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**Carbon market policy design:
Investigating the role of payments aggregation**

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Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2012 AAEA Annual Meeting, Seattle, Washington, August 12-14, 2012

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1 Introduction

Growing concerns about global climate change have led policy-makers to consider regulating emissions of greenhouse gases (GHGs), for example, through international agreements such as the Kyoto Protocol of the United Nations Framework Convention on Climate Change. The United States faces increasing pressure to adopt a meaningful climate policy (Stavins, 2008a,b). In the meantime, some states have already begun designing their own climate policy to cap emissions such as the ten northeastern states with the Regional Greenhouse Gas Initiative (RGGI) and California with Assembly Bill 32.

There is a general consensus among economists that market-based policy instruments are more efficient than command-and-control tools for limiting pollution when firms' abatement costs are heterogenous (Montgomery, 1972); and the more heterogeneous their costs, the greater the efficiency gains (Newell and Stavins, 2003). Tradable-permit systems are gaining momentum among policy-makers. They are less controversial than a tax on emissions and have a history of success for abating pollution cost-effectively such as under the SO_2 allowance trading system (Stavins, 1998).

It is not yet clear whether policy-makers will design cap-and-trade systems that allow credit offsets for GHG emission reduction in non-capped sectors such as agriculture

and forestry. Newell and Stavins (2000) suggest that this decision will partly be based on cost-effectiveness criterion. Research shows that these sectors could contribute significantly to the climate change mitigation effort, through carbon sequestration and reduction in nitrous oxide (N_2O) and methane (CH_4) emissions, two gases with very potent global warming power (GWP), e.g., Lal et al. (1998); Paustian et al. (2006); Smith et al. (2008); Snyder et al. (2009).¹ Economic studies find that U.S. agriculture and forests could cost-effectively reduce GHG emissions relative to capped energy-based sectors, e.g., Parks and Hardie (1995); Stavins (1999); McCarl and Schneider (2001); Pautsch et al. (2001); Lubowski et al. (2006); Antle et al. (2007).

Traditional approaches for predicting behavioral changes in agriculture and forestry rely on mathematical programming, e.g., De Cara and Jayet (2000); McCarl and Schneider (2001); Durandau et al. (2010), econometrics, e.g., Stavins (1999); Pautsch et al. (2001), or a hybrid approach where the parameters of the simulation model are econometrically estimated, e.g., Antle and Capalbo (2001). This paper uses positive mathematical programming (PMP), a method formalized by Howitt (1995). We calibrate the model's implied supply elasticities to exogenous elasticity estimates. Furthermore, we ensure that the model's yield responses to input use and tillage technology are consistent with agronomic responses derived from ecosystem process-based models.

Most studies have focused on mitigating emissions from a single GHG, for example, CO_2 through enhanced carbon sequestration (Pautsch et al., 2001; Antle et al., 2003; Lubowski et al., 2006) or N_2O (Mérel et al., 2011b; Rosas et al., 2011). Yet, changes in agricultural practices typically affect multiple GHGs. For example, there is evidence that tillage practices affect both carbon sequestration and N_2O emissions (Six et al., 2004) and, reciprocally, nitrogen fertilizer management can affect both N_2O emissions and carbon sequestration (Snyder et al., 2009). Six et al. (2004) find that reduced tillage may lead, over a 20-year period, to net increase or decrease in GWP, depending

¹International Panel on Climate Change (IPCC) (2001) estimates unit masses of CH_4 and N_2O have 23 and 296 times the GWP of a unit of CO_2 , respectively, over a 100-year time-frame.

on whether the enhanced carbon sequestration or increase in N_2O emissions effect predominates. Therefore, it appears critical to account for the GWP of the three GHGs combined to estimate the potential cost-effectiveness of GHG offsets from agricultural sources.² Some studies have looked at N_2O emissions from agricultural land and CH_4 emissions from livestock, e.g., De Cara et al. (2005); Neufeldt et al. (2006); Durandau et al. (2010), but few have accounted for the three GHGs simultaneously, e.g., De Cara and Jayet (2000); Schneider et al. (2007). Furthermore, some of these studies do not take into account the effects of some practices on multiple GHGs, as highlighted in Snyder et al. (2009), and rely on the linear IPCC coefficients to infer emissions from input use, contrary to suggestions by Bouwman et al. (2002); Durandau et al. (2010); Rosas et al. (2011), e.g., De Cara and Jayet (2000); De Cara et al. (2005).³ Ecosystem process-based models can prove very useful tools to understand and quantify the complex and non-linear relationships between agricultural practices and GHG emissions (Neufeldt et al., 2006; Durandau et al., 2010). Numerous studies have relied on ecosystem process-based models such as EPIC, e.g., McCarl and Schneider (2001); Pautsch et al. (2001), Century, e.g., Antle et al. (2003), DNDC, e.g., Neufeldt et al. (2006), and STICS and CERES, e.g., Durandau et al. (2010). However, previous studies do not carefully couple the economic and biophysical models, with the exceptions of Durandau et al. (2010); Mérel et al. (2011b). As a result, the economic yield responses to input use likely differ from the agronomic responses. Durandau et al. (2010); Mérel et al. (2011b) propose two distinctive methods to incorporate the agronomic information from the biophysical model into the economic model so that, at the margin, the economic and agronomic yield responses are consistent. In this study, we examine the GWP of the three main GHGs, expressed in metric tonne (Mg) of CO_2 -equivalent (CO_2e). We rely on the

²For example, Antle and Ogle (2011) find that accounting for the effect of no-till practices on both carbon sequestration and N_2O emissions in the central U.S. substantially shifts the GHG offset supply curve relative to studies that only consider carbon sequestration such as Antle et al. (2007).

