticities that are also as close a possible to the prior values.[8]

[7] A standard PMP approach is used to infer the dual values of constrained resources in the reference allocation.

[8] Since a calibration criterion was not available for models with two binding constraints at the time when this paper was written, the state averages reported in Table 2 only take into account regions where either land or water is binding. Out of the 27 regions, 23 have only one binding constraint. We note that crops for which calibrated statewide elasticities differ widely from the prior often correspond to less profitable crops: Corn, Dried Bean and Wheat, which make more sense because they do not require special soil quality or specialized technology and relatively easy

2.3 Estimating regional production functions for switchgrass

To analyze how the introduction of switchgrass affects input allocation decisions in each region, we estimate region-specific production functions for switchgrass. Since technology parameters for switchgrass cannot be recovered from observed economic behavior, we rely on information obtained from a calibrated biogeochemical crop simulation model (DAYCENT, Del Grosso et al. (2008)) to identify the essential relationship between input intensity and output. We here present a simple application where the production function for switchgrass essentially consists of a relationship between acreage and output, namely

$$q_{gs} = \mu_{gs} x_{gs}^{\delta_{gs}}$$

where x_{gs} is the acreage of switchgrass in region g, q_{gs} is output, and μ_{gs} and δ_{gs} are unknown technology parameters satisfying $\mu_{gs} > 0$ and $\delta_{gs} \in (0, 1)$. This production function is simply the fixed-proportions variant of the generalized CES specification.

We estimate the coefficients μ_{gs} and δ_{gs} econometrically using simulation data from DAYCENT at the regional level. The DAYCENT model can simulate the yields of six different varieties of switchgrass: Alamo, Blackwell, Cave in rock, Kanlow, Sunburst and Trailblazer. The water and fertilizer application rates used for each region correspond to "optimal" rates from a purely agronomic perspective. Predicted yield, conditional on water and fertilizer rates, is obtained at a given geographical "point." The DAYCENT yield prediction depends on local conditions at that point: temperature, soil characteristics, weather, etc. The California Central Valley is divided into 12×12 km squares (cells) that are treated as being homogenous in terms of these local conditions and therefore correspond to the same predicted yield, conditional on switchgrass variety. Each SWAP region g is large enough to cover multiple cells, allowing us to exploit multiple "observations" to econometrically recover the values of μ_{gs} and δ_{gs}.

For each region g, we estimate the production function based on the following method: for each cell included (even partially) in the region we select the highest yielding variety of switchgrass, and rank all the cells in descending order of yield. We then construct the first "observation" (x^1, q^1) as the acreage $x^1 = a^1$ of the highest yield cell contained in the region, coupled with the resulting output q^1 obtained by multiplying a^1 by the corresponding yield y^1. The second observation, (x^2, q^2) is constructed as the cumulative area of the two highest-yielding cells, $x^2 = a^1 + a^2$,

to be replaced by other crops in California.

coupled with the resulting cumulative output $q^2 = a^1y^1 + a^2y^2$, and so on. The number of observations for each region is given by the number of cells that intersect that region.

We then use OLS to estimate the parameters μ_{gs} and δ_{gs} in the following regression:

$$\ln(q_{gs}^n) = \ln(\mu_{gs}) + \delta_{gs}\ln(a_{gs}^n) + \epsilon_{gs}^n, \tag{2}$$

where n represents the nth observation. The way we construct cumulative acreage and cumulative output ensures that the coefficient δ_{gs} strictly lies between zero and one. The estimation results are reported in Appendix A.

The DAYCENT model actually provides 2 sets of possible yields, $y_{gs,1}$ and $y_{gs,2}$, under two weather scenarios (wet or dry year). To capture this uncertainty regarding expected yield, we calibrate production functions under both scenarios and then introduce expected revenue from switchgrass in the profit function, assuming an equal probability of a wet and a dry year.

The regionalized economic optimization model once switchgrass is introduced thus has the form

$$\begin{aligned}
\max_{\substack{q_{gi}\geq 0, x_{gij}\geq 0\\ q_{gs}\geq 0, x_{gs}\geq 0}} \quad & \textstyle\sum_g \sum_i p_{gi}q_{gi} - \Big[(c_{gi1}+\lambda_{gi1})x_{gi1} + (c_{gi2}+\lambda_{gi2})x_{gi2} + (c_{g3}+\lambda_{gi3})x_{gi3}\Big] \\
& + p_{gs}q_{gs} - C_{gs}x_{gs}
\end{aligned}$$

