Markets for Agricultural Greenhouse Gas Offsets: The Role of Policy Design on Abatement Efficiency

Cloé Garnache[*], Pierre Mérel[†], Juhwan Lee[‡] and Johan Six[‡]

[*] Department of Agricultural, Food, and Resource Economics, Michigan State University
[†] Department of Agricultural and Resource Economics, University of California, Davis
[‡] Environmental Systems Science, ETHZ, Switzerland

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Abstract

This article investigates the role of greenhouse gas (GHG) offset payment design on abatement efficiency in agriculture. We develop a regionally disaggregated positive mathematical programming model of California agriculture calibrated to economic and agronomic information. Regional yield and GHG emission responses to production practices are derived from a biophysical process model. The economic optimization model allows for simultaneous and continuous changes in water, nitrogen fertilizer, and tillage intensities, and captures crop substitution effects. Empirical results show that second-best policies relying on regionally aggregated emission factors lead to small abatement efficiency losses relative to the first-best policy with finer-scale emission factors. Because the costs of such second-best policies are substantially lower, this finding suggests that they could be cost-effective in California. In contrast, second-best policies targeting a single GHG or a single input entail significant abatement efficiency losses, which nonetheless can be reduced by combining policy instruments.

1 Introduction

Policymakers worldwide have recognized climate change as one of the greatest challenges of our time and agreed that substantial reductions in greenhouse gas (GHG) emissions are required (UNFCC, 2010). This political will has led to the emergence of international agreements such as the Kyoto Protocol, as well as national and subnational climate policies (Burtraw, 2013).[1] In 2006, the state of California approved the Global Warming Solutions Act, often referred to as AB 32, which aims at reducing the state's emissions to 1990 levels by 2020 (Assembly Bill 32, Nuñez, Chapter 488, Statutes of 2006).

A large body of literature indicates that the agricultural sector could cost-effectively reduce GHG emissions relative to capped energy-based sectors (McCarl and Schneider, 2001; Pautsch et al., 2001; Antle et al., 2007). In practice, policymakers have not yet endorsed credits for GHG offsets from agriculture. The California Air Resources Board (ARB), charged with the rulemaking process for AB 32, is considering the participation of the agricultural sector in an offset market.[2]

Quantifying how payment design would affect abatement efficiency is critical for designing cost-effective climate change mitigation policies (Pautsch et al., 2001; Antle et al., 2003, 2007; Durandeau

[1] Jurisdictions having initiated efforts to reduce GHG emissions include the European Union's Emissions Trading System launched in 2005 with an objective to reduce emissions from targeted sectors by 21% by 2020 relative to 2005, and the nine northeastern states participating in the Regional Greenhouse Gas Initiative (RGGI), a cap-and-trade system implemented since 2009 which aims at reducing emissions by 10% by 2018 relative to 2009 levels.

[2] ARB has already approved the Compliance Offset Protocol U.S. Forest Projects for crediting carbon sequestered on forest land (protocols/usforestprojects) and the Compliance Offset Protocol Livestock Projects for crediting GHG emission reductions associated with the installation of biogas control systems for manure management on dairy cattle and swine farms (protocols/livestock).

et al., 2010; Antle and Ogle, 2011). The first-best policy, which relies on local emission factors and controls all major agricultural GHGs, is efficient in the sense that it minimizes abatement costs (ignoring implementation costs), subject to a given abatement target. However, the costs of running such a program is likely prohibitive as accurately measuring net GHG emissions from fields or animals is virtually impossible. Second-best policies that are less ambitious in measuring emissions may thus be associated with significantly lower implementation costs. As such, a tradeoff exists between abatement efficiency and program implementation costs. It is this tradeoff that we propose to address in this article.

To this end, we develop a regionally disaggregated optimization model of California Central Valley agricultural production calibrated to economic and agronomic information. We generate the agronomic information at a relatively disaggregated level in order to capture heterogeneity in soil and climatic conditions. We first use the model to derive the Central Valley's marginal abatement cost curve under the first-best policy. We then investigate the abatement efficiency losses that would arise under four types of second-best policies aimed at mitigating GHG emissions from agriculture: (i) policies relying on spatially aggregated emission factors, (ii) policies regulating a single GHG, (iii) policies controlling a single agricultural input, and (iv) policies controlling two agricultural inputs.

Our estimates show that field crop agriculture in the Central Valley of California would abate 1.4 million metric tonnes of CO_2 equivalent ($MtCO_2e$) under the first-best policy at a carbon price of \$20/tCO_2e, the price targeted by ARB in 2020 (CARB, 2010).[3] Furthermore, our results reveal that second-best policies that rely on regionally aggregated emission factors lead to small abatement efficiency losses relative to the first-best policy with finer-scale emission factors, that is, additional information on spatial heterogeneity achieves only small abatement gains. Because the costs of second-best policies relying on aggregate emission factors would likely be lower, this finding suggests that such policies could be preferred to the first-best policy in California. Similarly, second-best policies targeting single GHGs like nitrous oxide (N_2O) or carbon dioxide (CO_2) seem to perform well relative to the first best. Because measuring GHG emissions is difficult, we examine policies directly controlling inputs. We find that such policies typically entail sizable abatement efficiency

[3]Burtraw and Szambelan (2012, p. 8) use an allowance price forecast of \$15.90 (\$2012/$MtCO_2e$) in 2013, \$20.92 in 2015, and \$36.94 in 2020. These allowance prices are based on the 2011 Market Price Referent, which uses the allowance prices from a 2009 CO_2 price forecast report from Synapse Energy Economics.

losses. Mixed policies that simultaneously control two adjustment margins partially mitigate these losses. More specifically, a combination of nitrogen and tillage taxes is predicted to achieve x% of the abatement potential at a price of $20/tCO$_2$e.

Our paper contributes to a rich and growing literature examining how various policy incentives might affect the supply of GHG offsets from agriculture. Indeed, the proper incentivization of GHG offset supply by the agricultural sector is fraught with challenges. Firstly, GHG emissions from fields or animals are costly or impossible to monitor, making reliance on simulated conditional emission factors often necessary for implementation. Second, the emission production process typically involves multiple margins of adjustment such as crop choice, fertilizer intensity, irrigation, and tillage, contributing to emissions in a nonlinear and sometimes non-monotonic fashion. This feature renders the derivation of conditional emission factors complex and prone to error. This process is complicated by emission uncertainties arising from variability in weather. Thirdly, GHG emissions are produced by many atomized sources having their own emission generation process and, therefore, heterogenous opportunity costs due to variation in local soil and climatic conditions. Because of this heterogeneity in opportunity costs, incentive schemes might appear as inequitable or discriminatory as they reward or penalize farmers differently. Finally, policies involving income transfers to the agricultural sector remain controversial.

One option to make a GHG incentive program workable is to rely on spatially aggregated conditional emission factors instead of field level ones. In addition, programs that reward practices based on spatially aggregated emissions factors may be more politically acceptable since farmers with similar observable practices would receive identical payoffs. Pautsch et al. (2001) and Antle et al. (2007) compare how aggregating information on emission factors, e.g., at the county- or state-level, affects marginal abatement costs relative to the first-best policy with detailed information at the field level. While Antle et al. (2007) find that little abatement efficiency is gained from relying on more disaggregated information for no-till adoption in the central U.S., Pautsch et al. (2001) find as much as a four-fold efficiency gain for conservation tillage adoption in Iowa. Therefore, mixed evidence exists on the extent to which programs with payments relying on aggregated emission factors can help realize the economic abatement potential. California is arguably one of the most complex agricultural states given the diversity of its environmental conditions and attendant crop mix. This makes it a suitable case study to examine how much environmental and economic heterogeneity affects abatement efficiency when implementing second-best policies that aggregate emission factors over large regions.

Because carbon sequestration is easier to monitor than N_2O or CH_4 fluxes, most studies have focused on regulating CO_2 (Pautsch et al., 2001; Antle et al., 2003; Lubowski et al., 2006).[4] Yet, evidence shows that changes in agricultural practices affect emissions of all GHGs, suggesting that the discrepancies between carbon sequestration and total emissions abated may be large.[5] For instance, Antle and Ogle (2011) find that accounting for the effect of no-till practices on both carbon sequestration and N_2O emissions shifts outward the GHG offset supply curve for wheat-pasture systems and inward for corn-soy-hay systems in the central U.S. relative to studies that omit N_2O emissions, e.g., Antle et al. (2007). Therefore, reasonably estimating total abatement from agricultural sources may require monitoring the emissions of all three major agricultural GHGs. Nonetheless, few studies have evaluated how much abatement efficiency is gained with policies targeting all three agricultural GHGs relative to policies that regulate a single GHG.

Under perfect information on the emissions generation process by the regulating agency, the first-best allocation can theoretically be achieved without any actual emissions measurement by simultaneously incentivizing the choice of activity (extensive margin) and the choice of management practices (intensive margin). Such incentives could be implemented, for instance, through crop-specific input taxes. Yet, regulating all inputs simultaneously and differently across uses may be politically difficult and very costly to implement.[6] To the best of our knowledge, no study on GHG mitigation has estimated how much second-best policies regulating a single input or a combination of inputs irrespective of their use would perform relative to the first-best policy.[7]

Mathematical programming, in particular linear programming (LP), has often been used to estimate the GHG emission abatement costs of agricultural sources (De Cara and Jayet, 2000; McCarl and Schneider, 2001; Schneider and McCarl, 2003; Schneider et al., 2007; Durandeau et al.,

[4] Mérel et al. (2014) and Rosas et al. (2011) study N_2O emissions, while De Cara and Jayet (2000) and Schneider et al. (2007) examine all three GHGs.

[5] More carbon sequestration does not imply a net decrease in total GHG emissions because emissions of GHGs other than CO_2 may predominate. For example, reduced tillage often enhances both carbon sequestration and N_2O emissions (Six et al., 2004), while reduced nitrogen (N) fertilizer application rate reduces them (Snyder et al., 2009).

[6] Because inputs are often regulated by different agencies, coordination among these agencies to determine the optimal taxation of all inputs can be problematic (Larson et al., 1996). For example, the state department may regulate fertilizers, while local irrigation districts control water use.

[7] Larson et al. (1996) find that in order to reduce nitrate pollution from lettuce production in California, regulating the water input leads to small welfare losses relative to the first-best policy.

2010).[8] Yet, LP models have been criticized for producing corner solutions and not calibrating to an observed baseline. One solution is to introduce flexibility constraints that force the model to replicate the observed allocation, but these may overly constrain the model's response to policy shocks. Another option is to use positive mathematical programming (PMP), a non-linear programming method formalized by Howitt (1995) that has been widely used for agricultural and agri-environmental policy analysis, including climate change-related policies (Egbendewe-Mondzozo et al., 2011; Mérel et al., 2014; Yi et al., 2013).[9] PMP relies on a positive approach where farmers' behaviors are rationalized so that their observed crop and input choices maximize profits in a reference year.

