A Regional Bio-economic Model of Nitrogen Use in Cropping

Abstract

We build a bio-economic model of crop production at the regional scale to predict the effects of environmental policies on agriculture and the environment. The model is calibrated against economic data on observed crop acreages and yields, as well as predetermined supply responses. In addition, crop-specific production functions are calibrated to exogenous agronomic information on yield responses to nitrogen and irrigation, through the use of crop-specific shadow prices for fertilizer and water. The calibrated model thus replicates economic information while being consistent, at the margin, with agronomic expectations regarding the responsiveness of yield to intensive margin adjustments. The model is applied to the study of a nitrogen tax in Yolo County, California, intended to mitigate non-point source nitrogen pollution from field crops. At low tax levels, the behavioral and environmental responses to the nitrogen tax appear to be largely due to changes in the intensive margin. As the tax level increases, intensive margin responses start to level out and acreage reallocation among crops begins to play a sizable part in the total response. Overall, the environmental effects of the policy can only be captured if intensive margin adjustments are correctly accounted for.

1 Introduction

The present paper develops an economic model of nitrogen use at the regional scale, for use in *ex ante* agri-environmental policy evaluation. The model is based on the principles of positive mathematical programming (PMP), as outlined in Howitt (1995b) and, more recently, Mérel et al. (2011). As such, the model exactly replicates an observed acreage allocation among activities, as well as an exogenous set of crop supply elasticities. The novelty of our approach lies in the fact that the model is also calibrated so as to replicate crop yield responses to irrigation and nitrogen application consistent with agronomic information obtained from a biophysical soil process model (DAYCENT, Del Grosso et al. (2008)). Consequently, our fully calibrated model is particularly fit for the analysis of policies that are likely to affect both crop choice and input intensities in multi-crop agricultural systems.

Programming models of agricultural supply, notably those based on PMP, have been a staple of agricultural policy analysis even before their popularization by Howitt (1995b). Most existing large-scale models of agricultural supply still rely on a fixed-proportion representation of the cropping technology.[1] That is, input intensities are assumed to be fixed at their observed values, typically obtained from farm survey averages. While this simplification may be acceptable when modeling farm-level production, it becomes questionable when the model is designed to delineate the production technology at a regional scale, where variation in input intensities is often undeniable and substitution possibilities arise due to the aggregation of heterogenous farm-level production functions (Hertel et al., 1996). The problem becomes even more critical when these regional models are utilized to assess the effects of agri-environmental policies, such as water conservation or nitrogen pollution reduction, that are designed to directly impact farmers' input intensities.

Howitt (1995a) first proposed a constant-elasticity-of-substitution (CES) PMP representation of regional agricultural supply, that exactly replicates observed acreage and input allocations among activities. His specification has been at the core of California's SWAP model ever since; it has also been used, for instance, by Graindorge et al. (2001) or, in a slightly modified version, by Medellín-Azuara et al. (2010). Recently, Heckelei and Wolff (2003) and Mérel et al. (2011) proposed a variant to Howitt's model that specifies a decreasing-returns-to-scale CES production function, eliminating the need to add *ad hoc* penalty terms to the objective function. However, none of those papers have attempted to use agronomic information as a source of calibration for the production functions. This is problematic, as the yield effects generated by such models remain largely uncontrolled for, and may be far from reasonable agronomic expectations.

This paper is not the first one to recognize the need to better represent farmers' input adjustment opportunities in programming models of agricultural supply, but it is the first one to propose a solution to the yield response calibration problem in the context of positive mathematical programming. Before us, Godard et al. (2008) have used local yield response curves derived from the biophysical model STICS (Brisson

[1]This is the case, in particular, for the US Regional Environment and Agriculture Programming model (Johansson et al., 2007) and the European Common Agricultural Policy Regionalised Impact (CAPRI) modelling system (`http://www.capri-model.org`).

et al., 2003) to represent farmers' nitrogen fertilizer application choice as a first stage to a linear programming representation of crop choice. Graveline and Rinaudo (2007) have exploited a yield response curve for corn to specify a discrete set of corn production activities in a pure linear programming framework. Our approach is different from these, as we focus on exact replication of observed economic behavior through non-linear PMP calibration, as opposed to constrained linear optimization. We also calibrate crop yield responses not only to nitrogen, but also irrigation, a critical margin of adjustment for the assessment of certain environmental outcomes such as nitrate leaching. Finally, we use the biophysical model to derive regional-level—as opposed to farm-level—yield response curves.

Our model is applied to field crop agriculture in Yolo County, California, to evaluate the economic and environmental effects of an exogenous increase in the price of nitrogen. A nitrogen tax represents a possible market-based instrument to help mitigate non-point source nitrogen pollution from agriculture. The effects of the tax on nitrate leaching and nitrous oxide fluxes are tracked. Results show that at low to moderate tax levels, most of the environmental benefits of the policy arise from input intensity adjustments, with crop reallocation playing a minor role.