subject to

$$\begin{cases}
\sum_{i=1}^I x_{gi1} + x_{gs} \leq b_{g1} & \forall g \in [|1, G|] \\
\sum_{i=1}^I x_{gi2} + w_g x_{gs} \leq b_{g2} & \forall g \in [|1, G|] \\
q_{gi} = \mu_{gi}\left[\sum_{j=1}^3 \beta_{gij}x_{gij}^{\rho_{gi}}\right]^{\frac{\delta_{gi}}{\rho_{gi}}} & \forall (g,i) \in [|1, G|] \times [|1, I|] \\
q_{gs} = \frac{1}{2}\hat{\mu}_{gs,1}x_{gs}^{\hat{\delta}_{gs,1}} + \frac{1}{2}\hat{\mu}_{gs,2}x_{gs}^{\hat{\delta}_{gs,2}} & \forall g \in [|1, G|]
\end{cases} \tag{3}$$

where q_{gs} is the regional quantity of switchgrass produced and x_{gs} the corresponding acreage. In the water availability constraint of program (3), the parameter w_g denotes the regional water application rate for switchgrass. The variable C_{gs} represents an estimate of the variable per-acre cost, based on the water and fertilizer application rates used to obtain the regional yield estimates, combined with the local prices of water and the price of fertilizer, as well as an exogenous estimate of other operating costs, including labor. Although not the focus of this particular study, sensitivity analysis on C_{gs} could be conducted to test the robustness of our results to this exogenous information.

Table 3 shows the average water, labor and nitrogen use for switchgrass in each

SWAP region	Input			
	Water ac-ft/ac	Labour hrs/ac	Nitrogen lb/ac	Variable cost $/ac
1	2.71	3	200	524.53
2	2.74	3	200	593.91
3A	2.99	3	200	597.08
3B	2.99	3	200	597.08
4	2.96	3	200	550.85
5	2.98	3	200	531.21
6	3.51	3	200	573.10
7	2.64	3	200	545.29
8	2.61	3	200	575.60
9	4.04	3	200	569.29
10	4.66	3	200	661.22
11	2.60	3	200	504.56
12	2.65	3	200	520.19
13	3.01	3	200	555.65
14A	4.53	3	200	800.08
14B	3.27	3	200	716.42
15A	4.08	3	200	693.16
15B	3.22	3	200	646.50
16	2.95	3	200	534.69
17	2.84	3	200	571.10
18	3.03	3	200	557.86
19A	4.64	3	200	708.42
19B	4.03	3	200	645.10
20	3.15	3	200	631.50
21A	2.95	3	200	650.56
21B	2.86	3	200	647.90
21C	2.91	3	200	649.48

Table 3: Regional input application rates

SWAP region. These values reflect optimal irrigation from a purely agronomic perspective, based on local agronomic conditions. The fertilizer application rate was set at 200 Lbs N/ac. In all regions and the labor rate was set at 3 hrs/ac based on expert advice. Other costs such as herbicide, pesticide and machinery are not dictated by the DAYCENT model, and we assume that they are equal to the corresponding costs for production of the closest perennial crop currently grown in California, alfalfa.

The calibrated model can then be used for policy analysis. The question we address here is the extent and location of switchgrass production at various hypothetical switchgrass prices, that is, the derivation of the regional and statewide supply curves for switchgrass. Such information is likely to be of interest to policy makers and potential entrants in the biofuel industry. The use of a regionalized model is of critical importance since biofuel feedstock is usually expensive to transport. It is, therefore, pertinent to know where potential biofuel production would be located. This particular question clearly illustrates the need for a pluridisciplinary approach that can combine technical information regarding regional yield possibilities and input intensities for the new crop (information that is typically not available to the econometrician) and economic information regarding the opportunity cost of growing switchgrass in each agricultural region, taking full account of the limited availability of some inputs, the existing technology set and observed market conditions.

3 A pattern of switchgrass adoption

3.1 Generalized CES model results

To illustrate the possibilities offered by our approach, we derived the regional supply patterns and the statewide supply curve for switchgrass in California using the fully calibrated SWAP model (3). To this end, we simply solved program (3) iteratively for $p_{gs} \in [0, \$60/\text{ton}]$[9]. We conducted this experiment under two market scenarios: (i) exogenous output prices and (ii) endogenous output prices. In scenario (i), model (3) was run as is. Scenario (ii) assumed downward-sloping state-level demand curves for all crops other than switchgrass. The initial state-level prices were calculated as $P_i = \frac{\sum_g p_{gi} q_{gi}}{\sum_g q_{gi}}$, and linear demand functions were fitted through the initial point using

[9]There is no market for switchgrass as of now, but current research about switchgrass production costs provide some information about the expected price for switchgrass. Perrin et al. (2008)'s experiments suggest that the average cost is between \$46/ton and \$88/ton; Bangsund et al. (2008)'s results are between \$35/ton and \$40/ton; Duffy (2001)'s estimations have a wide range, which is between \$49/ton and \$135/ton.