In this study, we develop a state-of-the-art PMP regionalized model of crop supply for California's Central Valley. The model is calibrated to an observed input-output allocation and a set of exogenous supply elasticities (Mérel et al., 2011; Garnache and Mérel, 2014). We specify the model so that the land, water, and nitrogen fertilizer inputs as well as the crop tillage intensities are explicit decision variables, allowing for continuous changes along all margins.[10] We use the biogeochemical process-based model Daycent to estimate crop- and region-specific yield and GHG emission responses to agricultural practices (Parton et al., 1996).[11] As such, our model accounts for the crop- and region-specific emissions associated with a given set of production practices. Several studies have relied on ecosystem process-based models to represent agricultural production possibilities, for instance EPIC (McCarl and Schneider, 2001; Pautsch et al., 2001), Century (Antle et al., 2003), DNDC (Neufeldt et al., 2006), and STICS and CERES (Durandeau et al., 2010). To our knowledge, the only PMP study having used agronomic information to carefully calibrate economic

[8]Other approaches, which are more data intensive, include econometrics (Stavins, 1999; Pautsch et al., 2001) and hybrid approaches where the parameters of the simulation model are econometrically estimated (Antle and Capalbo, 2001; Antle et al., 2003).

[9]PMP allows the exact calibration of agricultural production models against observed economic behavior, without the use of artificial flexibility constraints, while requiring minimal data. It is often preferred to LP as it avoids overspecialization and yields smooth responses to policy changes. Existing agricultural supply models that rely on PMP principles include, among others, the U.S. Regional Environment and Agriculture Programming (REAP, formerly USMP) model (Johansson et al., 2007), the European Common Agricultural Policy Regionalised Impact (CAPRI) modeling system (capri-model.org), and the California StateWide Agricultural Production (SWAP) model (swap.ucdavis.edu).

[10]McCarl and Schneider (2001) investigate similar adjustment margins across the U.S., however the linear nature of their model restricts their practices to a discrete set rather than a continuous interval.

[11]The Daycent model 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). De Gryze et al. (2010) calibrated the Daycent model for the main field crops grown under California conditions using data from several long-term field experiments.

production functions is Mérel et al. (2014). These authors show how to amend the original PMP procedure to ensure marginal calibration of crop yield responses to water and nitrogen fertilizer at the baseline. Here we extend their work to further ensure consistency of the economic and agronomic yield responses with respect to tillage intensity. From an empirical standpoint, allowing for this additional adjustment margin appears critical, as the literature suggests that tillage practices could go a long way in reducing GHG emissions from crops (Lal et al., 1998, 2003). Our empirical results are consistent with this finding.

Several studies have focused on changes in one production practice while ignoring how farmers may alter other practices to minimize abatement costs (Schneider et al., 2007). For example, Pautsch et al. (2001) and Antle and Ogle (2011) only allow changes in tillage, while Mérel et al. (2014) focus on nitrogen fertilizer and water without explicitly representing the choice of tillage technology. In addition to minimizing abatement costs, evidence suggests that simultaneous adjustments in tillage, nitrogen fertilizer and water application rates can achieve more abatement than adoption of a single practice by enhancing carbon sequestration and mitigating N_2O emissions (Six et al., 2004; Smith et al., 2008; Snyder et al., 2009; De Gryze et al., 2011). In this study, we compare the offset supply curve from the complete model (with adjustments in nitrogen fertilizer, water, and tillage) with that from restricted models where adjustments in one or more practice(s) are omitted.

The remainder of the paper proceeds as follows. Section 2 describes the disaggregated model of California Central Valley agriculture and the construction of the tillage index. Section 3 presents the estimation of the crop and region-specific yield, GHG emission factors, and cost responses that feed into the economic model. Section 4 describes the key features of the calibration procedure. Section 5 presents the marginal abatement cost curves for the first best. Section 6 presents the marginal abatement cost curves for the second-best policies and discusses the role of payment design on abatement efficiency. Section 7 concludes.

2 A disaggregated model of California Central Valley's agriculture

2.1 Model specification

The model maximizes regional agricultural profits subject to resource constraints. Mérel et al. (2014) specify profits with crop and region-specific generalized constant-elasticitiy-of-substitution

(CES) production functions. We extend their model to include farmers' choice of tillage technology. We define the tillage index T, which is continuous in the interval $[0,1]$, to represent the level of soil disturbance. The construction of the tillage index is described in greater detail in section 2.2.

Consider a regional model with $i = 1, \dots, I$ cropping activities, $j = 1, \dots, J$ inputs and $g = 1, \dots, G$ regions (denoted sets I, J and G, respectively). Let $j = 1$ be the land input, $j = 2$ the water input, and $j = 3$ the N fertilizer input. The economic optimization model for California Central Valley is defined as follows:

$$\begin{aligned}
&\max_{x_{gij} \geq 0, T_{gi} \geq 0} \; \textstyle\sum_{g,i} p_{gi} q_{gi} - \sum_j \left(c_{gij} + \lambda_{gij}\right) x_{gij} - \left(c_{giT}(T_{gi}) + \lambda_{giT} T_{gi}\right) x_{gi1} \\
&\text{subject to} \\
&\begin{cases}
\sum_i x_{gij} \leq v_{gj} & j = 1, 2, \ \forall g \in G \\
q_{gi} = \mu_{gi} \left(\sum_j \beta_{gij} x_{gij}^{\rho_{gi}} \right)^{\frac{\delta_{gi}}{\rho_{gi}}} & \forall i \in I, \ g \in G \\
\sum_{gik} e_{gik}(a_{gij}, T_{gi}) x_{gi1} \leq \overline{GHG} &
\end{cases}
\end{aligned} \tag{1}$$

where the choice variable x_{gij} represents input j's quantity allocated to crop i in region g and T_{gi} denotes the tillage index associated with the production of crop i in region g. p_{gi} is the regional price of crop i and c_{gij} is the regional price of input j in activity i.[12] The parameters v_{g1} and v_{g2} denote the regional land and water availability constraints, respectively. q_{gi} is the regional output of crop i associated with the generalized CES production function with tillage intensity T_{gi} and input employments x_{gij}. μ_{gi}, β_{gij} and δ_{gi} are the parameters of the CES function and satisfy $\mu_{gi} > 0$, $\beta_{gij} > 0$, $\sum_j \beta_{gij} = 1$ and $\delta_{gi} \in (0,1)$. The parameter ρ_{gi} is such that $\rho_{gi} = \frac{\sigma_{gi}-1}{\sigma_{gi}}$ where σ_{gi} is the regional elasticity of substitution between any two inputs.

The calibration parameters λ_{gij} are added to the input cost terms to replicate the input allocation observed in the baseline (Mérel et al., 2014). Furthermore, we introduce a calibration parameter λ_{giT} to the tillage cost term to allow calibration of the baseline tillage technology.

The biogeochemical model Daycent and the agronomic literature do not report a clear effect of reduced tillage technology on yield for the crops considered in this study. Therefore, we assume

[12] We assume that all inputs, except the water and fertilizer inputs and inputs related to the tillage technology are employed in fixed proportions with the land input, and we include their respective cost in the land cost, c_{gi1}. Similarly, we assume all fertilizer elements (N, P, K and others) are employed in fixed proportions for a given crop so that the price of N fertilizer c_{gi3} includes the non-nitrogen fertilizer costs. Because fertilizer elements are used in different proportions in different crops, c_{gi3} is crop-specific.

that the choice of tillage technology affects cost but does not affect yield. The last term in the objective function represents the cost associated with tillage technology T_{gi}. $c_{giT}(T_{gi})$ denotes the tillage cost per unit of land. It is convex in the tillage index and twice differentiable with $c'_{giT} > 0$ and $c''_{giT} > 0$, and is estimated in section 3.2.

The term $e_{gik}(a_{gij}, T_{gi})$ represents the regional emission rate for crop i and GHG k, for $k \in K = \{CO_2, N_2O, CH_4\}$, expressed in metric tonnes of CO_2 equivalent per hectare (tCO_2e/ha). Emission rates depend on the production practices, namely, the water and N fertilizer application rates, defined as $a_{gij} = \frac{x_{gij}}{x_{gi1}}$ for $j = 2, 3$, and the tillage index T_{gi}. They are estimated in section 3.3 for each region g. Total GHG emissions, $\sum_{gik} e_{gik}(a_{gij}, T_{gi})x_{gi1}$, are constrained by an exogenous emission cap, denoted $\overline{GHG}$.

2.2 Tillage index

The introduction of a continuous tillage index, T, is a novel feature of this modeling strategy. The index measures the soil disturbance caused by tillage practice, which is captured by the type of equipment used on the field and the frequency of its use. Table 1 describes the six tillage practices identified in California and their associated soil disturbance index (Mitchell et al., 2009).

Table 1 Characteristics of the six tillage practices identified in California.

Practice	Description	Residue cover after planting	Chisel, rip or subsoiling	Tillage index
Conv. tillage (K-CT)	high soil disturbance	none	yes	1
CA conv. tillage (CA-CT)	medium soil disturbance	none	yes	0.91
Reduced tillage (RT)	tractor passes reduced by 25%	15 to 30%	no	0.64
Mulch tillage (M)	tractor passes reduced by 75%	over 33%	no	0.54
Strip tillage (S)	only seed row is tilled	over 30%	no	0.41
No till (NT)	disturbance only at planting	over 30%	no	0

We construct the tillage variable $T \in [0, 1]$ by mapping existing tillage technologies into an index of soil disturbance where $T = 0$ describes no-till systems (low soil disturbance) and $T = 1$ represents conventional tillage systems (high soil disturbance). The tillage index is continuous because, while farmers may make discrete tillage choices at the field-level, we aggregate their tillage practices to the scale of the economic model—the 27 SWAP regions presented in the next section. Consequently, the resulting tillage index is continuous at the regional level.

2.3 Data

We use the 2005 input-output crop data from the California StateWide Agricultural Production (SWAP) model developed by R. Howitt (Jenkins et al., 2001).[13] The SWAP model consists of 27 regions in the Central Valley, California's agricultural heartland. These regions match water districts boundaries and, therefore, capture meaningful regional water constraints. The Sacramento Valley covers regions 1 through 9, while the San Joaquin Valley encompasses regions 10 through 21C.

The study includes seven major crop groups covering 1.29 million hectares (3.18 million acres) in 2005 (among which almost 1 million hectares are located in the San Joaquin Valley). The crop acreage covered in this study represents 70% of the 2005 non-perennial agricultural acreage in the Central Valley.[14] The acreage distribution among modeled crops is shown in table 2. The grain group is represented by wheat and the "other field crops" group by sunflower, while the remaining crop groups are represented by themselves.

Table 2 Crop acreage shares across the Central Valley (%).

Crop	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 tomatoes	9.50	17.48	7.28
Safflower	1.54	5.61	0.31
Total	100.00	100.00	100.00

Crop acreages and water prices for 2005 come from the California Department of Water Resources (DWR). Crop prices and yields for 2005 come from the Agricultural Commissioner Reports. Water application rates and prices come from DWR, when available, and from the University of California Cost and Return Studies (UCCE, 2007). Other input use and costs, including fertilizer, come from the Cost and Return Studies, which provide information on observed regional production practices.[15]

California's own-price supply elasticities for corn, cotton, safflower, sunflower and wheat come

[13] See swap.ucdavis.edu.
[14] We do not include tree crops because the Daycent model is not calibrated for these crops.
[15] These production practices are conventional.

from the SWAP model, while supply elasticities for alfalfa and processing tomatoes are updated based on the more recent study by Russo et al. (2008), see table 7 in appendix C.