These findings suggest that accurate modeling of farmers' intensive margin opportunities is warranted for sound agri-environmental policy analysis, including the study of climate change mitigation strategies, and call into question the use of fixed-proportion technologies in existing large-scale models of agricultural supply.

2 Calibration of the economic model

Our model is derived as a refinement to the generalized constant-elasticity-of substitution mathematical programming model of Mérel et al. (2011). We model regional crop production as the result of the rational maximization of aggregate farm returns, given input and crop prices, subject to a land constraint. The number of cropping activities is denoted I. The regional economic optimization model is defined as follows:

$$\begin{array}{l} \max\limits_{q_i \geq 0, x_{ij} \geq 0} \sum_i \left\{ p_i q_i - \left[(c_{i1} + \lambda_{i1}) x_{i1} + (c_{i2} + \lambda_{i2}) x_{i2} + (c_{i3} + \lambda_{i3}) x_{i3} \right] \right\} \\ \text{subject to} \\ \left\{ \begin{array}{ll} \sum_{i=1}^{I} x_{i1} \leq b_1 & \\ q_i = \mu_i \left[\sum_{j=1}^{3} \beta_{ij} x_{ij}^{\rho_i} \right]^{\frac{\delta_i}{\rho_i}} & \forall i = 1, \ldots, I \end{array} \right. \end{array} \tag{1}$$

where p_i is the price of crop i and c_{ij} is the price of input j in activity i ($j = 1, 2, 3$). The parameter b_1 represents the available agricultural land, calculated as the sum of all crop acreages in the reference allocation. The choice variables x_{ij} represent the amount of input j used in the production of crop i, and q_i denotes the output level, related to the input employments in a generalized CES production function with parameters μ_i, β_{ij} and δ_i, satisfying $\mu_i > 0$, $\beta_{ij} > 0$, $\sum_j \beta_{ij} = 1$ and $\delta_i \in (0, 1)$.

There are three explicit inputs in our model. The index $j = 1$ denotes land. The other inputs are water ($j = 2$) and fertilizer expressed in pounds of nitrogen ($j = 3$), assumed to be supplied in a perfectly elastic fashion to the farm sector. For the purpose of this study, all other inputs (such as pesticides, labor, custom operations etc.) are assumed to be employed in fixed proportions with land, and therefore their respective cost is included in the price of land, c_{i1}. The price of land thus varies by crop. Similarly, it is assumed that all fertilizer elements (N, P, K and others) are employed in fixed proportions, so that the cost of fertilizer c_{i3} is in fact crop-specific (different crops use different proportions of the various elements).

The parameter ρ_i is a pure substitution parameter and is given by $\rho_i = \frac{\sigma_i - 1}{\sigma_i}$, where σ_i is the elasticity of substitution between any two inputs. In the absence of crop-specific information on substitution elasticities, we set $\sigma_i = 0.2$ for all crops. This figure represents a lower bound of the figures we were able to find in the literature. Howitt (1995a) uses $\sigma = 0.7$ for field crop production functions with land, water, capital and chemical inputs in California and the rest of the United States. More recently, Medellín-Azuara et al. (2010) set $\sigma = 0.25$ for a production function with land, labor, water, supplies and machinery time in Northern Mexico. Hertel et al. (1996) empirically estimate the elasticity of substitution between land and nitrogen for corn production in Indiana to be around 1.15. Therefore, we believe our value of the substitution elasticity to be conservative.

Following common PMP practice, calibration parameters λ_{i1} are added to the land cost terms to allow for calibration against the reference acreage allocation. The calibration parameters λ_{i2} and λ_{i3} are added to allow calibration of the crop yield responses to water and fertilizer, as explained in section 2.4. As such, the main difference between our model and previous CES specifications of PMP objective functions is that we introduce shadow costs on *each* explicitly modeled input, as opposed to just one of them—typically, land. As such, our model is free from the under-determinacy inherent in previous models, where one of the inputs had to be singled out to allow for calibration against the reference allocation, and the attendant choice could have been seen as arbitrary. Hence, by further increasing the information set to include agronomic yield responses, one can remove the last piece of under-determinacy that was left in the specification of Mérel et al. (2011).

In the rest of the article, the calibration information at the reference allocation is denoted $(\bar{q}_i, \bar{x}_{ij}, \bar{\eta}_i, \bar{\lambda}, \bar{y}_{iW}, \bar{y}_{iN})$, where $\bar{\lambda}$ denotes the shadow price of land obtained from the first stage of PMP (Howitt, 1995b). The parameter $\bar{\eta}_i$ denotes the exogenous supply elasticity of crop i. The parameters $\bar{y}_{iW}$ and $\bar{y}_{iN}$ represent the agronomic information, in the form of elasticities of yield with respect to water and nitrogen application, respectively. The calibration problem consists of selecting the set of parameters $(\mu_i, \beta_{ij}, \delta_i, \lambda_{i1}, \lambda_{i2}, \lambda_{i3})$ so that the optimization model (1) replicates the observed input-output allocation $(\bar{q}_i, \bar{x}_{ij})$, the shadow price of land $\bar{\lambda}$ and the supply responses $\bar{\eta}_i$, and the yield responses calculated at the reference allocation coincide with $(\bar{y}_{iW}, \bar{y}_{iN})$.