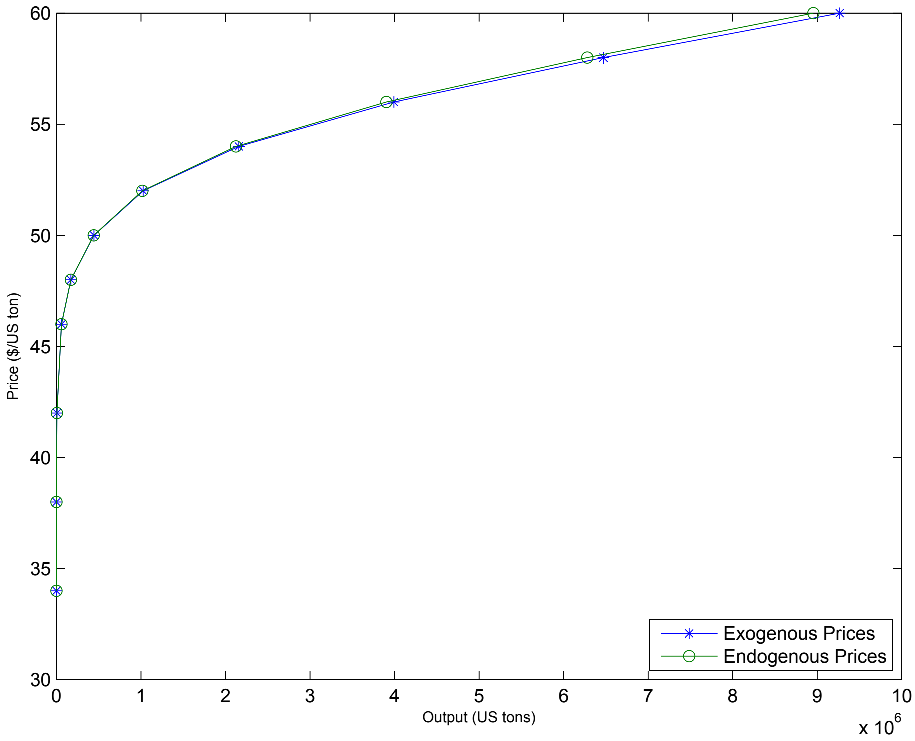

Figure 2: State supply curves for switchgrass

exogenous estimates of residual demand elasticities. The difference between the initial regional price p_{gi} and the state-level price P_i can be interpreted as a regional marketing cost (which is negative for some regions by construction). This regional price difference reflects differences in transportation costs among regions and is assumed to be constant per unit of output. The market equilibrium was found by maximizing total economic surplus, including consumer surplus and taking account of regional marketing costs.

Figure 2 depicts the state-level supply curve for switchgrass under the fixed and endogenous prices scenarios. The two curves are extremely close, reflecting the fact that California faces a highly elastic demand for the included crops. The supply curves show that the Central Valley starts to supply significant switchgrass from $46/ton. In addition, the supply curve corresponding to scenario (i) (fixed crop prices) lies to the right of the supply curve for scenario (ii) (endogenous crop prices). This is expected, since, as switchgrass enters the cropping pattern, fewer resources are allocated to other crops. When crop prices are endogenous, the prices of other crops therefore increase as switchgrass expands at their expense, which tends to mitigate their decline compared to the situation where crop prices do not change.