In the standard PMP specification, the shadow value of constrained resources is determined by the least profitable activity. A critique of this approach is that it may lead to underestimating the value of limiting resources. Kanellopoulos et al. (2010) suggest using the regional average gross margin observed in the baseline as shadow value for the land input. We propose to use as shadow values of the constrained resources the values that minimize the sum of squares of the adjustment cost terms required to rationalize farmers' observed behavior. The algorithm is defined for the land or water input as:

$$\min_{\bar{\lambda}_{gj}} \sum_i \lambda_{gij}^2$$

where the calibration parameters λ_{gij}, for $j = 1, 2$, can be expressed as a function of the data and model parameter δ_{gi}. We find that the water constraint is binding in all regions but the land constraint is not. The water shadow values are presented in table 8 in appendix C. Our choice of shadow values does not seem to influence the results. The marginal abatement cost curves presented in sections 5 and 6 are robust to alternative choices of shadow values based upon the gross margin of the two lowest profitable crops whether or not the corn and grain crop groups are removed in the first stage LP stage of PMP. One reason for removing the corn and grain crop groups to calculate the shadow values of the constrained resources is that their gross margins are negative or barely positive in many regions, and we believe they are hardly representative of the marginal value of the land and water resources.

3 Estimation of the responses to production practices

In this section, we estimate the yield and cost responses to production practices, as well as the associated GHG emission responses. We estimate the cost responses using the Cost and Return Studies and other sources when available (UCCE, 2007). We use the Daycent model, calibrated for crops under California conditions, to generate yield and GHG emission data for a series of production practices (De Gryze et al., 2009, 2010). The Central Valley is divided into cells of 15km×15km. The Daycent model is run for each cell using the average soil and climate conditions prevailing on that cell and over the years 1983-2008 for ten commonly observed crop rotations in the

Sacramento and San Joaquin Valleys. The use of the 1983-2001 period ensures that soil processes reach steady-state conditions under reference production practices, while we introduce alternative production practices in 2002 and maintain them throughout 2008. For each crop, we vary the N fertilizer and water application from 0 to 125% of the rates observed in the baseline, and for the six tillage practices described in section 2.3. Although a number of studies consider 20-year contracts for carbon sequestration (Antle et al., 2003; Antle and Ogle, 2011), West and Six (2007) conduct a meta-analysis and find that soil carbon sequestration reaches its steady state five to ten years after a change in agricultural practices in most systems in California. Therefore, we do not expect the results to dramatically change when extending the study duration beyond the current seven-year period.[16] We then aggregate the Daycent model's results to the scale of the economic model (each one of the 27 SWAP regions) and average them over the 2002-2008 period and over the ten crop rotations.

3.1 Estimation of the yield responses to production practices

We estimate the agronomic yield responses to N fertilizer, water and tillage by fitting the following models to the Daycent model's yield data. See appendix A for how we generate the data to ensure consistency between the yield, N fertilizer and water application rates, and tillage technology observed in the baseline at the regional level.

Following Godard et al. (2008) and Mérel et al. (2014), we fit for each crop and region an exponential yield response curve through the obtained simulation data:

$$y(a_3) = \beta_{03} + \beta_{13}\left(1 - e^{-\beta_{23}a_3}\right) \tag{2}$$

where a_3 is the N application rate and β_{03}, β_{13} and β_{23} are the regression parameters. $y_{a_3=0}$ represents the minimum yield as N fertilizer application goes to zero.

Following Mérel et al. (2014), we estimate a sigmoid yield response curve to the water application rate for each crop and region:

$$y(a_2) = \frac{\beta_{12}}{1 + e^{-\frac{a_2 - \beta_{02}}{\beta_{22}}}} \tag{3}$$

[16] De Gryze et al. (2011) use a ten-year average after the introduction of new practices to analyze the long-term mitigation potential of California Central Valley's agriculture.

where a_2 is the water application rate and β_{02}, β_{12} and β_{22} are the regression parameters.

Using expressions (2) and (3), we derive the associated agronomic yield elasticities with respect to N fertilizer and water application rates and tillage. The expressions for these elasticities are provided in appendix A. The agronomic yield elasticities, evaluated at the baseline and weighted by crop acreages, are presented for the Sacramento and San Joaquin Valleys in table 3. As a legume, alfalfa's yield does not significantly respond to N fertilizer. Therefore, we do not model changes in the N input for this crop. The "other field crops" group and cotton show large yield elasticity with respect to water. The "other field crops" group and grain exhibit very small yield elasticities with respect to N in the baseline (in the order of 10^{-4}) because the baseline N application rate lies on the relatively flat portion of the yield response to N fertilizer. Therefore, modest reductions in the N application rate lead to little yield loss (see figure 11 in appendix C).

Table 3 Average baseline agronomic yield elasticities in the Sacramento and San Joaquin Valleys (weighted by crop acreages).

	Sacramento Valley		San Joaquin Valley	
Crop	$\bar{y}_{iW}$	$\bar{y}_{iN}$	$\bar{y}_{iW}$	$\bar{y}_{iN}$
Alfalfa	0.20	-	0.24	-
Corn	0.26	0.12	0.27	0.13
Cotton	0.47	0.03	0.58	0.01
Grain	0.13	0.03	0.32	0.00
Other field crops	0.46	0.00	0.70	0.00
Processing tomatoes	0.25	0.02	0.37	0.02
Safflower	0.24	0.11	0.32	0.24

3.2 Estimation of the cost responses to production practices

Following Mérel et al. (2014), we assume that costs are linear in the land, N fertilizer and water inputs. The regional tillage cost for crop i, c_{giT}, is defined per unit of land. It consists of the costs of labor, machinery, fuel, etc, utilized for tillage activities. Reduced tillage is characterized by fewer pre-planting and/or post-harvest operations, however, no-till systems require one additional herbicide spraying operation to compensate for the lack of mechanical weed removal. The cost of California conventional tillage practices (CA-CT), described in table 1, is observed in the Cost and Return Studies (UCCE, 2007). We use Mitchell et al. (2009) and experts' opinions to modify the Cost and Return Studies and assess tillage costs for the five other tillage practices described in table 1. In particular, we modify the type of equipment used, the number of tractor passes, and the increase in cost for no-till systems due to one additional passage of herbicide spraying to compensate for the absence of mechanical weed removal. These modified practices translate into new equipment, labor and fuel costs associated with tillage.

We then estimate, for each crop and region, the tillage cost response to changes in the tillage index using these six data points by fitting a quadratic model. The fitted tillage cost function is strictly convex for all crops and in all regions, except alfalfa for which we do not model the tillage response since it is usually planted as a perennial.

3.3 Estimation of the GHG emission responses to production practices

Using the Daycent model, we obtain average CO_2, N_2O, and CH_4 emissions per hectare for each crop, region, and for a series of practices. We estimate the regional GHG emission responses $e_{gik}(a_{gij}, T_{gi})$ to N fertilizer, water and tillage. For each GHG, crop and region, we specify a model that is quadratic in production practices and includes interaction terms.

Total emissions responses to production practices are typically non-linear, as illustrated by the results in figure 1. In general, total emissions increase with N fertilizer and water intensity. However, responses are non-monotonic for some crops, e.g., corn. In most regions, processing tomatoes, cotton and the "other field crops" group have large total emission rates relative to grain and safflower, while corn's emission rate is moderate.

In general, changes in any of the three production practices considered in this study significantly affect both CO_2 and N_2O emissions. These findings demonstrate the importance of relying on process-based models and accounting for all three GHGs in order to accurately estimate agriculture's abatements. The emission responses for CO_2 and N_2O are presented in figure 10 in appendix B.[17]

4 Model calibration

One important feature of this research is the incorporation of the agronomic information from the biophysical process-based model into the economic model such that the economic and agronomic marginal yield responses to production practices are consistent at the baseline. We extend the

[17]Figure 10 illustrates that N fertilizer has a dual effect on GHG emissions. More N fertilizer increases N_2O emissions but reduces CO_2 emissions through enhanced crop growth and soil carbon sequestration.

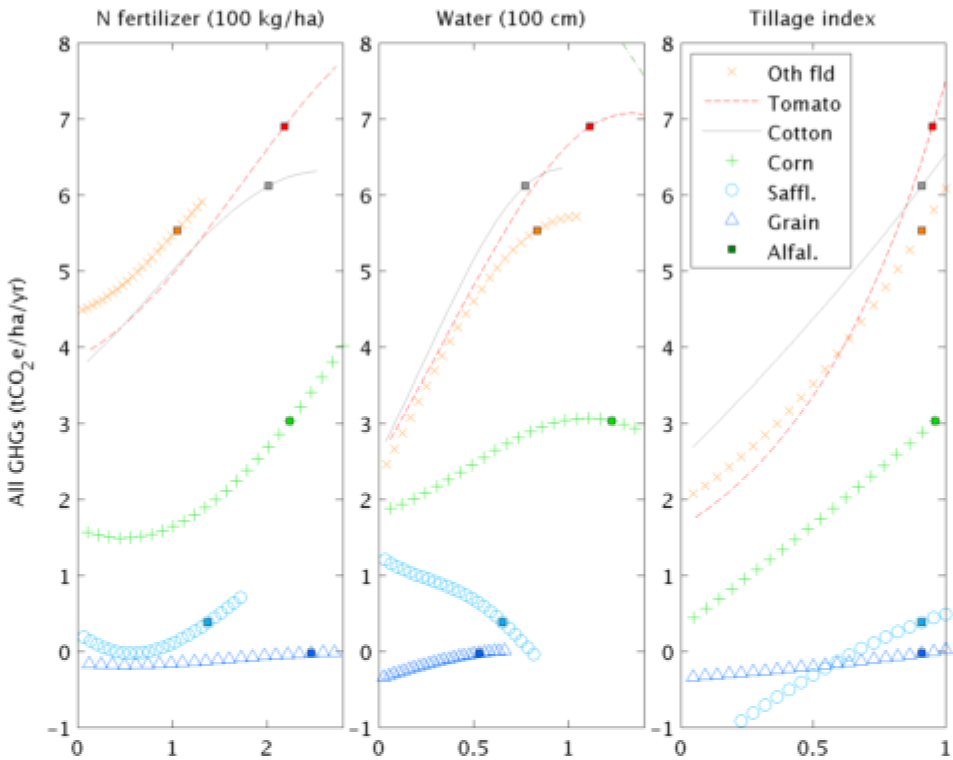

Figure 1 Emission responses for all GHGs combined to N fertilizer and water application rates and tillage intensity for the seven crops in region 6 in the Sacramento Valley. Squares indicate baseline practices. The changes in production practices considered correspond 0 to 125% of the baseline intensity. Also, there is no N fertilization or tillage responses for alfalfa.

work of Mérel et al. (2014) on N fertilizer and water to also calibrate the economic model to the agronomic information on tillage technology. This is critical since carbon sequestration and N_2O emissions are sensitive to tillage technology and N fertilizer and water application rates (Smith et al., 2008; Snyder et al., 2009).

The calibration problem consists of selecting for each activity i and region g the set of parameters $(\mu_{gi}, \beta_{gij}, \delta_{gi}, \lambda_{gij})$ so that the optimization model (1), presented in section 2, replicates *(i)* the economic information in terms of observed input-output allocation $(\bar{q}_{gi}, \bar{T}_{ig}, \bar{x}_{gij})$, the shadow prices of the constrained water resources, $\bar{\lambda}_{g2}$, obtained from the first stage of PMP (Howitt, 1995), and the supply responses $\bar{\eta}_{ig}$ (Mérel et al., 2011; Garnache and Mérel, 2014); and *(ii)* the agronomic information, such that the yield responses calculated at the baseline allocation coincide with the agronomic yield elasticities $(\bar{y}_{giW}, \bar{y}_{giN})$.