2.1 Data sources

We apply model (1) to the representation of cropping activities in Yolo County, California. For crop acreage, we construct an average based on values published in the county agricultural commissioner reports for the years 2002-2008.

We choose to model input allocation among major field crops only, excluding perennial tree crops and non-irrigated pasture. Tree crops are excluded for simplification purposes, and because they require significant establishment costs. Non-irrigated pasture is usually grown on marginal land that is not suitable for field crops. The acreage distribution among modeled crops is shown in table 1. The modeled crops represent about 51% of total agricultural land in Yolo County, the rest being covered mainly by non-irrigated pasture (32%) and orchard and vineyard (7%). For each crop, the county

Table 1: Acreage distribution for field crops

Crop	Acreage share (%)
Alfalfa	25.06
Corn	3.07
Pasture (irrigated)	6.03
Rice	16.20
Safflower	6.80
Sunflower	6.30
Processing tomato	18.79
Wheat	17.75
Total	100.00

agricultural commissioner reports also provide information on yields and prices, that are averaged over the same period as acreages.

Own-price supply elasticities for corn, pasture, safflower, sunflower and wheat come from the statewide agricultural production (SWAP) model developed by R. Howitt (Jenkins et al., 2001). The supply elasticities for alfalfa, rice and processing tomato are updated based on the recent study by Russo et al. (2008).

Baseline water application rates for each crop are taken from the Cost and return studies published by the Department of Agricultural and Resource Economics at UC Davis.[2] The water price for Yolo County is based on water prices computed for the California SWAP model (`http://swap.ucdavis.edu/`).

Per acre costs, excluding water and fertilizer, are calculated using the Cost and return studies. Nitrogen application rates are imputed based on the methodology described in section 2.2, and are checked against the values published in the Cost and return studies to avoid any large discrepancies. Baseline fertilizer costs for each crop are obtained from the Cost and return studies.

2.2 Derivation of yield response elasticities

Since we intend to use the calibrated model to predict how the response of the cropping system to economic conditions, notably intensive margin adjustments, may affect environmental outcomes, it is crucial that the specified economic functions be consistent with reasonable agronomic priors regarding the relationship between regional yields and input intensities. The main reason is that environmental outcomes are assessed based on the predictions of a biophysical soil process model that relates input intensities to crop yield and environmental outcomes, conditional on local conditions such as soil and climate. Exploiting such a model to infer the environmental effects of policy, without paying attention to consistency in predicted yields between the biophysical and economic models, would be highly questionable, because yield effects are essentially linked to environmental outcomes. For instance, if the plant takes up more of the available nitrogen, resulting in higher yield, there should be less nitrogen left in the soil to leach in the form of nitrates.

However, current PMP models are not geared towards ensuring such consistency: as of now, studies have focussed on the replication of observed economic behavior, that is, input allocation among activities and, somewhat more recently, supply responses (Heckelei, 2002; Heckelei and Wolff, 2003; Mérel and Bucaram, 2010; Mérel et al., 2011). Below, we outline how the common calibration procedure can be amended to ensure

[2] These water application rates are admittedly not specific to Yolo County—though they are to the Sacramento Valley,—but they still represent the most reliable information at our disposal.

consistency not only with respect to economic information, but also with respect to agronomic priors, at the margin.

The biophysical model used in this study is the DAYCENT model (Del Grosso et al., 2008), calibrated for crops under California conditions (De Gryze et al., 2009, 2010). DAYCENT is a version of the CENTURY ecosystem model (Parton et al., 1987, 1994), that uses a daily time step. We use DAYCENT to generate regional (here, county-level) yield responses to irrigation water and nitrogen fertilizer. The agricultural region is divided into cells that can be considered homogenous in terms of local conditions (soil, climate), and regional yields are calculated as the weighted sum of yields in each cell, where the weights are commensurate with the cell size.[3] The process to generate regional yield response curves is as follows:

(i) we select the irrigation intensity for each crop based on information from the Cost and return studies,

(ii) given the selected irrigation intensity, DAYCENT is run for various nitrogen application rates,

(iii) an exponential yield response curve to nitrogen is fitted through the obtained simulation data,

(iv) we select the nitrogen application rate that would replicate the observed regional yield, obtained from the county agricultural commissioner reports,[4]

(v) given this baseline nitrogen application rate, DAYCENT is run for various water application rates, and

(vi) a sigmoid yield response curve to water is fitted through the obtained simulation data.

Following this process, we have, for each crop, a reference water application rate $\bar{a}_{iW}$, a reference nitrogen application rate $\bar{a}_{iN}$, and a reference yield $\bar{y}_i$. By construction, our observed yield is consistent with "observed" water and nitrogen application rates, in the sense that the observation point lies on both yield response curves.