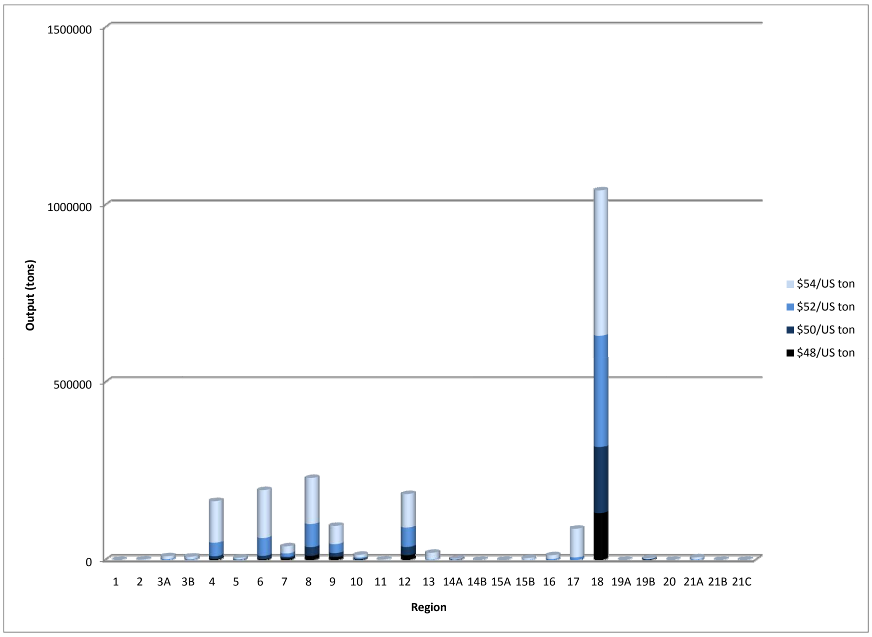

Figure 3: Regional switchgrass output at various prices

Since our model is regionalized, we can also derive regional supply curves for switchgrass. This type of information is particularly relevant when deciding where to locate processing plants, in order to minimize transportation costs. Figure 3 depicts switchgrass output for each agricultural region at four different price levels. Figure 4 depicts the corresponding acreage allocated to switchgrass as a percentage of total regional acreage. These figures are derived under scenario (ii) (endogenous crop prices).

Figures 3 and 4 show that the adoption of switchgrass is far from being uniform across regions, justifying *ex post* the use of a regionalized agricultural model. Figure 3 suggests that processing plants should primarily be located in or near region 18, located in the Southern San Joaquin Valley and corresponding to the counties of Kings and Tulare, because this region appears to be an early and massive adopter of switchgrass. This region covers a significant agricultural acreage, and a large share of its agricultural land is predicted to be allocated to switchgrass at prices above \$54/ton.[10] Regions 4, 6, 7, 8 and 9, located in the Southern Sacramento Valley

[10]The output and energy levels inferred from our model for prices at the upper end of the range seem to be consistent with the feedstock requirements of cellulosic ethanol plants. Perrin and Williams (2008) report that 80 gallon of ethanol can be extracted per ton of switchgrass. Grooms (2009) reports that a US company has begun constructing a commercial-scale cellulosic ethanol facility in Emmetsburg, IA. The capacity of this facility is 25 million gallon per year. At a price of \$54/ton, region 18 is predicted to supply a little more than 1 million tons, an equivalent of about

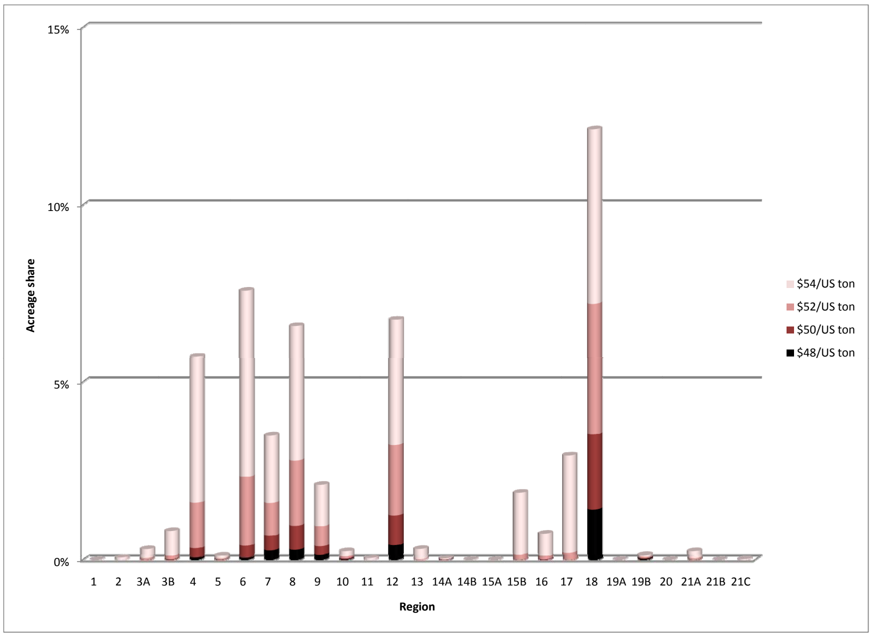

Figure 4: Regional switchgrass adoption at various prices

and Northern San Joaquin Valley, constitute another cluster of significant suppliers. These five contiguous regions are predicted to provide less feedstock than region 18, yet their total combined output at prices above \$54/ton lies above 0.6 million tons, which would be enough for at least two processing plants.[11] Region 12, corresponding to the counties of Merced and Stanislaus, also emerges as a potential supplier of switchgrass feedstock, but at the price levels considered here its predicted output could not support a plant with a capacity of 25 million gal per year.