The first-order condition associated with the economic model (1) specific to tillage for crop i

is:[18]

$$\lambda_{giT} = -\bar{c}'_{giT}(T_{gi}) \quad \forall g \in G \tag{4}$$

where the bar denotes that variables are evaluated at the baseline. From condition (4), one can see that the calibration of crop i's response to tillage, i.e., the identification of the shadow cost λ_{giT} that rationalizes farmers' tillage choice at the regional level, requires that crop i exhibits a strictly convex tillage cost function ($c''_{giT} > 0$).

5 California agriculture's GHG mitigation potential

5.1 California agriculture's marginal abatement cost curve

AB 32 implements a cap-and-trade system and the contribution of agriculture would be in terms of offsets. Therefore, we estimate the supply of offsets from agriculture in response to a GHG emission cap.[19] Although field-level emission factors are necessary to determine exact GHG emissions, in the present study we use the most disaggregated emission factors available, i.e., for the 27 Central Valley regions. This scenario represents the "feasible" first-best policy (hereafter referred to as first best) in the sense that we use the finest GHG emission estimates available to us. Furthermore, we assume that the Daycent model predicts emissions with certainty. We focus on the abatement costs incurred by farmers and abstract away from transaction costs and the costs of administering the program.

The marginal abatement cost curve for California's Central Valley is presented in figure 2. All results, except otherwise mentioned, are presented for a substitution elasticity of 0.2. The sensitivity of the results to this parameter value is discussed in section 5.2. ARB predicts an offset price of \$20/tCO_2e in 2020 under AB 32 (CARB, 2010).[20] At this price, California's agriculture supplies 1.18 million metric tonnes of offsets (MtCO_2e). This value is in the range of those estimated for other U.S. regions, suggesting California's agriculture could competitively supply GHG offsets relative to capped sectors and other U.S. agricultural sectors. At a price of \$50/tCO_2e, McCarl and Schneider (2001) estimate U.S. agriculture offsets of 3 MtCO_2e from N_2O emission reduction

[18] The complete system of first-order conditions is provided in appendix C.

[19] Equivalently, we could model a tax or subsidy on emissions abated.

[20] The U.S. EPA estimates that, under a congressional cap-and-trade proposal, allowance prices would be of \$12-41/tCO_2e in 2013 and \$13-59/tCO_2e in 2020 (Horowitz and Gottlieb, 2012).

and 70 $MtCO_2e$ from enhanced soil carbon sequestration. At \$20/tCO_2e, Antle and Ogle (2011) predict for the central U.S. (21 states) offsets of 5.5 $MtCO_2e$ from carbon sequestration and N_2O emission mitigation in response to no-till technology adoption. At \$20/tCO_2e, Pautsch et al. (2001) estimate offset less than 0.5 $MtCO_2e$ from conservation tillage adoption in Iowa.

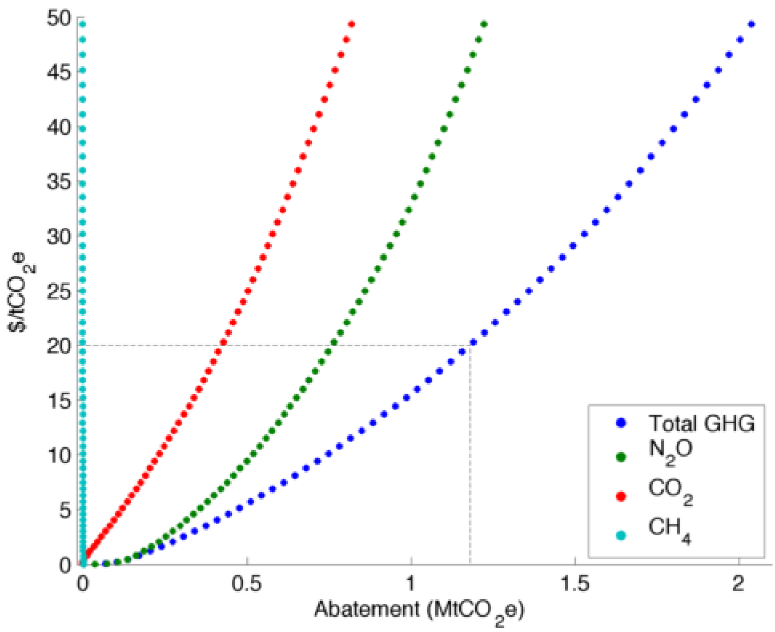

Figure 2 California agriculture's offset supply curve under the first-best policy. The different curves show total emissions abated as well as the contribution of each GHG to total abatement. The dashed line indicates the ARB predicted offset price of \$20/tCO_2e in 2020 (CARB, 2010).

Furthermore, both N_2O and CO_2 contribute substantially to total abatement as can be seen in figure 2. Although carbon sequestration often plays a predominant role in GHG emission mitigation from agricultural land (Lal et al., 1998; McCarl and Schneider, 2001), the present findings suggest that N_2O constitutes the majority of abatement in California (60%). This result is consistent with agronomic studies for California (De Gryze et al., 2011). Carbon sequestration contributes 40% to total abatement, while CH_4's contribution is negligible (less than 1%).[21]

The aggregated offset supply curve for California's Central Valley hides important regional heterogeneity, which stems partly from large variations in baseline N_2O and CO_2 emissions across the 27 Central Valley regions, as illustrated in figure 13 in appendix D. Large variations in the crop-specific baseline emission rates and net changes in total emissions at a price of \$20/tCO_2e

[21] CH_4's contribution to total abatement would substantially increase if rice were included. Yet, the Daycent model is not calibrated to simulate flooded system. As a result, this study somewhat underestimates total abatement from California agriculture.

are observed across the two valleys, as shown in table 4. For example, alfalfa is a net sequester in the San Joaquin Valley but a net emitter in the Sacramento Valley, while corn and safflower are both greater emitters in the Sacramento Valley. These regional differences are largely driven by variation in climate and soils, and to some extent by baseline production practices, across the two valleys (De Gryze et al., 2011). Consistent with the results of De Gryze et al. (2011), we observe large abatements for processing tomatoes.[22]

Table 4 Crop average total emission rates in tCO_2e/ha in the Sacramento and San Joaquin Valleys, weighted by crop acreages, for the baseline (GHG_0) and for a marginal price of $20/$tCO_2e$ ($GHG_{\$20}$).

	Sacramento Valley		San Joaquin Valley	
Crop	GHG_0	$GHG_{\$20}$	GHG_0	$GHG_{\$20}$
Alfalfa	1.4	1.3	-0.3	0.9
Corn	2.9	2.4	1.4	0.8
Cotton	3.8	3.7	5.0	0.7
Grain	-0.2	-0.3	-0.3	0.9
Other field crops	5.7	3.9	4.3	0.7
Processing tomatoes	6.2	3.8	6.2	0.7
Safflower	1.0	0.2	0.0	0.8

The crop average inputs and tillage intensities as well as the average yields for the Sacramento and San Joaquin Valleys in the baseline and their percentage changes at a marginal price of $20/$tCO_2e$ are presented in table 5. At this $20 price, the tillage index falls for all crops, with the most dramatic changes observed for processing tomatoes, the "other field crops" group, and safflower in the Sacramento Valley. In the baseline, crops generally use more water in the San Joaquin Valley (drier climate) than in the Sacramento Valley. This is particularly true for crops such as grain and safflower which are only partially irrigated in the Sacramento Valley. The water application rates increase substantially for cotton, safflower, and the "other field crops" group in the Sacramento Valley, while they substantially decrease for grain in the San Joaquin Valley at $20/$tCO_2e$. The N application rates show large variations across the two valleys and fall for all crops but safflower, and cotton in the Sacramento Valley, at a price of $20/$tCO_2e$. The largest reduction occurs for the "other field crops" group with N fertilizer reduction close over 60% on average. This is driven by the low yield elasticity with respect to N fertilizer presented in table 3.

[22] Despite of large spatial variation, De Gryze et al. (2011) find larger average abatement potentials, in absolute value, in the Sacramento Valley than in the San Joaquin Valley. Yet, their study does not consider abatement costs.

Changes in yields depend on the changes in production practices and changes in crop acreages.[23] At a \$20/tCO_2e price, average yield decreases for grain throughout the Central Valley.

Table 5 Crop average production practices and yield for the Sacramento and San Joaquin Valleys in the baseline and percentage changes for a marginal price of \$20/tCO_2e (weighted by crop acreages).

		Tillage index		Water intensity (cm)		N intensity (kg/ha)		Yield (t/ha)	
	Crop	T	%	$\bar{a}_2$	%	$\bar{a}_3$	%	$\bar{y}$	%
Sacramento V.	Alfalfa	0.91	-	119	6	12	-	14.8	1
	Corn	0.91	-14	116	3	189	-3	66.8	2
	Cotton	0.91	-17	81	19	154	14	1.4	22
	Grain	0.91	-19	16	-3	141	-10	5.3	-7
	Oth.field cr.	0.91	-26	81	21	105	-64	1.0	27
	Pr.tomato	0.91	-33	114	0	217	-7	81.0	3
	Safflower	0.91	-29	8	25	111	13	2.4	26
San Joaquin V.	Alfalfa	0.91	-	127	-1	10	-	17.6	-6
	Corn	0.91	-8	123	3	228	-3	57.7	0
	Cotton	0.91	-21	79	8	202	-11	1.3	11
	Grain	0.91	-4	52	-19	247	-24	5.8	-25
	Oth.field cr.	0.91	-18	83	13	105	-70	1.0	17
	Pr.tomato	0.91	-22	111	5	218	-5	84.0	6
	Safflower	0.91	-16	65	22	123	16	4.2	12

Adjustments at both the intensive and extensive margins substantially contribute to abatement in California. We approximate the contribution of each margin by decomposing total abatement into the abatement that arises when fixing the land input (intensive margin) and that when fixing the production practices to their baseline levels (extensive margin). Thus, we define

$$\underbrace{\sum_{gik} \Delta\left(e_{gik} x_{gi1}\right)}_{\textit{Total abatement}} \approx \underbrace{\sum_{gik} \Delta e_{gik} \bar{x}_{gi1}}_{\textit{Intensive margin}} + \underbrace{\sum_{gik} \bar{e}_{gik} \Delta x_{gi1}}_{\textit{Extensive margin}}$$

where the bar denotes baseline levels. Figure 3 suggests adjustments along both the intensive and extensive margins contribute equally to abatement at \$20/tCO_2e, although the contribution along the intensive margin predominates. This result highlights the importance of calibrating the model at the *(i)* intensive and *(ii)* extensive margins, i.e., by ensuring that *(i)* the model's yield elasticities with respect to input use and tillage technology are consistent with the agronomic information, and

[23] Although input intensities are reduced for some crops, their yield may not necessarily decrease because a reduction in acreage is associated with a higher yield on the remaining land. Therefore, the decreasing-returns-to-scale effect may predominate over the reduction in input intensities.

that *(ii)* the model's own-price supply elasticities replicate exogenous supply elasticities.