[3]Not all soils can support production of a given crop. Therefore, regional yields for a crop are obtained from aggregating over only those cells for which production is agronomically relevant.

[4]For a couple of crops we selected the yield that would be replicated by the nitrogen application rate reported in the Cost and return study. For these crops, replicating the observed yield would have resulted in a nitrogen application rate far from that provided in the Cost and return study, whereas selecting the fertilizer rate from the Cost and return study did not result in a large departure from the observed yield. Therefore, in choosing which information to retain, we sought to minimize the departure from observed average yields and nitrogen application rates.

The fitted yield response curves $y_i(a_{iW}, \bar{a}_{iN})$ and $y_i(\bar{a}_{iW}, a_{iN})$ are then used to calculate the elasticity of regional yield with respect to the water and nitrogen application rates. Following common practice, the relationship between yield and nitrogen application, at the reference water application rate, is specified as the exponential function[5]

$$y_i(a_{iN}) = y_{i0} + \alpha_{iN}\left(1 - \exp(-\beta_{iN} a_{iN})\right)$$

where y_{i0} represents the minimum yield as nitrogen application goes to zero. Values for the parameters y_{i0}, α_{iN} and β_{iN} are obtained through nonlinear regression of a series of simulated yields on various nitrogen application scenarios, and by construction we have $\bar{y}_i = y_{i0} + \alpha_{iN}\left(1 - \exp(-\beta_{iN}\bar{a}_{iN})\right)$.[6] The elasticity of yield with respect to nitrogen application at the reference allocation can then be computed as

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

In a parallel fashion, the relationship between yield and water application, at the reference nitrogen application rate, is specified as

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

where the parameters a_{i0}, α_{iW} and β_{iW} are again estimated using nonlinear regression on a series of simulated yields. By construction, the reference yield lies on the fitted curve at the reference water application:

$$\bar{y}_i = \frac{\alpha_{iW}}{1 + \exp\left(-\frac{\bar{a}_{iW} - a_{i0}}{\beta_{iW}}\right)}.$$

[5]The same functional form is used by Godard et al. (2008).

[6]All of the regression coefficients of the agronomic yield response functions to water and nitrogen are statistically significant at the 1% level or better. Coefficient estimates for each crop are not reported here, but are available upon request to the authors.

The elasticitiy of output with respect to water can then be computed as

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

All yield response elasticities are reported in table 2.[7]

2.3 Calibration of supply elasticities

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

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

This paper follows the calibration method developed by Mérel et al. (2011), which permits the exact replication of an exogenous set of own-price supply elasticities. These authors show that the calibration problem for model (1) is recursive, in the sense that the parameters δ_i can be chosen independently of the other calibration parameters, in order to calibrate the model's own-price supply elasticities. The other parameters are then chosen, conditional on the values of the δ_is. Mérel et al. (2011) also show

[7] As a legume, alfalfa does not have a significant yield response to nitrogen application. Therefore, we set $\beta_{\text{alfalfa3}} = 0$. Similarly, rice is a flooded crop that does not show much response to water application around the calibration point, therefore we set $\beta_{\text{rice2}} = 0$. Irrigated pasture is not part of the set of calibrated crops in DAYCENT, thus we assume fixed proportions for this crop, that is, we set $\sigma_{\text{pasture}} = 0$.

Table 2: Crop yield and supply elasticities

Crop	b_i	$\bar{y}_{iW}$	$\bar{y}_{iN}$	$\bar{\eta}_i$
Alfalfa	72.99	0.21	-	0.44
Corn	11.86	0.22	0.11	0.55
Pasture (irrigated)	24.91	-	-	0.24
Rice	32.97	-	0.17	0.48
Safflower	46.83	0.05	0.25	0.45
Sunflower	26.03	0.26	0.00	0.63
Processing tomato	20.85	0.01	0.09	0.55
Wheat	132.77	0.06	0.11	0.36

Note: b_i denotes the ratio of acreage over gross revenue per acre. The parameters $\bar{\eta}_{iW}$ and $\bar{\eta}_{iN}$ denote the yield elasticities with respect to water and nitrogen. The parameter $\bar{\eta}_i$ denotes the own-price supply elasticity.

that not all sets of supply elasticities can be reproduced by model (1). They derive an explicit calibration criterion, and argue that when this criterion is met the solution to the calibration problem is unique. Adapting their notation to that used in the present paper, the calibration criterion requires that for all $i = 1, \ldots, I$:

$$\begin{cases} \bar{\eta}_i > \frac{\bar{y}_{iW}+\bar{y}_{iN}}{1-\bar{y}_{iW}-\bar{y}_{iN}} \\ b_i\bar{\eta}_i\left(1-\frac{\sigma_i(\bar{y}_{iW}+\bar{y}_{iN})}{\bar{\eta}_i(1-\bar{y}_{iW}-\bar{y}_{iN})}\right) < \sum_{j\neq i} b_j\bar{\eta}_j\left(1+\frac{1}{\bar{\eta}_j}\right)^2\left(1+\frac{\sigma_j(\bar{y}_{jW}+\bar{y}_{jN})}{\bar{\eta}_j(1-\bar{y}_{jW}-\bar{y}_{jN})-(\bar{y}_{jW}+\bar{y}_{jN})}\right) \end{cases} \tag{3}$$