In contrast, some regions appear as late and/or insignificant adopters, in particular those located in the Southern San Joaquin Valley such as region 14A, 14B, 15A, 19A, 19B and 20. This is not surprising, as irrigated switchgrass is a water-intensive crop, and water is relatively more expensive in this part of the Central Valley. Note that our finding that region 18 is the most significant region in terms of switchgrass output is not a mere consequence of its relatively large size. Figure 4 shows the acreage share of switchgrass at various prices. Region 18 appears to allocate the largest share of cropland to switchgrass. Region 15A is the second largest region, yet it does not adopt switchgrass at any of the price levels considered here (less than \$54/ton). In other words, the quantity of swichgrass produced in a region is not merely determined by

80 million gal of ethanol, and could thus supply three such facilities.

[11]The number of ethanol plants is based on the assumption that the plant capacity is 25 million gal per year.

Crops	Initial acreage (%)	% change in acreage switchg. price	
		$p_s = 50$	$p_s = 54$
Almond and Pistachio	11.84	-0.10	-0.58
Alfalfa	10.30	-0.45	-2.36
Corn	9.85	-1.19	-5.41
Cotton	9.77	-0.30	-1.18
Melons, Squash and Cucumbers	1.35	-0.11	-1.03
Dried bean	0.92	-0.69	-5.84
Fresh tomato	0.57	-0.04	-0.28
Wheat	5.37	-1.62	-7.77
Onion and Garlic	0.67	-0.04	-0.22
Other deciduous fruits and nuts	8.85	-0.23	-1.46
Other field crops	6.39	-1.15	-4.99
Other truck crops	3.08	-0.05	-0.34
Pasture	4.52	-0.49	-3.49
Potato	0.37	-0.05	-0.23
Processing tomato	4.45	-0.06	-0.60
Rice	8.31	-0.11	-1.49
Safflower	0.72	-0.80	-6.45
Sugar beet	0.31	-0.26	-1.09
Citrus	3.64	-1.06	-4.39
Grape vine	8.72	-0.49	-2.96

Note: Corn includes grain and sileage. Other deciduous fruits and nuts include apples, apricots, cherries, plums, walnuts, etc. Other field crops include grain sorghum, sudan grass, sunflower, etc. Other truck crops include artichokes, asparagus, green beans, carrots, celery, lettuce, flowers, berries, peppers, cabbage, etc. Grape vine includes wine grapes, table grapes and raisins.

Table 4: Statewide acreage reduction for existing crops

the available cropland. It is, to a large extent, determined by the region-specific water requirements and expected yields, combined with the opportunity cost of displacing existing crops.

The calibrated bio-economic model can also be used to predict the contraction of crops that are competing with switchgrass for limited resources. Table 4 shows the percentage reduction in acreage for the existing crops at the state level, at various switchgrass prices. At a price of \$54/ton, all competing crops experience acreage contractions, although crops that are considered "specialty crops" in California seem to experience relatively smaller contractions. The crops that are the least affected by the introduction of switchgrass at this price level are Onions and Garlic, Potato, Fresh tomato, and Other truck crops. The most affected crops are Wheat, Safflower, Dried bean, Corn, and Other field crops.

Crops	Initial acreage (%)	% change in acreage	
		switchg. price	
		$p_s = 50$	$p_s = 54$
Almond and Pistachio	4.60	-1.21	-4.47
Alfalfa	14.00	-2.83	-9.98
Corn	21.61	-4.17	-14.87
Cotton	8.33	-3.05	-11.02
Melons, Squash and Cucumbers	0.11	-2.58	-9.31
Dried bean	0.31	-6.31	-20.99
Fresh tomato	0.20	-0.29	-1.13
Wheat	4.15	-12.14	-31.73
Onion and Garlic	0.06	-1.74	-6.57
Other deciduous fruits and nuts	7.96	-1.65	-6.02
Other field crops	15.94	-3.72	-13.34
Other truck crops	0.63	-0.36	-1.42
Pasture	0.22	-5.08	-15.74
Potato	0.06	-1.61	-6.29
Processing tomato	0.20	-1.26	-4.69
Safflower	0.15	-13.28	-35.55
Sugar beet	0.10	-5.58	-18.78
Citrus	14.56	-2.51	-9.21
Grape vine	6.81	-3.68	-13.40

Table 5: Acreage reduction for existing crops in region 18

Table 5 shows the reduction in the acreages of competing crops for the early and large switchgrass adopter, namely region 18. In this region, at a price of $54/ton, where switchgrass is predicted to take over about 10% of acreage, the acreage contraction exceeds 15% for Safflower, Wheat, Dried Bean, Sugar Beet and Pasture. All these crops either represent a relatively small share of initial acres or are low value. In contrast, crops that are high value (Fresh tomato, Other truck crops, Almond and Pistachio, Processing tomato, Other deciduous fruits and nuts) experience the smallest contractions.