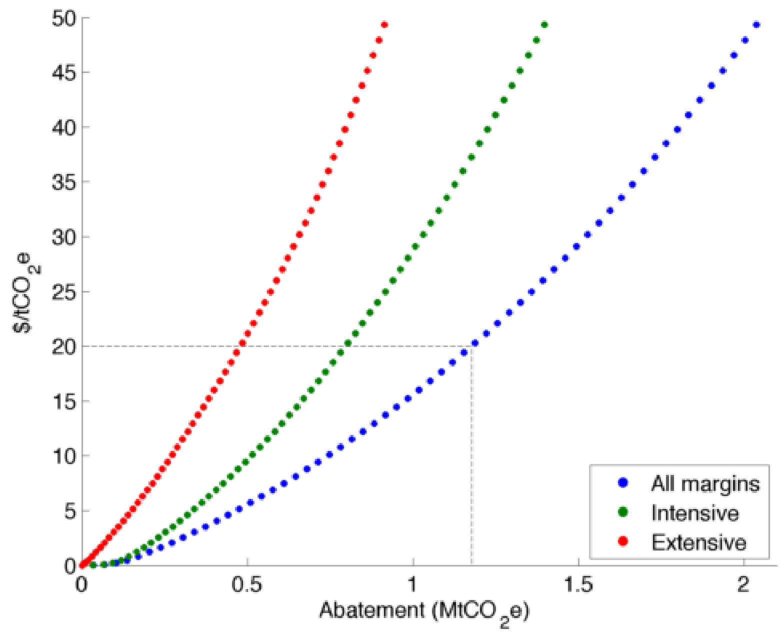

Figure 3 Contribution of the intensive and extensive margins of adjustments to California agriculture's offset supply curve under the first-best policy.

In general, farmers respond to higher offset prices by substituting away from crops with small abatement potentials and/or large abatement costs such as cotton and the "other field crops" group, and towards crops with large abatement potentials and/or small abatement costs such as grain and alfalfa, as indicated in figure 4.

5.2 Sensitivity analysis on the substitution elasticity

We model uncertainty on the value of the substitution elasticity through a Monte Carlo simulation. Mérel et al. (2014) use substitution elasticity values of 0.1, 0.2, and 0.3, while Graveline and Mérel (2014) assumes a central value of 0.15. We assume the substitution elasticity σ_{ig} follows a lognormal distribution with central value 0.25 and with 95% of the values being below one. 100 sets of σ_{ig} are independently drawn from this distribution for each crop i and region g. Figure 5 presents the mean offset supply curve plus or minus one standard deviation.

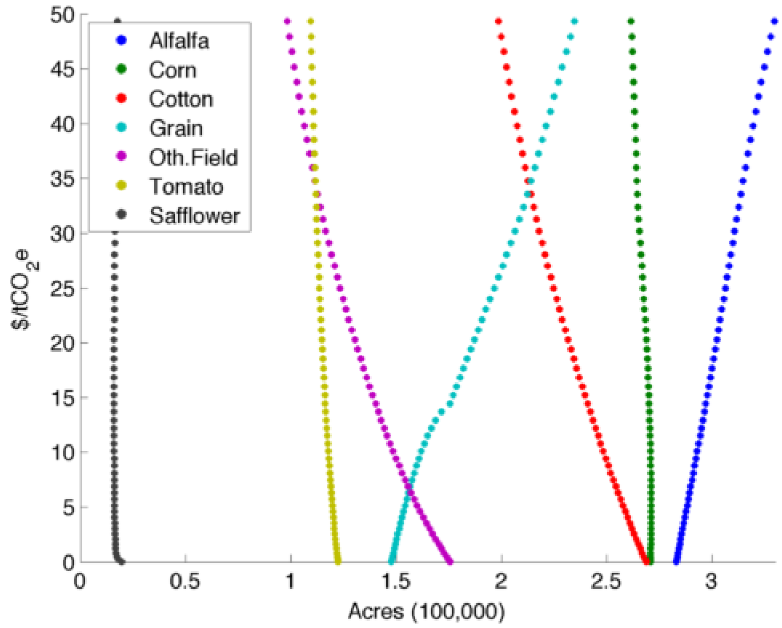

Figure 4 Changes in the California agriculture's crop mix under the first-best policy.

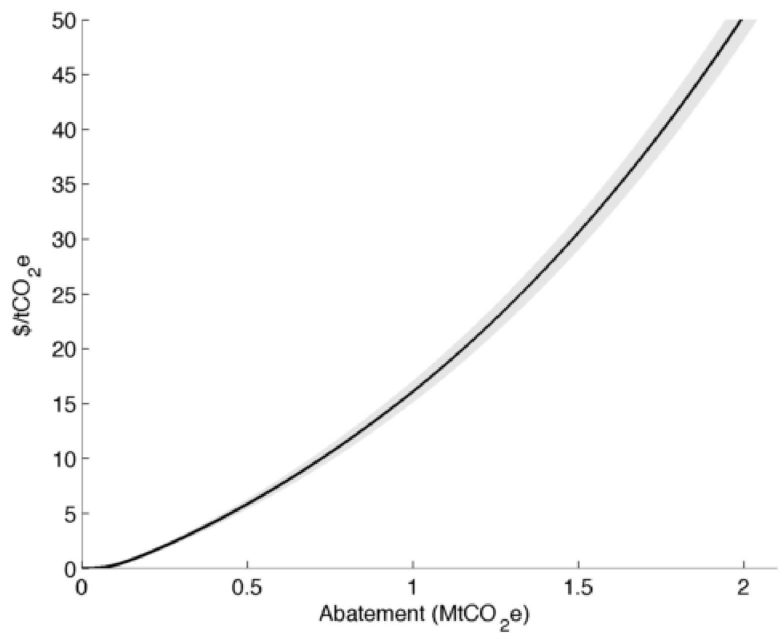

Figure 5 California agriculture's offset supply curve under the first-best policy resulting from the Monte Carlo simulation on the elasticity of substitution (100 independent draws of set σ_{gi}). The solid line shows the mean and the edges of the shaded area show the mean plus or minus one standard deviation.

5.3 Abatement cost overestimation under restricted models

In the unrestricted model farmers optimize crop choices and all production practices, here, the water, N fertilizer and tillage intensities.[24] Previous studies often focus on a single production practice, e.g., adoption of conservation tillage or no-till (Pautsch et al., 2001; Antle et al., 2007; Antle and Ogle, 2011). Restricting the set of variables farmers optimize over leads to overestimating abatement costs. Therefore, it is useful to quantify by how much analysts may underestimate the supply of agricultural offsets when simplifying the realm of possible choices available to farmers.

Results reveal that model restrictions can lead to large underestimation of total abatement, as shown in figure 6. Recall that figure 3 indicates that omitting the adjustments at the intensive or extensive margins leads to underestimating abatement by half at \$20/tCO_2e. We consider five additional restricted models. In model (1), the regional water application rate is restricted to its baseline level, while in model (2) it is the regional N fertilizer application rate that is restricted to its baseline level. In model (3), the regional N fertilizer and water application rates are restricted to their baseline levels, as specified in Antle et al. (2007) and Antle and Ogle (2011), leading to underestimating total abatement by 40% at \$20/tCO_2e in California.[25] In model (4), the regional tillage choices are restricted while farmers optimize N fertilizer and water application rates along with their crop mix, as modeled in Mérel et al. (2014), capturing only 59% of total abatement in California. Lastly, in model (5), only the tillage choice is optimized, while the crop mix and all other inputs are restricted to their baseline levels, as in Pautsch et al. (2001), resulting in underestimating total abatement by 45%.These findings illustrate large underestimation of the total abatement when omitting adjustment over some practices. Yet, if the analyst had to restrict the set of choice variables, first, leaving crop choice out, then, second, restricting crop, N fertilizer and water choices would best approximate the supply of offsets from California's agriculture.

[24] Note that the model restricts choice variables to crop mix, N fertilizer, water and tillage. Future work could account for other practices affecting GHG emissions, e.g., cover crops.

[25] Antle et al. (2007) and Antle and Ogle (2011) allow for adoption of fallow but do not consider crop substitution effect. This is because two production systems dominate the central U.S. region, therefore, adjustments at the extensive margin are limited.

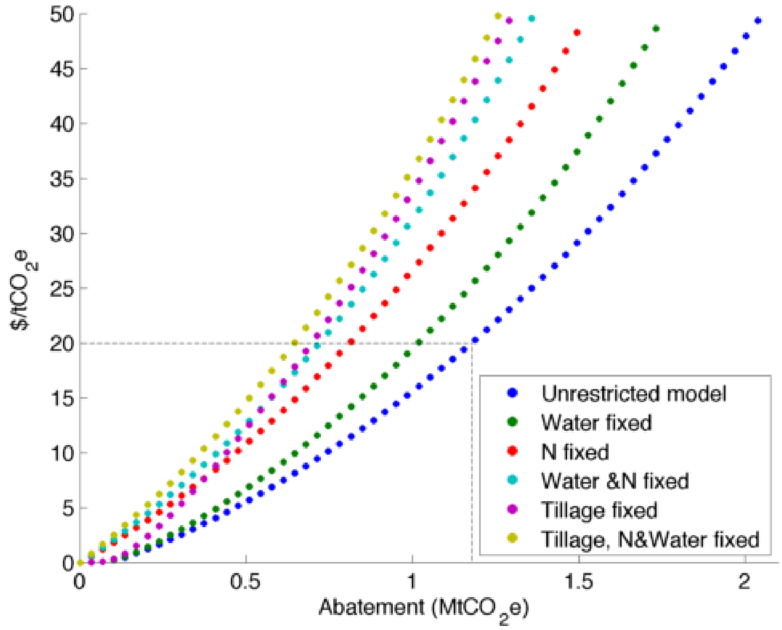

Figure 6 California agriculture's offset supply curve under the first-best policy for the unrestricted model and the five restricted models, where (1) N fertilizer, (2) water, (3) N fertilizer and water application rates, (4) tillage practices, or (5) crop mix, N fertilizer and water application rates are fixed at their baseline levels.

6 Policy design for agricultural offset payments

Although the first-best policy achieves abatement efficiency, it may be very costly and politically difficult to implement. In this section, we investigate how payment design for agricultural GHG offsets affects abatement efficiency. We examine three types of second-best payment designs: (1) payments using aggregated emission factors, (2) payments targeting a single GHG, and (3) payments regulating production practices. For each second-best policy, we estimate the abatement efficiency loss that arises relative to the first best.

6.1 Policies using aggregated emission factors

Under the feasible first-best policy, "actual" emissions are inferred using the most disaggregated data available, i.e., the 27 sets of emission factors. Here, we consider two levels of aggregation: (1) with two sets of emission factors at the Sacramento Valley and San Joaquin Valley levels, and (2) with a single set of emission factors at the California level. We aggregate the Daycent model's GHG emission data to the valley or California level using crop acreages as weights. We then fit new GHG emission functions to the data and obtain the aggregate emission factors $\tilde{e}_{ik}$ for crop i and GHG k for the two valleys and for California. The constraint on total GHG emissions in program (1) is now expressed as $\sum_{gik} \tilde{e}_{gik} x_{gi1} \leq \overline{GHG}$. *Ex-post* we estimate the "actual" abatement that corresponds to the new regional input, crop mix, and tillage choices using the disaggregated emission factors e_{gik}.

Perhaps surprisingly, although similarly to Antle et al. (2007) for the central U.S., the abatement efficiency losses from using payments with aggregated emission factors are small, with offsets within 8% of those obtained under the first-best policy at a price of \$20/tCO_2e, see figure 7. This suggests that the distortions that arise from farmers facing incorrect incentives, with aggregated emission factors instead of the finer regional factors, may be acceptable, provided these second-best policies are significantly less costly to implement than the first-best.