where $b_i \equiv \frac{\bar{x}_{i1}^2}{p_i\bar{q}_i}$ represents the ratio of acreage to gross revenue per acre. The first inequality in (3) ensures that myopic elasticity calibration of the model would be feasible.[8] The second inequality puts an upper bound on each of the supply elasticities $\bar{\eta}_i$, that depends on the elasticities of other crops, thereby ensuring that no crop response "dominates" all others. In our application, the calibration criterion (3) is met for the set of elasticities reported in table 2, so that the model exactly replicates the exogenous supply response pattern.

2.4 Calibration to biophysical information

Calibration against agronomic yield response curves is achieved by setting the two elasticities derived in section 2.2 equal to the elasticities derived using the generalized

[8]Myopic elasticity calibration refers to calibration of the δ_is where the change in the shadow price of land λ is ignored. As such, a myopically calibrated model does not exactly replicate the exogenous supply elasticities.

CES economic production function:

$$\begin{cases} \bar{y}_{iW} = \delta_i \frac{\beta_{i2}\bar{x}_{i2}^{\rho_i}}{\sum_j \beta_{ij}\bar{x}_{ij}^{\rho_i}} \\ \bar{y}_{iN} = \delta_i \frac{\beta_{i3}\bar{x}_{i3}^{\rho_i}}{\sum_j \beta_{ij}\bar{x}_{ij}^{\rho_i}} \end{cases} \tag{4}$$

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), the first-order conditions of model (1) are:

$$\begin{cases} p_i\bar{q}_i\left(\delta_i - \bar{y}_{iW} - \bar{y}_{iN}\right) = \left(c_{i1} + \lambda_{i1} + \bar{\lambda}\right)\bar{x}_{i1} \\ p_i\bar{q}_i\bar{y}_{iW} = \left(c_2 + \lambda_{i2}\right)\bar{x}_{i2} \\ p_i\bar{q}_i\bar{y}_{iN} = \left(c_3 + \lambda_{i3}\right)\bar{x}_{i3} \end{cases} . \tag{5}$$

As long as $\bar{y}_{iW} + \bar{y}_{iN} < \delta_i$, a condition that is ensured by the first inequality in (3) and the fact that $\delta_i > \frac{\bar{\eta}_i}{1+\bar{\eta}_i}$,[9] system (5) determines acceptable values for the parameters λ_{ij}, $j = 1, \ldots, 3$. In essence, the shadow prices are chosen so that given the exogenously determined responsiveness of output to input intensities, embedded in the yield elasticities $\bar{y}_{iW}$ and $\bar{y}_{iN}$, the marginal value products of factors are equated to their full social cost, $c_j + \lambda_{ij}$. As such, this calibration rule follows the classical paradigm of PMP, whereby observed behavior is rationalized by adding unobserved, idiosyncratic components to market prices. Negative values for the λ_{ij}s thus indicate a "hidden benefit" from factor use, while negative values indicate a "hidden cost". For instance, a negative value of λ_{i3} would indicate that farmers obtain a shadow benefit from applying more fertilizer to crop i, that is not being captured by the yield effect, for instance an insurance value against weather shocks.

Table 3 reports the calculated values of the parameters λ_{ij}. The signs of the cost adjustments for water and nitrogen vary by crop. For all crops but processing tomato and safflower, the sign of λ_{i2} is positive, indicating a hidden cost for water, that could be related to water scarcity at the county level. In contrast, for processing tomato the hidden benefit offsets most of the market cost of water, indicating that farmers are benefiting from adding water well beyond the agro-economic optimum dictated by observed market prices and the yield response function.

Half of the crops display a hidden benefit from nitrogen application. Sunflower displays the largest relative benefit from nitrogen, as the shadow benefit nearly offsets the market price of fertilizer. Figure 10 in Appendix B provides an explanation for this fact, as the observation point lies in the flatter portion of the agronomic yield response curve, indicating that farmers could reduce nitrogen without losing much

[9]See Mérel et al. (2011), proposition (2).

yield. One explanation for over-fertilization that is often discussed among experts is that "fertilizer is so cheap that farmers apply it without really counting." This departure from standard economic principles, if it existed, would indeed be captured in our model by the parameter λ_{i3}: though the market price of fertilizer is \$0.53/lb N for sunflower, farmers behave as if it were only \$0.01. In contrast, rice displays a large shadow cost for fertilizer, indicating that farmers are not applying as much nitrogen as would be dictated by the yield response and the market prices.