3.2 Results from a fixed-proportion variant

The above results are based on generalized CES specification for existing crops, with an elasticity of substitution exogenously set at $\sigma_{gi} = 0.21$. Here we conduct a robustness check based on a fixed-proportion variant of the previous model, that is, we set $\sigma_{gi} = 0$.

The regionalized economic optimization model becomes

$$\max_{\substack{q_{gi}\geq 0, x_{gi1}\geq 0\\ q_{gs}\geq 0, x_{gs}\geq 0}} \quad \sum_g \sum_i p_{gi}q_{gi} - (C_{gi}+\lambda_{gi})x_{gi1} + p_{gs}q_{gs} - C_{gs}x_{gs}$$

$$\text{subject to} \quad \begin{cases} \sum_{i=1}^{I} x_{gi1} + x_{gs} \leq b_{g1} & \forall g \in [|1, G|] \\ \sum_{i=1}^{I} a_{gi}x_{gi1} + w_g x_{gs} \leq b_{g2} & \forall g \in [|1, G|] \\ q_{gi} = \mu_{gi} x_{gi1}^{\delta_{gi}} & \forall (g,i) \in [|1, G|] \times [|1, I|] \\ q_{gs} = \frac{1}{2}\hat{\mu}_{gs,1} x_{gs}^{\hat{\delta}_{gs,1}} + \frac{1}{2}\hat{\mu}_{gs,2} x_{gs}^{\hat{\delta}_{gs,2}} & \forall g \in [|1, G|] \end{cases} \tag{4}$$

where p_{gi} is the price of crop i in region g, q_{gi} the output level, related to input employment in a fixed-proportion production function with parameters μ_{gi} and δ_{gi}, satisfying $\mu_{gi} > 0$ and $\delta_{gi} \in (0, 1)$. We define the parameters a_{gi} as the per acre quantity of water applied to crop i in region g. As before, the parameters b_{g1} and b_{g2} represent the limited land and water resources in each region. Following common PMP practice, calibration parameters λ_{gi} are added to the per acre cost term to allow for calibration against the reference allocation. The technology parameters λ_{gi}, μ_{gi} and δ_{gi} are recovered following Mérel et al. (2011a), so that the model replicates the same set of region-specific supply elasticities and the same base-year allocation as in the previous section. For switchgrass, the fixed-proportion production functions are the same as in the previous section.

Figure 5 shows the statewide supply curves for the generalized CES model and the fixed-proportion model, under the two scenarios regarding the endogeneity of output prices. As expected, the fixed-proportion model predicts less switchgrass supply at any price level, as existing crops are more constrained than under input substitution, resulting in higher shadow prices for constrained resources. Yet, the statewide supply curves are very close for the two model specifications, indicating that for this simulation the use of the simple fixed-proportion variant may be sufficient.

The two models also generate very similar regional patterns regarding switchgrass acreage and output. Figures 6 and 7 show that the fixed-proportion model consistently predicts a smaller acreage of switchgrass than the generalized CES model. Figures 8 and 9 show similar results for switchgrass output. However, both models imply that region 18 on the one hand and regions 4, 6, 7, 8 and 9 on the other hand are the two main adopting clusters at a price of \$54/US ton.