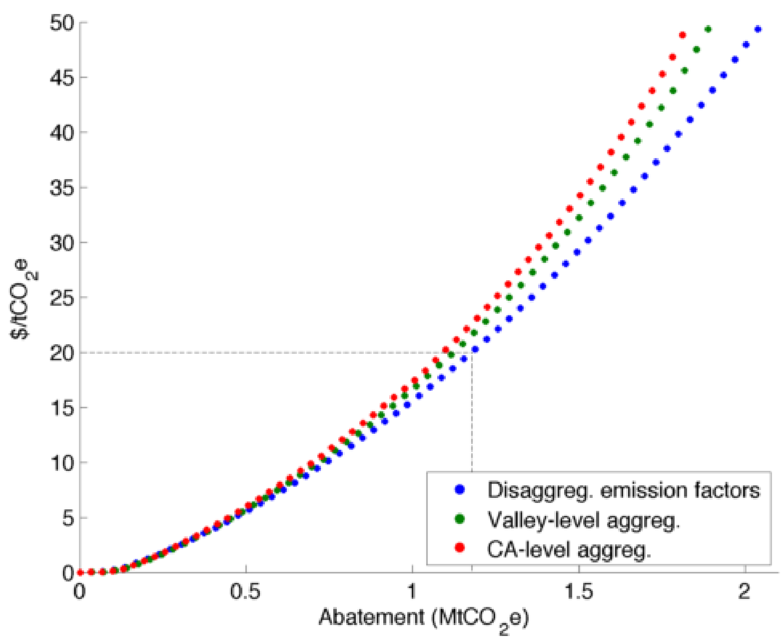

Figure 7 California agriculture's offset supply curve under the first best and two second-best policies with valley and state-level aggregated emission factors.

Yet, the small discrepancy in total abatement for California hides more pronounced regional variations because of spatial heterogeneity. Figure 14 shows that while in most regions the differences in total regional abatement at \$20/tCO_2e under the first-best and the two second-best policies are small, the second-best policies achieve less than 20% of total abatement relative to the first-best policy in some regions, e.g., in region 9 in the Sacramento Valley.

6.2 Policies targeting a single GHG

Programs focusing on all three GHGs are likely more costly to administer, therefore, it is relevant to question how much abatement efficiency is lost by targeting a single GHG. Most studies focus on carbon sequestration (Pautsch et al., 2001; Antle et al., 2003; Lubowski et al., 2006).[26] Yet, because California agriculture presents a substantial N_2O emission abatement potential, policy-makers may be interested in targeting this GHG. Thus, we examine two second-best policies where payments are made for: (1) enhanced carbon sequestration or (2) N_2O emission mitigation. As a result, the constraint on total GHG emissions in program (1) is now expressed as $\sum_{gi} e_{giCO_2} x_{gi1} \leq \overline{CO_2}$ or $\sum_{gi} e_{giN_2O} x_{gi1} \leq \overline{N_2O}$. *Ex-post* we estimate the abatement of the other GHGs that corresponds to the new regional production practices and crop mix to calculate total GHG emissions abated.

The abatement efficiency losses that arise from targeting a single GHG are substantial: 16% under payments for N_2O and 20% for CO_2 at \$20/tCO_2e, as illustrated in figure 8.[27] However, efficiency losses are only slightly smaller under policies targeting N_2O emissions rather than carbon sequestration.

6.3 Regulation of production practices

Monitoring all inputs contributing to GHG emissions simultaneously, such as N, water and tillage, is likely costly and may be politically difficult. Here, we investigate the abatement efficiency losses that arise from second-best policies focusing on a single input instead of all inputs under the first-best policy. We examine payments for reductions in tillage intensity (in \$/tillage index/ha) and N fertilizer (in cent/kg of N).[28] A tax on N fertilizer or irrigation water could be easily levied, however, we do not report results for a policy targeting water because the supply of offsets is very inelastic given that water is binding in all regions. The regulator may use satellite imagery at some cost to observe crop residue cover and infer the tillage index.

The regulator may also combine multiple instruments, such as a tax on tillage and a tax on N fertilizer, to reduce the distortions created when using a single instrument. Minimizing efficiency

[26] A few recent studies look at N_2O emission abatement (Mérel et al., 2014; Rosas et al., 2011).

[27] Whether the distortions that arise from farmers facing incorrect incentives are less than the costs saved from operating a program targeting a single GHG is relevant for policy-makers. However, answering this question requires estimating program implementation costs and is beyond the scope of the present study.

[28] The marginal abatement cost curve is equivalent under a tax on input use or tillage intensity, although the income transfer goes from the farmers to society, rather than the other way around with the subsidy.

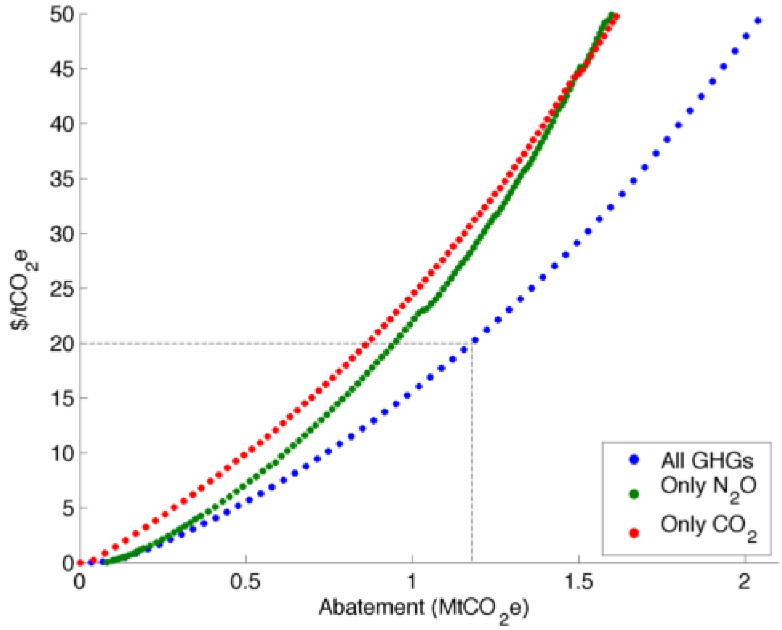

Figure 8 California agriculture's offset supply curve under the first-best and two second-best policies targeting carbon sequestration and N_2O emission reduction.

losses requires that, conditional on the level of one instrument, the other instrument be optimized. For the joint regulation of tillage and N fertilizer, with optimal taxes t_N and t_T, respectively, program (1) becomes:

$$\max_{x_{gij}\geq 0, T_{gi}\geq 0, t_N\geq 0, t_T\geq 0} \sum_{gi} p_{gi}q_{gi} - \sum_{j\neq 3}(c_{gij}+\lambda_{gij})\,x_{gij} - (c_{gi3}+\lambda_{gi3}+t_N)\,x_{gi3} - (c_{giT}(T_{gi}) + (\lambda_{giT}+t_T)T_{gi})\,x_{gi1}$$

subject to

$$\begin{cases} \sum_i x_{gij} \leq v_{gj} & j = 1,2,\ \forall g \in G \\ q_{gi} = \mu_{gi}\left(\sum_j \beta_{gij} x_{gij}^{\rho_{gi}}\right)^{\frac{\delta_{gi}}{\rho_{gi}}} & \forall i \in I,\ g \in G \\ \sum_{gik} e_{gik}(a_{gij}, T_{gi})x_{gi1} \leq \overline{GHG} & \end{cases}$$

The program solves for the optimal tax level when a single input is taxed, t_N or t_T, or for jointly optimal tax levels, t_N and t_T, i.e., that minimize abatement cost while satisfying the total emissions constraint. *Ex-post* we estimate the marginal cost of supplying GHG offsets (in $/tCO$_2$e) under the different taxes. This offset price p^* corresponds to the marginal change in total surplus, which consists of the agricultural profit and the tax revenue, over the marginal change in total abatement, that is

$$p^* = \frac{d\,(Profit + Tax\,Revenue)}{dGHG}.$$

At the marginal price of \$20/tCO_2e, the equivalent tax on N fertilizer is of 13 cents/kg of N, while on tillage it is \$45/tillage index/ha.

Not surprisingly, regulating a single production practice rather than all of them leads to substantial abatement efficiency losses, with only 20% of the abatement achieved under the first-best policy at \$20/tCO_2e when targeting N fertilizer as shown in figure 9. Abatement efficiency losses are slightly less pronounced when targeting tillage technology with 60% losses at \$20/tCO_2e relative to the first-best policy. Discontinuities in the offset supply curve may arise when a choice variable hits a bound in a given region. For instance, when taxing tillage two discontinuities occur when the tillage index hits the 0-lower bound, i.e., no till, for grain in the Sacramento Valley at a price of \$29/tCO_2e and in the San Joaquin Valley at a price of \$48/tCO_2e. The social cost of abatement then drops as another margin of adjustment, which leads to fewer distortion, is exploited. For the N input, the findings suggest farmers can curtail N fertilizer use to some extent without incurring much yield loss. Therefore, the offset supply is relatively elastic at low offset prices (below \$3/tCO_2e). However, when regulating the N input, the offset supply rapidly becomes very inelastic with an upper bound of 0.4 MtCO_2e for the price range considered here. Intuitively, the less correlated the production practice is with total GHG emissions, the greater the distortion relative to the first-best policy. This is why regulating tillage, which is positively correlated with emissions, entails smaller deadweight loss than regulating the N input (see figure 1).

6.4 Effect of the substitution elasticity

Total abatement at a price of \$20/tCO_2e are presented in table 6 for the first-best and for the second-best policies previously examined for three levels of the elasticity of substitution σ_{gi}: 0.1, 0.2, and 0.3. The results are sensitive to the elasticity of substitution in absolute value but not relatively, i.e., the policy results are robust to the value of σ_{ig}.

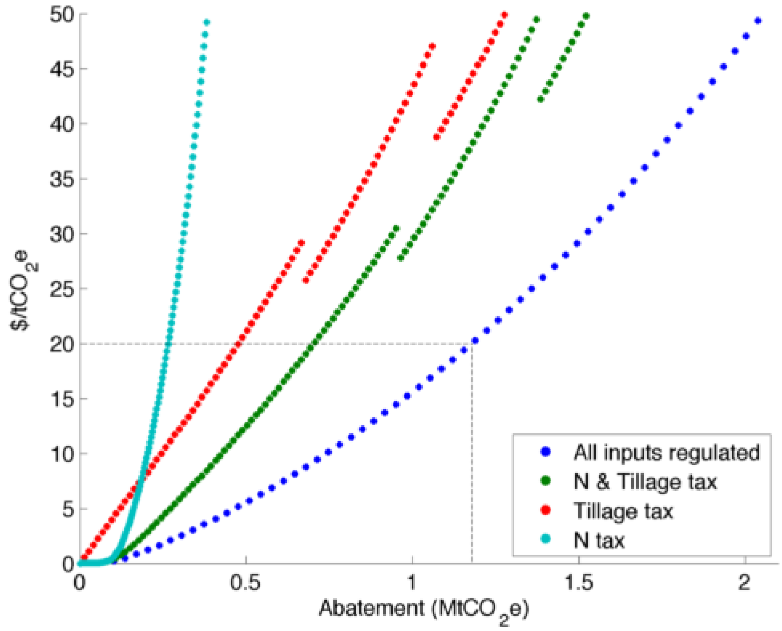

Figure 9 California agriculture's offset supply curve under the first-best and second-best policies regulating tillage or N fertilizer and under a mixed policy regulating both tillage and N fertilizer.

Table 6 Total GHG emission abated in $MtCO_2e$ at a price of $\$20/tCO_2e$ under the first-best and second-best policies for three levels of the elasticity of substitution σ_{gi}.