³The IPCC Tier 1 method does not take into account the effects of soil characteristics, climate, crop management and land use on N_2O emissions and ignores the complexity of the microbiological processes responsible for N_2O emissions (Durandau et al., 2010).

biogeochemical process-based model Daycent to estimate GHG emissions for a series of agricultural practices (Parton et al., 1996).⁴ We extend on the work by Mérel et al. (2011b) to ensure consistency of the economic and agronomic yield responses, at the margin, to input use (N fertilizer and water) and tillage technology.

Previous studies typically consider a single alternative practice for GHG emission reduction. For example, Pautsch et al. (2001); Antle and Ogle (2011) look at reduced tillage, and Mérel et al. (2011b); Rosas et al. (2011) look at reduced nitrogen fertilizer application. Yet, allowing farmers to choose from a set of practices, including combining multiple alternative practices, can lower the supply costs of GHG offset (Schneider et al., 2007). In this paper, we examine two agricultural practices simultaneously: nitrogen fertilizer management and tillage intensity. Farmers choose the crops, tillage intensity and nitrogen application rate that maximize their expected net profit. Considering these two practices jointly is relevant for two reasons. First, in practice there is no reason why farmers would change one practice without adjusting the other, since altering the marginal productivity of one input likely affects the productivity of the other. Second, scientific evidence suggests that adjusting both tillage and nitrogen management simultaneously may positively affect carbon sequestration and N_2O emission reduction (Six et al., 2004; Smith et al., 2008; Snyder et al., 2009).

There is a debate among economists and policy analysts about what contract design—with payment per unit of output (in Mg of CO_2e abated) or per practice—is the most cost-effective (and politically feasible). The most cost-effective contract is the one for which the sum of the total payment required to achieve a given abatement target and the administrative costs is the lowest. Under contracts per unit of output, farmers abate GHG emissions until their marginal cost is equal to the price of a Mg of CO_2e . Because of spatial heterogeneity in economic and environmental conditions, farmers' marginal

⁴Daycent is the daily time step-version of the well-known Century model (Parton et al., 1987). It was developed to simulate ecosystem carbon and nutrient dynamics and trace gas fluxes. It includes sub-models for nitrification and denitrification (Parton et al., 1996) and CH_4 oxidation (Del Grosso et al., 2000).

abatement costs typically differ. Farmers receive a fixed price per Mg of CO_2e abated and choose the agricultural practices with the lowest marginal cost. Under contracts per practice, farmers receive a fixed price per hectare regardless of the actual GHG offset. Contracts per unit of output are the most efficient since they enroll lands with the lowest costs per unit of output rather than lands with the lowest costs per hectare, thus, minimizing total payment for the same GHG emission reduction target (Pautsch et al., 2001; Antle et al., 2003; Lubowski et al., 2006).

Yet, contracts per unit of output may incur substantially greater administrative costs than simpler contracts based on observed input use. In the case of contracts for carbon sequestration, the carbon sequestered in the soil or in trees must be measured at the beginning (baseline) and at the end of the contract to establish net sequestration. Stavins (1999); Lubowski et al. (2006) claim that on forested lands contracts per practice have lower administrative costs and are easier to monitor, and Parks and Hardie (1995) suggest that contracts per practice may be more cost-effective than contracts per unit of output. Antle et al. (2003) propose a sampling design for measuring carbon sequestered on agricultural lands that may reduce administrative costs, provided the measurement error deemed acceptable is large enough. For example, with a 10% measurement error, they find that in Montana the measurement costs incurred under the contract per unit of output do not offset its costs savings. However, the measurement costs associated with this sampling design increase with spatial heterogeneity. This may result in the measurement error, such that the contract per unit of output is at least as efficient as the contract per practice, being unacceptably large in regions more heterogeneous than Montana.

In addition, contracts per unit of output have only been proposed for carbon sequestration, for which measurement simply consists in quantifying the net change in carbon stock at two points in time—at the beginning and end of the contract. However, measuring emissions of the two other GHGs (N_2O and CH_4) necessitates monitoring

the yearly fluxes of gases. Because N_2O and CH_4 emissions may take many years to stabilize after a change in agricultural practices, Six et al. (2004) emphasize the need for monitoring cumulative emissions over the length of the contract. Therefore, measuring N_2O and CH_4 offset requires continuous measurements starting one year before the beginning of the contract (to establish the baseline) and until the end of the contract. Measuring the emissions of all three GHGs is likely to be difficult to implement and the costs very large (Antle and Ogle, 2011). Uncertainty about measurement feasibility and prohibitive costs are clear arguments in favor of contracts per practice over contracts per unit of output. In the rest of the paper we restrict our analysis to contracts per practice.