Table 3: Factor costs and shadow costs

Crop	$c_{i1} + \tilde{\lambda}$ (\$/acre)	λ_{i1} (\$/acre)	c_{i2} (\$/ac-ft)	λ_{i2} (\$/ac-ft)	c_{i3} (\$/lb N)	λ_{i3} (\$/lb N)
Alfalfa	358.37	-259.40	17.72	20.46	-	-
Corn	266.06	-246.44	17.72	10.42	0.56	-0.29
Pasture (irrigated)	265.76	-158.74	-	-	-	-
Rice	329.67	-149.68	-	-	0.30	1.29
Safflower	89.71	-80.01	17.72	-4.48	0.33	0.43
Sunflower	173.09	-101.17	17.72	24.42	0.53	-0.52
Processing tomato	847.57	-329.67	17.72	-14.35	0.65	0.37
Wheat	182.18	-136.95	17.72	12.15	0.95	-0.63

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 $\bar{q}_i = \mu_i \left(\sum_j \beta_{ij} \bar{x}_{ij}^{\rho_i}\right)^{\frac{\delta_i}{\rho_i}}$. This last step concludes the calibration phase.

Figures 1-6 in Appendix A illustrate the resulting calibration of the yield responses to water. The blue curve depicts the fitted agronomic response, while the green curve shows the economic yield function, evaluated at the reference acreage $\bar{x}_{i1}$ and the reference nitrogen application rate $\bar{a}_{iN}$. The calibrated yield responses with respect to nitrogen, evaluated at $\bar{x}_{i1}$ and $\bar{a}_{iW}$, are shown in figures 7-12 in Appendix B. Overall, the curves demonstrate that at the observed acreage allocation, the yield responses of the economic model are consistent with agronomic priors over a reasonable range of input application rates around the calibration point.

3 Policy experiments

Our economically- and agronomically-calibrated model is applied to the study of the economic and environmental effects of a nitrogen tax in Yolo County, California. Nitrogen taxes have been suggested as a potential remedy to non-point source nitrogen pollution in agriculture (Huang and LeBlanc, 1994; Choi and Feinerman, 1995; Helming, 1998; Graveline and Rinaudo, 2007; Durandeau et al., 2010). The two main avenues of nitrogen pollution in cropping are field emissions of nitrous oxide (N_2O), a very potent greenhouse gas (GHG), and nitrate leaching in groundwater and streams.

California's Air Resources Board estimates that N_2O contributed 2.8% of California's total GHG emissions in 2004 (Air Resources Board, 2011). Agricultural soil was the largest source of N_2O, accounting for approximately 50% of the State's total N_2O emissions. Current methods estimate that on average, approximately 50% of the nitrogen fertilizer applied in the field is lost to the transport pathways of volatilization, leaching and runoff (Ladha et al., 2005).

To comprehend the effect of a nitrogen tax on behavioral and environmental outcomes, it is useful to decompose the total effect into its two elementary economic responses: an *extensive margin* effect, that is, the reallocation of acreage among crops, and an *intensive margin* effect, that is, the change in input intensity per acre, for a given crop. Both effects are operating simultaneously, and we show below that in our application the intensive margin effect, which has been overlooked in existing PMP studies (Helming, 1998), is likely to be large. Hence, to anticipate the full effect of a nitrogen tax policy, it is necessary to accurately model the intensive margin response, in addition to the extensive margin response.

3.1 Behavioral adjustments

We focus most of our discussion on the effect of the tax on nitrogen employment, although it is clear from the specification in (1) that the tax will also induce changes in water application. The total amount of nitrogen applied at the regional level is $X_3 = \sum_{i=1}^{I} x_{i3}(c_{i3})$, where economic variables other than c_{i3} are being held constant and hence are omitted from the notation. Let us denote by c_N the price of nitrogen. We consider nitrogen taxes ranging from 4 ¢/lb N up to 16 ¢/lb N. The highest tax considered would represent a 50% increase in the price of urea. Because the fertilizer rates x_{i3} are counted in pounds of nitrogen, with other nutrients held in fixed proportions, it is the case that $\frac{dc_{i3}}{dc_N} = 1$. Writing $x_{i3}(c_{i3}) = \frac{x_{i3}}{x_{i1}}(c_{i3}) \times x_{i1}(c_{i3}) = a_{iN}(c_{i3}) \times x_{i1}(c_{i3})$, the total behavioral effect can be decomposed as:

$$\underbrace{\frac{dX_3}{dc_N}}_{\text{total effect}} = \underbrace{\sum_{i=1}^{I} a_{iN} \times \underbrace{\frac{dx_{i1}}{dc_{i3}}}_{\text{acreage effects}}}_{\text{extensive margin effect}} + \underbrace{\sum_{i=1}^{I} x_{i1} \times \underbrace{\frac{da_{iN}}{dc_{i3}}}_{\text{N rate effects}}}_{\text{intensive margin effect}} \tag{6}$$

where the first term can be interpreted as the extensive margin (acreage reallocation) effect and the second term as the intensive margin (nitrogen application) effect.