		Second-best policies						
		Aggregated emission factors		Regulation of a single GHG		Regulation of inputs		
						Single input		Multiple inputs
σ	First-best	Valley	CA	CO_2	N_2O	Tillage	N	Tillage & N
0.1	1.05	1.01	0.97	0.82	0.86	0.46	0.17	0.59
0.2	1.18	1.12	1.10	0.86	0.95	0.48	0.26	0.70
0.5	1.49	1.40	1.34	0.98	1.22	0.50	0.46	0.97

7 Conclusion

The paper makes several important contributions to the literature on the GHG abatement costs from agriculture and environmental regulatory design for agricultural GHG offsets. First, we estimate California Central Valley agriculture's marginal abatement cost curve under the first-best policy using a disaggregated model of crop production that is calibrated to both economic and agronomic information. This is the first disaggregated large-scale study for California. It is important because California's agriculture is highly valuable with a diverse crop mix and rich set of resource constraints. Furthermore, California is a leader in designing climate policy and ARB is examining the development of protocols for crediting GHG offsets from cropland management.

Second, the paper systematically quantifies the abatement efficiency losses that arise from second-best policies. Such policies are simpler and less costly to implement than the first-best policy. This is important because there exist tradeoffs when designing payments for GHG offsets between efficiency and the costs of implementing the program. The results show that second-best policies that rely on regionally aggregated emission factors yield offset supply curves close to that obtained under the first-best policy with fine-scale emission factors. That is, additional information has a small impact on the supply of offsets. The findings are important because the costs of such second-best policies are substantially lower than that of the first-best policy, suggesting these policies would be efficient in California. In contrast, all other second-best policies examined lead to substantial efficiency losses. Yet, depending on the costs of implementing such programs relative to the first-best policy, regulating tillage, N_2O emissions or carbon sequestration may be more cost-effective. Results reveal that a tax on N fertilizer is a poor instrument to abate GHG emissions and entails large deadweight loss. However, policies simultaneously taxing tillage and N fertilizer substantially improve abatement efficiency relative to the single tax policy.

Lastly, the paper develops new methodology to integrate information on tillage technology into economic models. The model reproduces available economic information on input-output observed allocation and exogenous supply elasticities, as well as, agronomic information in terms of yield elasticities with respect to input use (N fertilizer and water). Therefore, the model is calibrated at both the intensive and extensive margins. This is critical because the results reveal both margins contribute substantially to total abatement.

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Appendix

A Derivation of the yield elasticities with respect to input use and tillage

Mérel et al. (2014) propose a methodology to ensure that the observed input-ouput allocation, i.e., observed N fertilizer and water application rates and yield described in section 2.3, are consistent with the information from the agronomic model. We extend their methodology to the tillage technology. The regional yield response curves are generated as follows.

First, we generate the yield response to N fertilizer application, holding the tillage index and water application rate at their observed levels. We then estimate the yield response to N fertilizer as presented in (2). If the N fertilizer application rate a_3 that replicates the observed regional yield, given the fitted yield response (2), is not too far from the observed N fertilizer application rate, we retain that value for the reference N application.[29] For the crops and regions for which this is not true, we verify that the yield that would be replicated by the observed N fertilizer application rate, based on the fitted yield response (2), is not too far from the observed yield and we retain that value for the reference yield and the reference N fertilizer application rate remains the observed rate.

Second, we generate the yield response to water application, holding the tillage index at its observed level and reference N fertilizer application rate. We then estimate the yield response to water as described in (3). We verify that the water application rate a_2 that replicates the reference yield is similar to the observed water application rate, and retain that value for the reference water application.

Therefore, for each crop and region we have reference water and N fertilizer application rates and yield, $\bar{a}_2$, $\bar{a}_3$ and $\bar{y}$, respectively. By construction, the reference yield is consistent with the "reference" water and N fertilizer application rates, in the sense that this yield lies on each yield response curve.

Given expressions (2) and (3), the crop and region-specific agronomic yield elasticities with respect to N fertilizer and water application rates and tillage, evaluated at the reference allocation,

[29] We consider "not too far" as within 30% of the observed value.

are, respectively:

$$
\begin{aligned}
\bar{y}_3 &= \frac{dy}{da_3}\frac{\bar{a}_3}{\bar{y}} \\
&= \frac{\beta_{13}\beta_{23}\bar{a}_3 e^{-\beta_{23}\bar{a}_3}}{\bar{y}},
\end{aligned}
$$

$$
\begin{aligned}
\bar{y}_2 &= \frac{dy}{da_2}\frac{\bar{a}_2}{\bar{y}} \\
&= \frac{\bar{a}_2 e^{-\frac{\bar{a}_2-\beta_{02}}{\beta_{22}}}}{\beta_{22}\left(1+e^{-\frac{\bar{a}_2-\beta_{02}}{\beta_{22}}}\right)}, \text{ and}
\end{aligned}
$$

B GHG emission responses

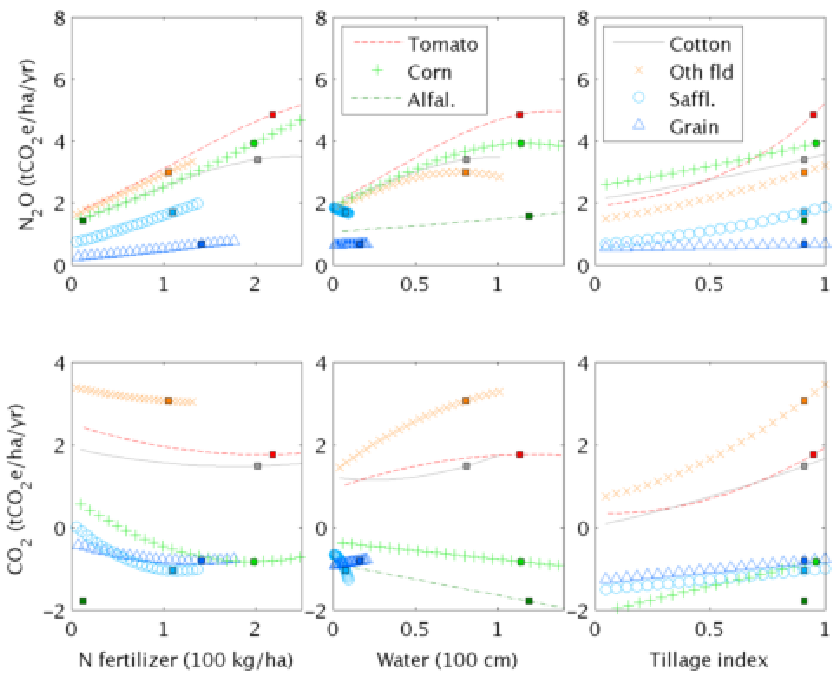

Figure 10 CO_2 (top panels) and N_2O (bottom panels) responses to N fertilizer and water application rates and tillage intensity for the seven crops in region 6. Squares indicate the baseline. The changes in production practices considered correspond 0 to 125% of the intensity observed at the baseline. Also, there is no N fertilization or tillage responses for alfalfa.

C Model calibration

The first-order conditions associated with the economic model (1) presented in section 2 for crop $i \in I$, evaluated at the reference allocation, are:

$$\begin{cases} \frac{\delta_i p_i \bar{q}_i \beta_{i1} \bar{x}_{i1}^{\rho_i}}{\sum_j \beta_{ij} \bar{x}_{ij}^{\rho_i}} = \left(c_{i1} + \lambda_{i1} + c_{iT}(\bar{T}_i) + \lambda_{iT}\bar{T}_i\right) \bar{x}_{i1} \\ \frac{\delta_i p_i \bar{q}_i \beta_{i2} \bar{x}_{i2}^{\rho_i}}{\sum_j \beta_{ij} \bar{x}_{ij}^{\rho_i}} = \left(c_2 + \lambda_{i2} + \bar{\lambda}_2\right) \bar{x}_{i2} \\ \frac{\delta_i p_i \bar{q}_i \beta_{i3} \bar{x}_{i3}^{\rho_i}}{\sum_j \beta_{ij} \bar{x}_{ij}^{\rho_i}} = \left(c_3 + \lambda_{i3}\right) \bar{x}_{i3} \\ \bar{c}'_{iT} = -\lambda_{iT} \\ \beta_{ij} > 0 \quad \forall j \\ \mu_i > 0. \end{cases} \tag{5}$$

To calibrate the economic model to the agronomic yield responses, we set the elasticities derived using the generalized CES economic production functions equal to the agronomic elasticities derived in section A:

$$\begin{cases} \bar{y}_{i2} = \delta_i \frac{\beta_{i2} \bar{x}_{i2}^{\rho_i}}{\sum_j \beta_{ij} \bar{x}_{ij}^{\rho_i}} \\ \bar{y}_{i3} = \delta_i \frac{\beta_{i3} \bar{x}_{i3}^{\rho_i}}{\sum_j \beta_{ij} \bar{x}_{ij}^{\rho_i}} \end{cases}$$

which can be expressed, using (5), as

$$\begin{cases} \bar{y}_{i2} = \frac{\left(c_2 + \lambda_{i2} + \bar{\lambda}_2\right) \bar{x}_{i2}}{p_i \bar{q}_i} \\ \bar{y}_{i3} = \frac{(c_3 + \lambda_{i3}) \bar{x}_{i3}}{p_i \bar{q}_i}. \end{cases}$$

The system for calibrating model (1)'s implied supply elasticities to available priors, when the land and/or water constraints are binding, is available upon request. Note that not all elasticity priors can be replicated, i.e., such that a solution $\mathbf{0} < \boldsymbol{\delta} < \mathbf{1}$ exists (Mérel et al., 2011; Garnache and Mérel, 2014).[30]

Table 7 shows California's own-price supply elasticity priors and the crop acreage weighted average "feasible" elasticities in the Sacramento and San Joaquin Valley. The feasible elasticities minimize the departure from the priors, while ensuring the calibration system has a (unique)

[30] The derivation of the calibration conditions for an acceptable solution $\boldsymbol{\delta}$ to exist when the land or water constraint is binding is available upon request.

Table 7 California's own-price supply elasticity priors and average "feasible" elasticities (weighted by crop acreages).

		Modeled regional elasticities	
Crop	State-wide prior	Sacramento Valley	San Joaquin Valley
Alfalfa	0.44	0.44	0.44
Corn	0.55	0.66	0.71
Cotton	0.50	1.01	1.53
Grain	0.36	0.36	0.59
Other field crops	0.63	0.86	3.96
Processing tomatoes	0.55	0.56	0.72
Safflower	0.45	0.54	1.40

solution $\mathbf{0} < \boldsymbol{\delta} < \mathbf{1}$.

After solving the elasticity calibration system for the return-to-scale parameter $\boldsymbol{\delta}$, we recover the inputs λ_{ij} and tillage shadow costs λ_{iT} for crop i by solving system:

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

The average cost data with the shadow prices of the water input, $\bar{\boldsymbol{\lambda}}_2$, and the inputs and tillage shadow costs, are presented for the Sacramento and San Joaquin Valleys in table 8 in appendix C. These shadow costs represent the cost adjustments needed to rationalize observed economic behavior, given prices and technology. A positive shadow cost indicates a hidden cost, while a negative value indicates a hidden benefit. For most crops, there are shadow benefits associated with the land, N fertilizer, and tillage technology, justifying why farmers cultivate more land, apply more N or till more intensely in the baseline than would first appear optimal. These shadow benefits may capture fixed costs, contracts, subsidies for the land input, insurance against weather risk for N fertilizer, and increased weed resistance to herbicide in reduced tillage systems. Hidden benefits are particularly large for crops such as corn and processing tomato for tillage, and for corn, grain, the "other field crops" group, and processing tomatoes for N fertilizer. In contrast, farmers obtain a hidden cost from the water input, justifying that they apply less water than would be thought optimal based on the yield effect.