An important component for the design of cost-effective GHG offset programs is the level of payment aggregation. Payments are tied to the GHG offset generated over a specific spatial entity from implementing a given set of practices. The spatial unit may be the field, the county, the state, the nation or some other geographical unit. Programs designed at the field-level are the most efficient but are likely politically infeasible and with prohibitive administrative costs. The more aggregated the payment level is, the simpler the program is to implement and the lower the administrative costs, but the larger the total payment to reach a given GHG offset target may be (Pautsch et al., 2001).⁵ This suggests that cost-effective programs may feature some level of spatial aggregation. Based on previous studies, it is not clear how much the level of payment aggregation may affect the supply curve of GHG offset. In the case of no-till in the central U.S., Antle et al. (2007) find similar GHG offset supply curves for programs designed at the county-level and at the level of the central U.S. Yet, Pautsch et al. (2001) find that, for the case of conservation tillage in the state of Iowa, the supply curve shifts upward substantially (by as much as a factor four) when aggregating payments

⁵In addition, Feng and Kling (2005) find that in the presence of co-benefits, such as erosion and water contamination prevention, the social efficiency of GHG offset programs may increase with payment aggregation, provided GHG offset potential and co-benefits are positively correlated.

from the farm to the state-level. Therefore, large-scale studies are needed to quantify how aggregation may affect the efficiency of market mechanisms for GHG emission mitigation.

In this paper, we investigate the role of payment aggregation on the cost-effectiveness of a GHG offset program for California agriculture. We estimate the GHG offset supply curves for different levels of payment aggregation. We look at the role of spatial aggregation from the regional to state-level, including intermediate aggregation levels. In addition, we examine the role of aggregation over crops from individual crops, groups of crops, to a single composite crop for California. California is arguably one of the most complex agricultural states given the variety of its environmental conditions and attendant agricultural mix. This makes it a relevant case study to examine how much environmental and economic heterogeneity matters for aggregation. Intuitively, aggregation will have less severe effects on cost-effectiveness in somewhat more homogeneous states—with fewer major crop systems.⁶ Thus, the results derived for California can provide an upper bound on the extent that aggregation may affect cost-effectiveness of GHG offset programs.

We develop a bio-economic model of California agricultural production to predict the effects of a cap-and-trade system on agriculture and the environment. The model is calibrated using observed economic information on outputs, inputs use, regional constraints and exogenous supply elasticities (Mérel et al., 2011a). Crop-specific production functions are calibrated to exogenous agronomic information on yield responses to nitrogen, irrigation and tillage, through the use of crop-specific shadow prices for fertilizer, water and tillage intensity, expanding on the methodology developed in (Mérel et al., 2011b). As a result, the crop production functions are consistent, at the margin, with the yield responses to intensive margin and technology adjustments estimated using the agronomic model Daycent.

⁶Furthermore, extending this study to the rest of the U.S., in particular to more homogenous states, will be straightforward.

2 Model calibration

Our model maximizes regional agricultural profits subject to resource constraints such as land and water. Profits are specified with a generalized constant-elasticity-of-substitution (CES) production functions with cost functions linear in inputs as proposed in Mérel et al. (2011a). There are I cropping activities. The economic optimization model for a given region is defined as follows:

$$\begin{aligned} & \max_{q_i \geq 0, x_{ij} \geq 0, T_i \geq 0} \sum_i p_i q_i - (c_{i1} + \lambda_{i1} + c_{iT}(T_i) + \lambda_{iT} T_i) x_{i1} - (c_{i2} + \lambda_{i2}) x_{i2} - (c_{i3} + \lambda_{i3}) x_{i3} \\ & \text{subject to} \\ & \begin{cases} \sum_{i=1}^I x_{ij} \leq v_j & j = 1, 2 \\ q_i = \mu_i \gamma_i(T_i) \left(\sum_{j=1}^3 \beta_{ij} x_{ij}^{\rho_i} \right)^{\frac{\delta_i}{\rho_i}} & \forall i = 1, \dots, I \end{cases} \end{aligned} \quad (1)$$

where the choice variables x_{ij} represent the amount of input j and T_i the tillage intensity used in the production of crop i . We construct the tillage variable $T_i \in [0, 1]$ by mapping existing tillage technologies into an index of soil disturbance such that $T_i = 0$ describes no-till systems and $T_i = 1$ conventional tillage systems. See data section. $\gamma_i(T_i)$ is a function of tillage that shifts the production function. p_i is the price of crop i , c_{ij} is the price of input j in activity i and $c_{iT}(T_i)$ denotes the per acre cost of tillage, which is a differentiable function of tillage intensity with $\frac{dc_{iT}}{dT_i} = c'_{iT} > 0$. The parameters v_j represent the regional resource constraints where v_1 and v_2 denote the land and water constraints, respectively. q_i is the output of crop i associated with the generalized CES production function with tillage intensity T_i and input employments x_{ij} . μ_i , β_{ij} and δ_i are the parameters of the CES function and satisfy $\mu_i > 0$, $\beta_{ij} > 0$, $\sum_j \beta_{ij} = 1$ and $\delta_i \in (0, 1)$. The parameter ρ_i is such that $\rho_i = \frac{\sigma_i - 1}{\sigma_i}$ where σ_i is the elasticity of substitution between any two inputs.