Table 4 shows the acreage reallocation pattern for all crops under various nitrogen tax scenarios. Alfalfa and safflower expand, while other crop acreages decrease or remain stable. At all tax levels, corn and wheat experience the largest relative reductions in acreage. To understand the pattern of land reallocation, it suffices to derive the acreage reactivities of each crop to the two prices that are changing, namely the price of fertilizer and the shadow price of land. To see why, note that the total acreage effect for a crop can itself be decomposed as

$$\frac{dx_{i1}}{dc_N} = \frac{\partial x_{i1}}{\partial \lambda}\frac{d\lambda}{dc_N} + \frac{\partial x_{i1}}{\partial c_{i3}} \tag{7}$$

where $\frac{\partial x_{i1}}{\partial \lambda}$ denotes the acreage reactivity of crop i to changes in the price of land, and $\frac{\partial x_{i1}}{\partial c_{i3}}$ denotes its acreage reactivity to changes in the price of fertilizer. Because a nitrogen tax decreases the overall returns to land, the derivative $\frac{d\lambda}{dc_N}$ is negative. The acreage reactivity to land price changes can be calculated as[10]

$$\frac{\partial x_{i1}}{\partial \lambda} = -\left(\frac{b_i}{\delta_i(1-\delta_i)} + \frac{\sigma_i b_i(\bar{y}_{iW} + \bar{y}_{iN})}{\delta_i(\delta_i - \bar{y}_{iW} - \bar{y}_{iN})}\right) \tag{8}$$

where the first condition in (3) ensures that both terms in the bracket are positive (law of derived demand). The acreage reactivity to fertilizer price changes is[11]

$$\frac{\partial x_{i1}}{\partial c_{i3}} = -\left(\frac{b_i}{\delta_i(1-\delta_i)} - \frac{\sigma_i b_i}{\delta_i}\right)\frac{\bar{x}_{i3}}{\bar{x}_{i1}} \tag{9}$$

a relation that shows that under our maintained assumption that $\delta_i < 1$ and $\sigma_i < 1$, fertilizer and land are gross complements, in the sense that a rise in the price of fertilizer, holding constant all other prices (including λ), results in a reduction in acreage. (The same would be true for water employment.) Therefore, the two terms in equation (7) always have opposite signs and thus the sign of the total effect $\frac{dx_{i1}}{dc_N}$ essentially depends on the relative magnitudes of the two acreage reactivities in (8) and (9).

Note that, if the elasticity of substitution between inputs σ_i were arbitrarily small, then the sign of the total acreage effect would only depend on the ratio $\frac{\bar{x}_{i3}}{\bar{x}_{i1}}$, that is, the fertilizer application rate, and the ratio $\left|\frac{d\lambda}{dc_N}\right|$. Since $\left|\frac{d\lambda}{dc_N}\right|$ does not depend on the crop, crops experiencing an acreage contraction would be those that have higher

[10]The derivation of this expression can be found on page 9 of the appendix to Mérel et al. (2011).
[11]See Appendix C for the derivation of this expression.

fertilization rates. Though we assume here that $\sigma_i = 0.2$, this characterization remains true to some extent. In particular, corn, processing tomatoes and rice are the crops with the highest fertilization rates, and they all experience acreage contractions, at the margin. In contrast, wheat acreage is contracting while safflower acreage is expanding, though safflower has a marginally higher nitrogen fertilization rate than wheat in the reference allocation (102.3 lbs/ac, as opposed to 101.7 lbs/ac for wheat). This is due to substitution between inputs: safflower experiences a greater reduction in nitrogen fertilization than wheat, and thus becomes less nitrogen-intensive than wheat.

Table 4: Acreage effects

Crop		Increase in nitrogen price			
		4 ¢/lb N	8 ¢/lb N	12 ¢/lb N	16 ¢/lb N
Alfalfa	(%)	1.30	2.46	2.86	2.52
Corn	(%)	-2.11	-4.00	-7.29	-11.95
Pasture (irrigated)	(%)	0.62	0.99	0.14	-1.80
Rice	(%)	-0.60	-1.28	-2.41	-3.95
Safflower	(%)	2.97	7.04	7.47	2.61
Sunflower	(%)	-0.09	-0.03	-0.82	-2.44
Processing tomato	(%)	-0.76	-1.56	-2.56	-3.75
Wheat	(%)	-1.42	-2.97	-6.07	-10.47

Tables 5 and 6 show the induced changes in input intensities per acre for all activities. All crops experience a reduction in their fertilizer and water application rates when the nitrogen price increases. The crop that is the most responsive to the nitrogen price increase, in terms of the application rate of fertilizer, is sunflower. Looking at figures 7-12 in Appendix B, this does not come as a surprise, since this is the only crop for which the observation point seems to lie on the flatter portion of the yield response curve to nitrogen. That is, for other crops reductions in nitrogen application cause more drastic losses in yields. Also note that at the higher tax level considered, the intensive margin responses appear to level out, particularly for water application. Therefore, input application rates stabilize at higher tax levels, as the implied yield loss from further reductions in input intensity becomes very large.