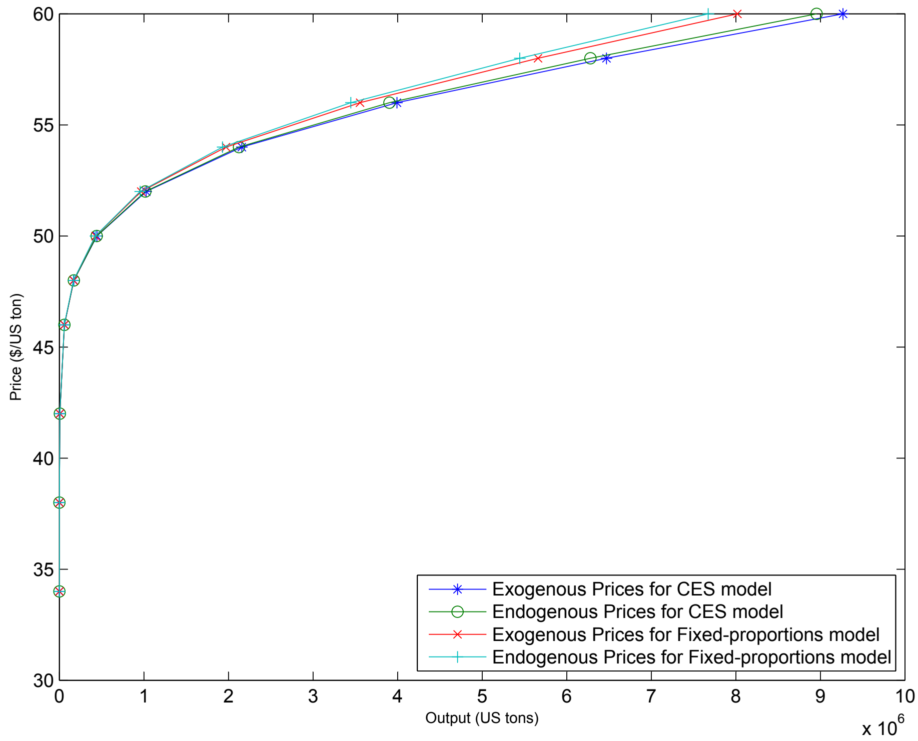

Figure 5: State supply curves for switchgrass

4 Conclusion

This study has demonstrated the usefulness of combining information obtained from observed economic behavior (regionalized input and output allocation, econometrically estimated crop supply elasticities) with information simulated using a biogeochemical model (regionalized yield estimates) to infer the pattern of adoption of a new crop in a diverse agricultural region. The innovative feature of this study is the recovery of region-specific technology parameters for the new crop using information on average yields and yield variability obtained from a biogeochemical model of plant growth.

Once calibrated, our model was used to infer the pattern of adoption of a new energy crop, switchgrass in California. The use of regionalized economic information combined with regionalized yield estimates allowed for the derivation of a spatially explicit supply pattern. Our results suggest that adoption rates differ widely among California SWAP regions, meaning that the location of processing plants may be an important issue. They also suggest that switchgrass adoption is not likely to displace specialty crops by much statewide. The generalized CES model and the

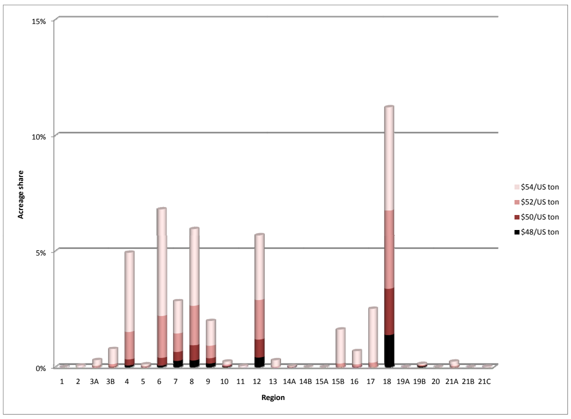

Figure 6: Regional swithchgrass adoption for the fixed-proportion model

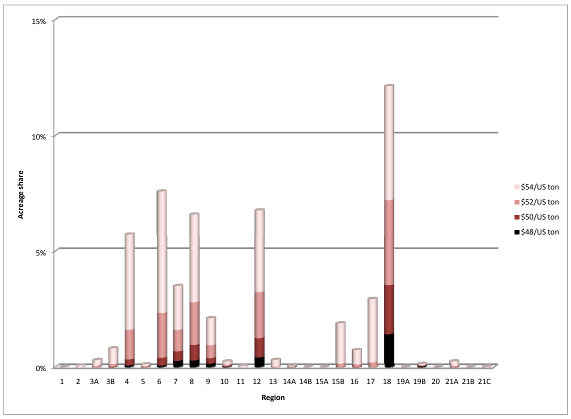

Figure 7: Regional swithchgrass adoption for the generalized CES model

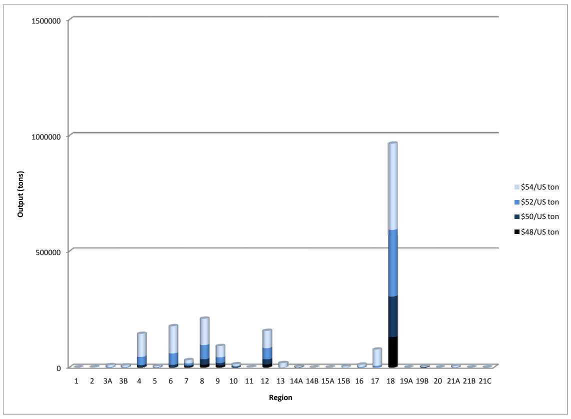

Figure 8: Regional swithchgrass output for the fixed-proportion model

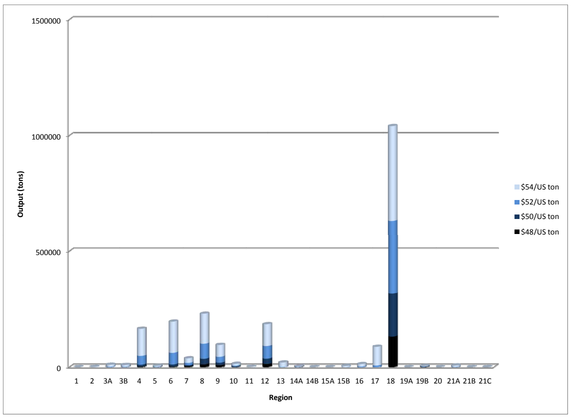

Figure 9: Regional swithchgrass output for the generalized CES model

fixed-proportion model yielded very comparable results in terms of acreage and output adoption patterns, indicating that the move to more sophisticated technology specifications, when no inference on intensive margin changes is sought, may not be needed.