We explicitly model the land ($j = 1$), water ($j = 2$) and nitrogen fertilizer ($j = 3$) inputs and the tillage technology. The tillage cost c_{iT} represents the per hectare cost

of labor, machinery, fuel, etc, utilized for tillage activities. We assume all other inputs (such as pesticides, non-tillage machinery, custom operations, etc) are employed in fixed proportions with land, and we include their respective cost in the price of land, c_{i1} . Similarly, we assume that all fertilizer elements (N, P, K and others) are employed in fixed proportions, so that the price of nitrogen fertilizer c_{i3} includes the non-nitrogen fertilizer cost.

The calibration parameters λ_{i1} , λ_{i2} , λ_{i3} and λ_{iT} are added to the land, water, fertilizer and tillage cost terms, respectively, to allow replicate the observed allocation of land, water and fertilizer use and tillage technology.

The calibration information at the reference allocation is denoted $(\bar{q}_i, \bar{T}_i, \bar{x}_{ij}, \bar{\eta}_i, \bar{\lambda}_1, \bar{\lambda}_2, \bar{y}_{iT}, \bar{y}_{iW}, \bar{y}_{iN})$ where $\bar{\lambda}_1$ and $\bar{\lambda}_2$ denote the shadow price of the constrained resources, land and water, respectively, obtained from the first stage of PMP (Howitt, 1995). The parameter $\bar{\eta}_i$ denotes the exogenous supply elasticity of crop i . The parameters \bar{y}_{iT} , \bar{y}_{iW} and \bar{y}_{iN} represent the agronomic information, in the form of elasticities of yield with respect to tillage intensity, water and nitrogen application, respectively. See section Calibration to agronomic yield responses. The calibration problem consists of selecting the set of parameters $(\mu_i, \beta_{ij}, \delta_i, \lambda_{i1}, \lambda_{i2}, \lambda_{i3}, \lambda_{iT})$ so that the optimization model (1) replicates the observed input-output allocation $(\bar{q}_i, \bar{T}_i, \bar{x}_{ij})$, the shadow price of land $\bar{\lambda}_1$ and water $\bar{\lambda}_2$ and the supply responses $\bar{\eta}_i$; and the yield responses calculated at the reference allocation coincide with $(\bar{y}_{iT}, \bar{y}_{iW}, \bar{y}_{iN})$. Based on the region, the land and/or water constraints are binding, i.e., $\bar{\lambda}_1$ and/or $\bar{\lambda}_2$ are greater than zero.

2.1 Data sources

We use the 2005 data from the California StateWide Agricultural Production (SWAP) model developed by R. Howitt (Jenkins et al., 2001).⁷ The SWAP model consists of 27 regions in the Central Valley, California's agricultural heartland. These regions cor-

⁷See swap.ucdavis.edu.

respond to water districts and allow to capture meaningful regional water constraints. Our study includes seven major field crops covering about 3.18 million acres in 2005, representing 70% of the non-perennial agricultural acreages in the Central Valley.⁸ The acreage distribution among modeled crops is shown in table 1. Crop acreages and water prices for 2005 come from the California Department of Water Resources. Crop prices and yields for 2005 come from the Agricultural Commissioner Reports. Water application rates come from the California Department of Water Resources when available and from the University of California Cost and return studies for the remaining crops. Fertilizer prices and application rates and other production costs come from the Cost and return studies.

Own-price supply elasticities for corn, cotton, safflower, sunflower and wheat come from the SWAP model, while the supply elasticities for alfalfa, rice and processing tomato are updated based on the recent study by Russo et al. (2008).

The Cost and return studies provide information on observed regional management practices. Overall, these practices can be characterized as conventional with medium soil disturbance. Based on expert opinions we modify these practices to derive the cost of tillage for systems ranging from no-till, conservation tillage to conventional tillage with high soil disturbance.

2.2 Derivation of yield response elasticities

One important contribution of this research is to incorporate the agronomic information from the biophysical process-based model into the economic model such the economic yield responses to input use and tillage technology are consistent, at the margin, with the agronomic responses. This is critical since carbon sequestration and N_2O emissions are sensitive to tillage technology and intensive margin adjustments, in particular, nitrogen fertilizer and water application rates (Smith et al., 2008; Snyder et al., 2009).

⁸We do not include perennial tree crops because these crops require large establishment costs (and Daycent is not calibrated for tree crops).

Table 1: Acreage distribution across the Central Valley

Crop	Acreage share (%)		
	Central Valley	Sacramento Valley	San Joaquin Valley
Alfalfa	21.98	24.22	18.97
Corn	21.02	22.29	21.24
Cotton	20.86	0.82	27.77
Grain	11.46	20.56	8.94
Other field crops	13.64	9.01	15.49
Processing tomato	9.50	17.48	7.28
Safflower	1.54	5.61	0.31
Total	100.00	100.00	100.00

Mérel et al. (2011b) propose a methodology to replicate to agronomic yield responses to nitrogen and water inputs. We build on their work and allow for incorporation of agronomic information on tillage technology.

We use the Daycent model, calibrated for crops under California conditions (De Gryze et al., 2009, 2010), to generate yield responses to tillage technology and nitrogen fertilizer and water inputs. The Central Valley is divided into cells of $15\text{km} \times 15\text{km}$. The Daycent model is run for each cell using the average soil and climate conditions prevailing on that cell. We then aggregate Daycent’s results to the scale of the economic model.