Table 8 Average cost data and shadow costs in the Sacramento and San Joaquin Valleys (weighted by crop acreages).

		Land (\$/ha)		Water (\$/cm)			N (\$/kg of N)		Tillage (\$/index/ha)	
	Crop	c_1	λ_{i1}	c_2	$\bar{\lambda}_2$	λ_{i2}	c_3	λ_{i3}	c_T	λ_{iT}
Sacramento Valley	Alfalfa	876	-482	0.5	4.1	-1.6	3.1	-	-	-
	Corn	830	-398	0.5	4.1	-0.6	2.1	-1.0	238	-426
	Cotton	1347	-1229	0.7	5.8	12.6	0.6	0.1	107	-225
	Grain	411	-333	0.5	4.3	1.1	1.4	-1.2	77	-80
	Oth.field cr.	392	-236	0.5	4.5	4.4	1.2	-1.2	128	-263
	Pr. tomato	2770	-2153	0.5	4.6	4.2	1.4	-1.0	340	-462
	Safflower	187	-150	0.4	4.6	13.0	0.7	-0.1	41	-85
San Joaquin Valley	Alfalfa	1013	-716	1.1	7.4	-3.9	6.7	-	-	-
	Corn	830	-464	0.9	6.4	-3.8	2.1	-1.2	238	-426
	Cotton	1347	-1094	1.5	11.6	9.4	0.6	-0.4	107	-225
	Grain	448	-366	1.4	9.4	-5.2	1.5	-1.5	61	-84
	Oth.field cr.	392	-216	0.9	7.4	4.4	1.2	-1.2	128	-263
	Pr. tomato	3095	-2623	1.7	13.3	0.2	1.3	-0.8	232	-497
	Safflower	216	-172	1.4	10.4	-6.1	0.6	1.7	36	-86

It is then straightforward to solve for the technology parameters μ_i and β_{ij}, using (5) and the equalities $\sum_j \beta_{ij} = 1$ and $\bar{q}_i = \mu_i \left(\sum_j \beta_{ij} \bar{x}_{ij}^{\rho}\right)^{\frac{\delta_i}{\rho}}$. This last step concludes the calibration phase.

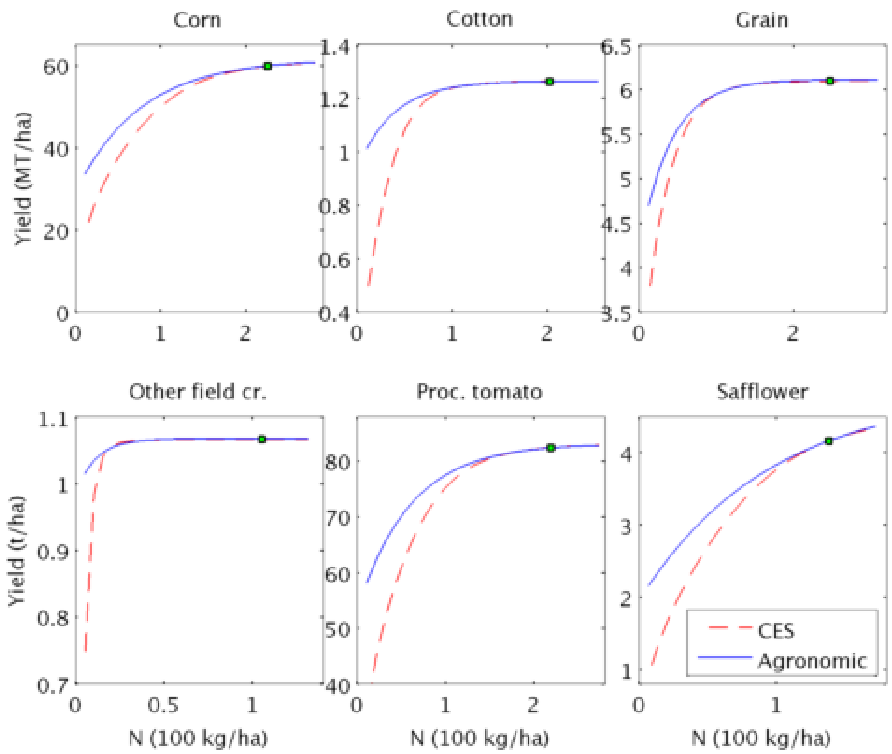

Figure 11 Yield response to N fertilizer application rate for region 10. Squares indicate the baseline. Alfalfa's yield is not depicted because it is not sensitive to N fertilizer.

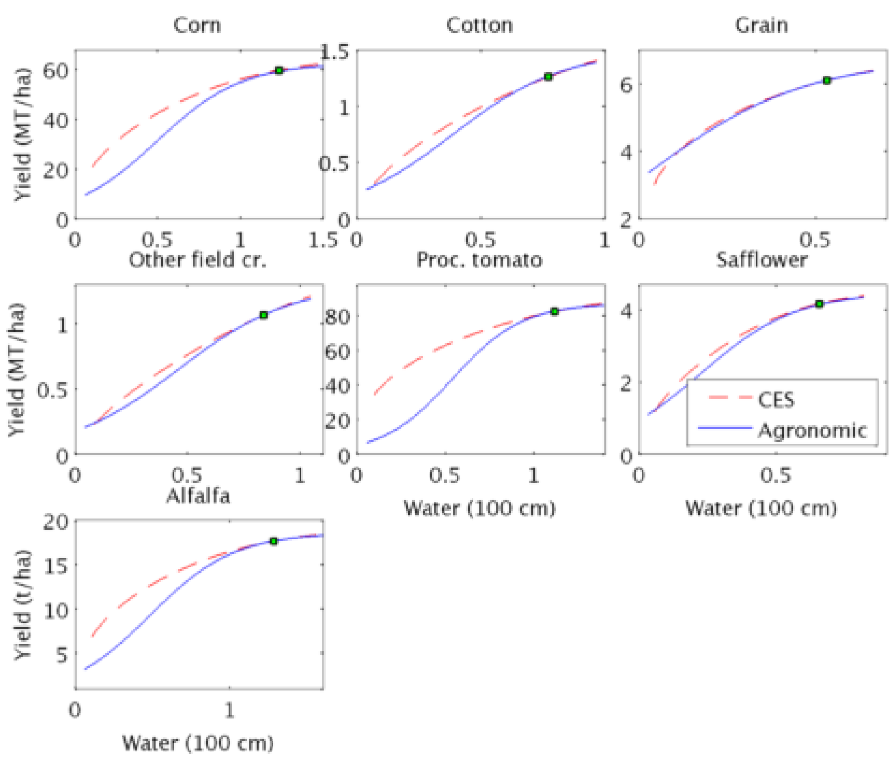

Figure 12 Yield response to water application rate for region 10. Squares indicate the baseline.

D Marginal abatement costs

Baseline emissions for N_2O and CO_2 show large variations across the 27 Central Valley regions, as illustrated in figure 13 in appendix D.[31] Differences in the regional per hectare average N_2O and CO_2 emissions come from variation in crop mix, production practices and region-specific emission factors.

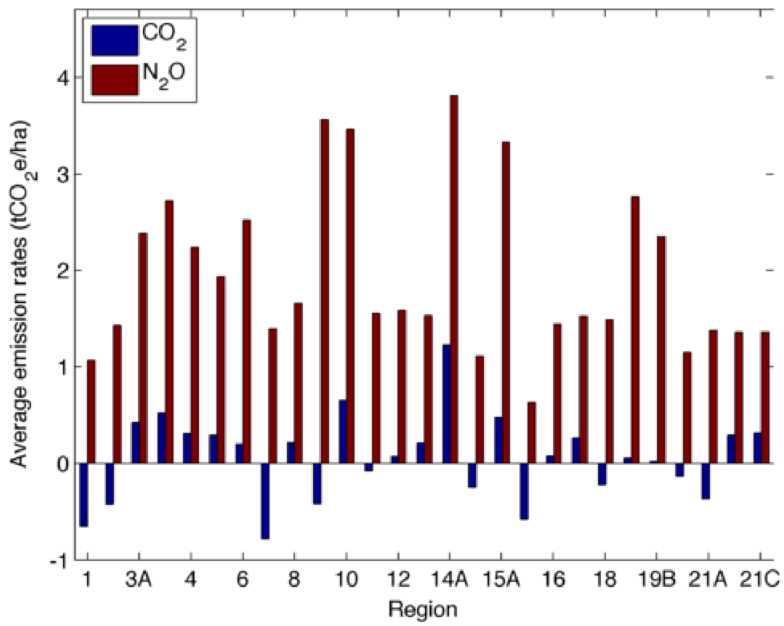

Figure 13 Average regional CO_2 and N_2O emissions in tCO_2e in the baseline (weighted by crop acreages).

The small discrepancy in total abatement under second-best policies relying on aggregated emission factors, presented in figure 7, hides more pronounced regional variations because of spatial heterogeneity. Figure 14 shows total regional abatement at \$20/tCO_2e under the first-best and the two second-best policies. Although in most regions discrepancies are small, the second-best policies achieve only 76% of total abatement relative to the first-best policy in region 9 and 92% in region 15A.

[31] Because CH_4 emissions are small in all 27 regions relative to the two other GHGs, they are not depicted.

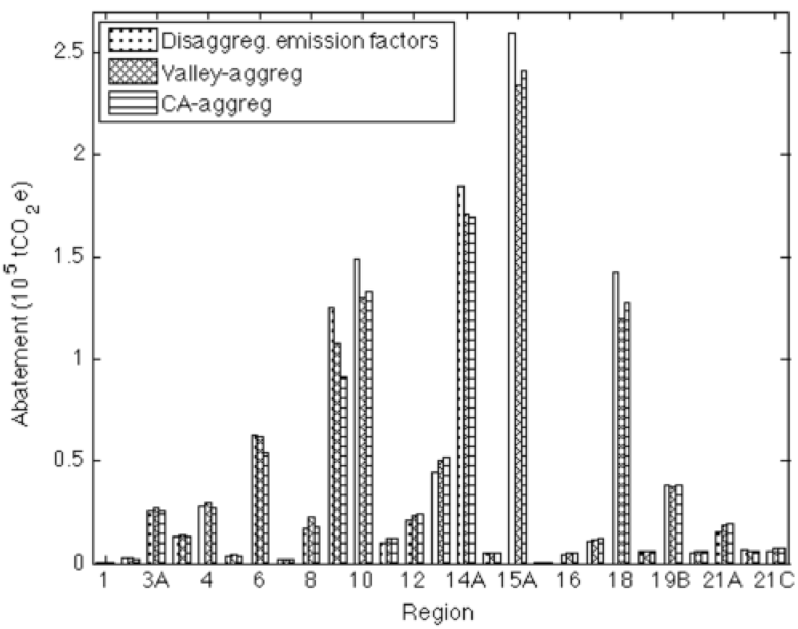

Figure 14 Total regional abatement in 100,000 tCO_2e at a marginal price of $\$20/tCO_2e$ under the first-best and two second-best policies using aggregated emission factors at the valley or state-level.