Although our approach represents a significant step forward in terms of the sophistication of the calibration methodology used, it is not exempt from limitations. First of all, even though our model is regionalized, the level of disaggregation (27 regions) is not commensurate with the possibilities offered by the DAYCENT model in terms of predicted yields. This aspect can be overcome by obtaining more disaggregated economic data, but the cost of doing so is likely high.

Second, one can regret that the technology specified for the new crop in our application is less flexible than that of existing crops, in the sense that it does not allow for substitution between factors as in the generalized CES specification. Indeed, agronomic process models such as DAYCENT are specified and calibrated to accurately reflect the effects of changes in levels of inputs such as fertilizer or water, which generally can be considered as the intensive marginal adjustment. Multi-product economic models with fixed-proportion production functions can only represent crop switching at the extensive margin. To avoid losing information from the underlying biogeochemical process models, bio-economic models could certainly take the form of interdependent multi-input production functions, which are able to reflect rational economic adjustment at both the extensive and intensive margins, as well as externalities from specific inputs such as nitrogen or water.

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Appendix

A.

The regional switchgrass production function estimations are listed in the following table 6.

SWAP Region	Regression method				Mérel et al. (2011b) method			
	Scenario 1		Scenario 2		Scenario 1		Scenario 2	
	$\hat{\mu}^1_{gs}$	$\hat{\delta}^1_{gs}$	$\hat{\mu}^2_{gs}$	$\hat{\delta}^2_{gs}$	$\hat{\mu}^1_{gs}$	$\hat{\delta}^1_{gs}$	$\hat{\mu}^2_{gs}$	$\hat{\delta}^2_{gs}$
1	11.71	0.98	10.75	0.99	18.00	0.93	13.63	0.96
2	12.89	0.98	11.59	0.99	12.05	0.99	13.02	0.98
3A	14.75	0.98	12.87	0.98	12.69	0.99	15.37	0.97
3B	14.75	0.98	12.87	0.98	12.69	0.99	15.37	0.97
4	15.88	0.97	12.33	0.99	12.68	0.99	13.17	0.98
5	15.06	0.97	13.10	0.97	12.34	0.99	11.97	0.99
6	14.47	0.98	12.60	0.98	17.01	0.96	13.27	0.98
7	15.68	0.96	16.48	0.95	21.22	0.94	15.85	0.97
8	14.58	0.98	16.62	0.96	22.42	0.94	16.23	0.97
9	15.25	0.97	18.26	0.95	12.89	0.99	11.43	0.99
10	20.31	0.95	14.67	0.97	15.38	0.98	11.29	0.99
11	12.31	0.98	10.82	0.99	11.42	0.99	10.26	0.99
12	17.47	0.95	12.99	0.98	17.13	0.96	12.10	0.98
13	13.02	0.99	11.93	0.99	16.79	0.97	14.25	0.97
14A	20.91	0.96	20.41	0.95	16.73	0.98	14.93	0.98
14B	16.24	0.97	14.86	0.97	20.38	0.95	11.29	0.99
15A	17.42	0.97	15.95	0.96	13.36	0.99	16.24	0.95
15B	14.99	0.99	11.52	0.99	14.79	0.99	13.14	0.98
16	14.04	0.98	11.73	0.99	12.04	0.99	10.82	0.99
17	13.33	0.99	11.58	0.99	17.51	0.91	14.15	0.94
18	19.96	0.96	16.78	0.96	14.12	0.99	12.59	0.99
19A	18.15	0.96	22.27	0.93	17.96	0.97	21.14	0.94
19B	16.29	0.98	36.82	0.90	14.13	0.99	23.20	0.95
20	17.98	0.97	15.88	0.97	13.66	0.99	13.24	0.99
21A	14.51	0.99	15.19	0.97	16.99	0.97	25.01	0.93
21B	13.24	0.98	12.39	0.98	15.97	0.96	32.31	0.82
21C	13.87	0.98	13.79	0.98	17.57	0.97	38.59	0.88

Note: All the coefficients from the regression method are statistically significant at 0.1% level.

Table 6: Estimations of regional production functions for switchgrass