The regional yield response curves are generated as follows. First, we generate the yield response to nitrogen application, holding the tillage intensity and water application rate at their observed levels based on the Cost and return studies. Following Godard et al. (2008); Mérel et al. (2011b), we fit an exponential yield response curve through the obtained simulation data:

$$y_i(a_{iN}) = y_{a_{iN}=0} + \alpha_{iN} (1 - \exp(-\beta_{iN} a_{iN}))$$

where a_{iN} is the nitrogen application rate and $y_{a_{iN}=0}$, α_{iN} and β_{iN} are parameters. $y_{a_{iN}=0}$ represents the minimum yield as nitrogen application goes to zero. If the nitrogen

application rate a_{iN} that replicates the observed regional yield is not too far from the observed nitrogen application rate based on the Cost and return studies, we retain that value for the reference nitrogen application.⁹ For the crops and regions for which this is not true, we verify that the yield that would be replicated by the observed nitrogen application rate reported in the Cost and return study is not too far from the observed yield and we retain that value for the reference yield and the reference nitrogen application rate remains the observed rate.

Second, we generate the yield response to water application, holding the tillage intensity at its observed level and reference nitrogen application. We estimate a sigmoid yield response curve to the water application rate as in Mérel et al. (2011b):

$$y_i(a_{iW}) = \frac{\alpha_{iW}}{1 + \exp\left(-\frac{a_{iW} - a_{i0}}{\beta_{iW}}\right)} \quad (2)$$

where a_{iW} is the water application rate and a_{i0} , α_{iW} and β_{iW} are parameters. We verify that the water application rate a_{iW} that replicates the reference yield is similar the observed irrigation rate, and retain that value for the reference water application.¹⁰

Last, we generate the yield response to tillage technology, holding nitrogen and water application at their reference levels. We specify the relationship between yield and tillage intensity with an exponential function such that

$$y_i(T_i) = y_{T_i=0} + \alpha_{iT} (1 - \exp(-\beta_{iT}T_i)) \quad (3)$$

where T_i is tillage intensity and $y_{T_i=0}$, α_{iT} and β_{iT} are parameters. $y_{T_i=0}$ represents the yield for a no-till system. When the tillage technology T_i that replicates the reference yield is similar to the observed tillage intensity, we retain that value for the reference tillage intensity.¹¹ For the crops and regions for which this is not true, we verify that

⁹"Not too far" means, here, within 30% of the observed value.

¹⁰"Similar" means, here, within 10% of the observed value.

¹¹"Not too far" means, here, within 30% of the observed value.

the yield that would be replicated by the observed tillage intensity reported in the Cost and return study is not too far from the observed yield and we retain that value for the reference yield and the reference tillage intensity remains at the observed level.

Therefore, for each crop and region we have reference water and nitrogen application rates, \bar{a}_{iW} and \bar{a}_{iN} , respectively, a reference tillage intensity \bar{T}_i , and a reference yield \bar{y}_i . By construction, our reference yield is consistent with “reference” tillage intensity and water and nitrogen application rates, in the sense that this yield lies on each yield response curve.

The fitted yield response curves to tillage $y_i(T_i, \bar{a}_{iW}, \bar{a}_{iN})$, water application rate $y_i(\bar{T}_i, a_{iW}, \bar{a}_{iN})$ and nitrogen application rate $y_i(\bar{T}_i, \bar{a}_{iW}, a_{iN})$ are used to calculate the elasticity of regional yield with respect to tillage technology and input use.

Using the estimated yield response to nitrogen, the elasticity of yield with respect to nitrogen application at the reference allocation is

$$\begin{aligned}\bar{y}_{iN} &= \frac{dy_i}{da_{iN}} \frac{\bar{a}_{iN}}{\bar{y}_i} \\ &= \frac{\alpha_{iN} \beta_{iN} \exp(-\beta_{iN} \bar{a}_{iN}) \bar{a}_{iN}}{\bar{y}_i}.\end{aligned}$$

Similarly, the elasticity of yield with respect to water application at the reference allocation is

$$\begin{aligned}\bar{y}_{iW} &= \frac{dy_i}{da_{iW}} \frac{\bar{a}_{iW}}{\bar{y}_i} \\ &= \frac{\bar{a}_{iW} e^{-\frac{\bar{a}_{iW} - a_{i0}}{\beta_{iW}}}}{\beta_{iW} \left(1 + e^{-\frac{\bar{a}_{iW} - a_{i0}}{\beta_{iW}}}\right)}\end{aligned}$$

and the elasticity of yield with respect to tillage intensity at the reference allocation is

$$\begin{aligned}\bar{y}_{iT} &= \frac{dy_i \bar{T}_i}{dT_i \bar{y}_i} \\ &= \frac{\alpha_{iT} \beta_{iT} \exp(-\beta_{iT} \bar{T}_i) \bar{T}_i}{\bar{y}_i}.\end{aligned}$$

Table (2) shows the average agronomic yield response elasticities for the Sacramento and San Joaquin valleys weighted by crop acreages.¹²

Table 2: Agronomic yield response elasticities

Crop	Sacramento Valley			San Joaquin Valley		
	\bar{y}_{iW}	\bar{y}_{iN}	\bar{y}_{iT}	\bar{y}_{iW}	\bar{y}_{iN}	\bar{y}_{iT}
Alfalfa	0.20	-	-	0.24	-	-
Corn	0.26	0.12	0.07	0.27	0.13	0.07
Cotton	0.46	0.03	0.00	0.49	0.01	0.00
Grain	0.13	0.03	0.00	0.31	0.00	0.00
Other field crops	0.45	0.00	0.00	0.50	0.00	0.00
Processing tomato	0.25	0.02	0.05	0.36	0.02	0.05
Safflower	0.24	0.11	-	0.26	0.24	-

¹²The agronomic yield response elasticities for the 27 regions are available upon request. As a legume, alfalfa does not have a significant yield response to nitrogen application. Therefore, we set $\beta_{alfalfa3} = 0$. Alfalfa is typically grown as a perennial crop for two or three years. The DAYCENT results have not been validated for simulating tillage for safflower. Therefore, we do not model tillage for alfalfa and safflower.

2.3 Calibration of the model parameters

2.3.1 Calibration of supply elasticities

The first-order conditions associated with model (1) and evaluated at the observed allocation are:

$$\left\{ \begin{array}{l} \frac{\delta_i p_i \bar{q}_i \beta_{i1} \bar{x}_{i1}^{\rho_i}}{\sum_j \beta_{ij} \bar{x}_{ij}^{\rho_i}} = (c_{i1} + \lambda_{i1} + \bar{\lambda}_1 + \bar{c}_{iT} + \lambda_{iT} \bar{T}_i) \bar{x}_{i1} \\ \frac{\delta_i p_i \bar{q}_i \beta_{i2} \bar{x}_{i2}^{\rho_i}}{\sum_j \beta_{ij} \bar{x}_{ij}^{\rho_i}} = (c_{i2} + \lambda_{i2} + \bar{\lambda}_2) \bar{x}_{i2} \\ \frac{\delta_i p_i \bar{q}_i \beta_{i3} \bar{x}_{i3}^{\rho_i}}{\sum_j \beta_{ij} \bar{x}_{ij}^{\rho_i}} = (c_{i3} + \lambda_{i3}) \bar{x}_{i3} \\ p_i \bar{q}_i \frac{\bar{\gamma}'_i}{\bar{\gamma}_i} = (\bar{c}'_{iT} + \lambda_{iT}) \bar{x}_{i1} \\ \beta_{ij} > 0 \quad \forall j \\ \mu_i > 0 \end{array} \right. \quad (4)$$

where $\gamma_i(T_i)$ is the agronomic yield response to tillage technology defined in (3). \bar{c}_{iT} and $\bar{\gamma}_i$ denote the functions $c_{iT}(\bar{T}_i)$ and $\gamma_i(\bar{T}_i)$ evaluated at the observed tillage intensity \bar{T}_i , and \bar{c}'_{iT} and $\bar{\gamma}'_i$ denote their derivative with respect to the tillage intensity, evaluated at \bar{T}_i , respectively.

The economic model is calibrated to the agronomic yield response curves such that it replicates the agronomic elasticities with respect to tillage technology, and water and nitrogen inputs at the reference allocation. We set the elasticities derived using the generalized CES economic production function equal to agronomic elasticities derived in section 2.2:

$$\left\{ \begin{array}{l} \bar{y}_{iW} = \delta_i \frac{\beta_{i2} \bar{x}_{i2}^{\rho_i}}{\sum_j \beta_{ij} \bar{x}_{ij}^{\rho_i}} \\ \bar{y}_{iN} = \delta_i \frac{\beta_{i3} \bar{x}_{i3}^{\rho_i}}{\sum_j \beta_{ij} \bar{x}_{ij}^{\rho_i}} \\ \bar{y}_{iT} = \frac{\bar{\gamma}'_i}{\bar{\gamma}_i} \bar{T}_i \end{array} \right. \quad (5)$$

where the reference water and fertilizer employments satisfy $\bar{x}_{i2} = \bar{a}_{iW} \bar{x}_{i1}$ and $\bar{x}_{i3} =$

$\bar{a}_{iN}\bar{x}_{i1}$. Taking account of (4), we can express (5) as

$$\begin{cases} \bar{y}_{iW} = \frac{(c_2 + \lambda_{i2} + \bar{\lambda}_2)\bar{x}_{i2}}{p_i \bar{q}_i} \\ \bar{y}_{iN} = \frac{(c_3 + \lambda_{i3})\bar{x}_{i3}}{p_i \bar{q}_i} \\ \bar{y}_{iT} = \frac{(\bar{c}'_{iT} + \lambda_{iT})\bar{T}_i \bar{x}_{i1}}{p_i \bar{q}_i} \end{cases} \quad (6)$$

The derivation of the calibration conditions for an acceptable solution δ to exist and the calibration elasticity systems are provided in the appendix.

2.3.2 Calibration of the shadow costs

Once the return-to-scale parameter δ are recovered we can estimate the cost adjustment terms λ_{ij} for crop i and input j . We solve the system:

$$\begin{cases} p_i \bar{q}_i (\delta_i - \bar{y}_{iW} - \bar{y}_{iN}) = (c_{i1} + \lambda_{i1} + \bar{\lambda}_1 + \bar{c}_{iT} + \lambda_{iT} \bar{T}_i) \bar{x}_{i1} \\ p_i \bar{q}_i \bar{y}_{iW} = (c_2 + \lambda_{i2} + \bar{\lambda}_2) \bar{x}_{i2} \\ p_i \bar{q}_i \bar{y}_{iN} = (c_3 + \lambda_{i3}) \bar{x}_{i3} \\ p_i \bar{q}_i \bar{y}_{iT} = (\bar{c}'_{iT} + \lambda_{iT}) \bar{T}_i \bar{x}_{i1} \end{cases} \quad (7)$$

As long as $\bar{y}_{iW} + \bar{y}_{iN} < \delta_i$, system (7) determines acceptable values for the parameters λ_{ij} for $j = 1, \dots, 3$.

2.3.3 Calibration of the CES parameters

Once the cost adjustment parameters λ_{ij} have been derived, it is straightforward to recover the technology parameters μ_i and β_{ij} , using (4) and the equalities $\sum_j \beta_{ij} = 1$ and $\bar{q}_i = \mu_i \bar{\gamma}_i \left(\sum_j \beta_{ij} \bar{x}_{ij}^\rho \right)^{\frac{\delta_i}{\rho}}$. This last step concludes the calibration phase.

3 Policy scenarios and abatement curves for California agriculture

We are currently running the DAYCENT model to simulate the GHG emissions associated with various combinations of nitrogen application rate, irrigation and tillage intensity. Then, we will examine a series of policy scenarios with compensation for the three major GHGs and estimate the GHG emission abatement curves for California agriculture. In particular, we will evaluate how the level of aggregation affects the cost-effectiveness of GHG offset programs.

References

- Antle, J. and Capalbo, S. (2001). Econometric-process models for integrated assessment of agricultural production systems. *American Journal of Agricultural Economics*, 83(2):389–401.
- Antle, J. M., Capalbo, S., Mooney, S., Elliott, E., and Paustian, K. (2003). Spatial heterogeneity, contract design, and the efficiency of carbon sequestration policies for agriculture. *Journal of Environmental Economics and Management*, 46:231–250.
- Antle, J. M., Capalbo, S., Paustian, K., and Ali, M. K. (2007). Estimating the economic potential for agricultural soil carbon sequestration in the Central United States using an aggregate econometric-process model. *Climatic Change*, 80:145–171.
- Antle, J. M. and Ogle, S. M. (2011). Influence of soil C, N₂O and fuel use on GHG mitigation with no-till adoption. *Climatic Change*.
- Bouwman, A., Boumans, L., and Batjes, N. (2002). Modeling global annual N₂O and NO emissions from fertilized fields. *Global Biogeochemical Cycles*, 16(4):28–1–28–8.
- De Cara, S., Houze, M., and Jayet, P. (2005). Methane and nitrous oxide emissions from agriculture in the EU: A spatial assessment of sources and abatement costs. *Environmental and Resource Economics*, 32(4):551–583.
- De Cara, S. and Jayet, P.-A. (2000). Emissions of greenhouse gases from agriculture: the heterogeneity of abatement costs in France. *European Review of Agricultural Economics*, 27(3):281–303.
- De Gryze, S., Albarracin, M. V., Catala Luque, R., Howitt, R. E., and Six, J. (2009). Modeling shows that alternative soil management can decrease greenhouse gases. *California Agriculture*, 63(2):84–90.

-
- De Gryze, S., Wolf, A., Kaffka, S., Mitchell, J., Rolston, D., Temple, S., Lee, J., and Six, J. (2010). Simulating greenhouse gas budgets of four California cropping systems under conventional and alternative management. *Ecological Applications*, 20(7):1805–19.
- Del Grosso, S. J., Parton, W. J., Mosier, A. R., Ojima, D. S., Kulmala, A. E., and Phongpan, S. (2000). General model for N₂O and N₂ gas emissions from soils due to denitrification. *Global biogeochemical cycles*, 14:1045–1060.
- Durandeaun, S., Gabrielle, B., Godard, C., Jayet, P. A., and Le Bas, C. (2010). Coupling biophysical and micro-economic models to assess the effect of mitigation measures on greenhouse gas emissions from agriculture. *Climatic Change*, 98(1-2):51–73.
- Feng, H. and Kling, C. L. (2005). The consequences of co-benefits for the efficient design of carbon sequestration programs. Working paper 05-WP 390, Center for Agricultural and Rural Development.
- Godard, C., Roger-Estrade, J., Jayet, P.-A., Brisson, N., and Le Bas, C. (2008). Use of available information at a European level to construct crop nitrogen response curves for the regions of the EU. *Agricultural Systems*, 97:68–82.
- Howitt, R. E. (1995). Positive mathematical programming. *American Journal of Agricultural Economics*, 77(2):329–342.
- International Panel on Climate Change (IPCC) (2001). Climate change 2001: the scientific basis. Contribution of working group I to the third assessment report of the intergovernmental panel on climate change. Technical report, Cambridge, UK: Cambridge University Press.
- Jenkins, M. W., Draper, A. J., Lund, J. R., Howitt, R. E., Tanaka, S., Ritzema, R., Marques, G., Msangi, S. M., Newlin, B. D., Van Lienden, B. J., Davis, M. D., and

-
- Ward, K. B. (2001). Improving California water management: Optimizing value and flexibility.
- Lal, R., Kimble, L., Follett, R., and Cole, C. (1998). *The Potential of U.S. Cropland to Sequester C and Mitigate the Greenhouse Effect*. Ann Arbor Press, Chelsea, MI.
- Lubowski, R. N., Plantinga, A. J., and Stavins, R. N. (2006). Land-use change and carbon sinks: Econometric estimation of the carbon sequestration supply function. *Journal of Environmental Economics and Management*, 51(2):135–152.
- McCarl, B. A. and Schneider, U. A. (2001). Greenhouse gas mitigation in U.S. agriculture and forestry. *Science*, 294(5551):2481–2482.
- Mérel, P., Simon, L. K., and Yi, F. (2011a). A Fully Calibrated Generalized Constant-Elasticity-of-Substitution Programming Model of Agricultural Supply. *American Journal of Agricultural Economics*, 93:936–948.
- Mérel, P. R., Yi, F., Lee, J., and Six, J. (2011b). A regional bio-economic model of nitrogen use in cropping. Working paper, University of California, Davis.
- Montgomery, W. D. (1972). Markets in licenses and efficient pollution control programs. *Journal of Economic Theory*, 5:395–418.
- Neufeldt, H., Schafer, M., Angenendt, E., Li, C., Kaltschmitt, M., and Zeddies, J. (2006). Disaggregated greenhouse gas emission inventories from agriculture via a coupled economic-ecosystem model. *Agriculture, Ecosystems and Environment*, 112(2-3, SI):233–240. International Conference on Greenhouse Gas Emissions for Agriculture - Mitigation Options and Strategies, Leipzig, Germany, February 10-12, 2004.
- Newell, R. G. and Stavins, R. N. (2000). Climate change and forest sinks: Factors affecting the costs of carbon sequestration. *Journal of Environmental Economics and Management*, 40(3):211–235.

-
- Newell, R. G. and Stavins, R. N. (2003). Cost heterogeneity and the potential savings from market-based policies. *Journal of Regulatory Economics*, 23(1):43–59.
- Parks, P. and Hardie, I. (1995). Least-cost forest carbon reserves: Cost-effective subsidies to convert marginal agricultural land to forests. *Land Economics*, 71(1):122–136.
- Parton, W. J., Mosier, A. R., Ojima, D. S., Valentine, D. W., Schimel, D. S., Weier, K., and Kulmala, A. E. (1996). Generalized model for N₂ and N₂O production from nitrification and denitrification. *Global Biogeochemical Cycles*, 10:401–412.
- Parton, W. J., Schimel, D. S., Cole, C. V., and Ojima, D. S. (1987). Analysis of factors controlling soil organic matter levels in great plains grasslands. *Soil Science Society of America Journal*, 51:1173–1179.
- Paustian, K., Antle, J. M., Sheehan, J., and Paul, E. A. (2006). Agriculture’s role in greenhouse gas mitigation. Pew Center on Global Climate Change, New York.
- Pautsch, G., Kurkalova, L., Babcock, B. A., and Kling, C. (2001). The efficiency of sequestering carbon in agricultural soils. *Contemporary Economic Policy*, 19(2):123–134.
- Rosas, F., Babcock, B. A., and Hayes, D. J. (2011). A nonlinear offset program to reduce nitrous oxide emissions induced by excessive nitrogen application. Working Paper 11-WP 521, Center for Agricultural and Rural Development.
- Russo, C., Green, R., and Howitt, R. E. (2008). Estimation of Supply and Demand Elasticities of California Commodities. Working paper 08-001, University of California, Davis.
- Schneider, U. A., McCarl, B. A., and Schmid, E. (2007). Agricultural sector analysis on greenhouse gas mitigation in US agriculture and forestry. *Agricultural Systems*, 94(2):128–140.

-
- Six, J., Ogle, S. M., Jay breidt, F., Conant, R. T., Mosier, A. R., and Paustian, K. (2004). The potential to mitigate global warming with no-tillage management is only realized when practised in the long term. *Global Change Biology*, 10(2):155–160.
- Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., Kumar, P., McCarl, B., Ogle, S., O’Mara, F., Rice, C., Scholes, B., Sirotenko, O., Howden, M., McAllister, T., Pan, G., Romanenkov, V., Schneider, U., Towprayoon, S., Wattenbach, M., and Smith, J. (2008). Greenhouse gas mitigation in agriculture. *Philosophical Transactions of the Royal Society B*, 363(1492):789–813.
- Snyder, C., Bruulsema, T., Jensen, T., and Fixen, P. (2009). Review of greenhouse gas emissions from crop production systems and fertilizer management effects. *Agriculture, Ecosystems and Environment*, 133:247–266.
- Stavins, R. N. (1998). What can we learn from the grand policy experiment? Lessons from SO₂ allowance trading. *Journal of Economic Perspectives*, 12(3):69–88.
- Stavins, R. N. (1999). The costs of carbon sequestration: A revealed-preference approach. *American Economic Review*, 89(4):994–1009.
- Stavins, R. N. (2008a). A meaningful US cap-and-trade system to address climate change. *Harvard Environmental Law Review*, 32(2):293–371.
- Stavins, R. N. (2008b). Addressing climate change with a comprehensive US cap-and-trade system. *Oxford Review of Economic Policy*, 24(2):298–321.