Although the decomposition of the total behavioral effect in (6) holds at the margin only, we can decipher the relative importances of the extensive margin effect and the intensive margin effect for non incremental nitrogen price changes by comparing the following metrics: $\sum_i \bar{a}_{iN} \times \Delta x_{i1}$ (extensive margin effect) and $\sum_i \bar{x}_{i1} \times \Delta a_{iN}$ (intensive margin effect). Results are presented in table 7. It appears that the intensive margin

Table 5: Water intensity effects

Crop		Increase in nitrogen price			
		4 ¢/lb N	8 ¢/lb N	12 ¢/lb N	16 ¢/lb N
Alfalfa	(%)	-0.36	-0.68	-0.79	-0.70
Corn	(%)	-2.36	-4.70	-5.92	-5.92
Pasture (irrigated)	(%)	-	-	-	-
Rice	(%)	-	-	-	-
Safflower	(%)	-5.03	-10.71	-14.09	-14.09
Sunflower	(%)	-0.62	-1.19	-1.48	-1.48
Processing tomato	(%)	-0.09	-0.16	-0.20	-0.20
Wheat	(%)	-0.99	-1.93	-2.39	-2.39

Table 6: Fertilizer intensity effects

Crop		Increase in nitrogen price			
		4 ¢/lb N	8 ¢/lb N	12 ¢/lb N	16 ¢/lb N
Alfalfa	(%)	-	-	-	-
Corn	(%)	-5.05	-9.56	-12.65	-14.35
Pasture (irrigated)	(%)	-	-	-	-
Rice	(%)	-0.74	-1.44	-2.02	-2.47
Safflower	(%)	-6.00	-12.48	-16.57	-17.30
Sunflower	(%)	-22.75	-31.06	-35.89	-39.11
Processing tomato	(%)	-0.85	-1.65	-2.39	-3.06
Wheat	(%)	-3.26	-6.13	-8.32	-9.88

effect is responsible for the bulk of the behavioral response, with acreage adjustments playing only a minor role, except at higher tax levels where the intensive margin adjustments are starting to level out. These results suggest that for small increases in nitrogen price, reductions in total nitrogen application at the regional scale will mostly be due to intensive margin responses, while at higher tax levels further reductions will essentially come from crop reallocation. However, it is notable that even at moderate tax levels, some individual crops are predicted to experience sizable variations in acreage. As such, assuming that crop acreages remain constant would likely not constitute a reasonable modeling choice.

Table 7: Extensive and intensive margin effects

Effect	Increase in nitrogen price			
	4 ¢/lb N	8 ¢/lb N	12 ¢/lb N	16 ¢/lb N
Extensive margin (%)	-0.54	-1.03	-2.48	-4.93
Intensive margin (%)	-3.34	-5.66	-7.29	-8.30
Total (%)	-3.87	-6.68	-9.65	-12.81

3.2 Welfare effects

The behavioral adjustments derived previously dictate changes in economic welfare measures. Because the tax is distorting production decisions, it has a negative effect on social surplus, ignoring the environmental benefits from reduced nitrogen losses. In our model, land is the sole residual claimant. Table 8 reports the calculated changes in returns to land ownership, the tax revenue generated, and the change in social surplus, defined as the sum of land returns and tax revenue. Land returns are equal to the maximized value of the objective function in (1), and are thus inclusive of all shadow costs. The values reported imply that the deadweight cost of the policy is moderate, about -0.2% in social surplus at the highest tax level considered.

Table 8: Returns to land ownership and tax revenue

Scenarios	Returns to land ownership		Tax revenue	Social surplus loss
	(million dollar)	% change	(1,000 dollar)	(1,000 dollar)
Base case	124.79	-	-	-
4 ¢/lb N	124.00	-0.63	771.65	-14.01
8 ¢/lb N	123.24	-1.24	1498.13	-47.61
12 ¢/lb N	122.50	-1.83	2175.80	-107.92
16 ¢/lb N	121.79	-2.40	2799.60	-196.47

3.3 Environmental outcomes

Nitrogen employment at the regional level is not necessarily monotonically related to the environmental outcomes of interest. That is, an overall reduction in nitrogen employment ($\Delta X_3 < 0$) may or may not be related to a decrease in nitrate leaching or a decrease in N_2O emissions from agricultural fields, mainly because these environmental effects are highly dependent on the crop, and acreage is being reallocated among crops. One complicating factor in particular is that the more nitrogen-saving crops may not be the ones with lower nitrogen leaching and/or N_2O emissions per acre. For instance, in our model wheat has a higher nitrogen fertilization rate than sunflower, yet its N_2O emission rate is less than a fourth of that of sunflower. Therefore, to correctly infer the environmental effects of the policy, it is essential to couple the economic optimization representation of the cropping system with a biophysical model that can predict nitrogen losses, conditional on the choice of crop and input intensities.

Here, we exploit the predictions of the DAYCENT model in terms of nitrate leaching and N_2O emissions to recover the environmental effects of the tax policy. Since irrigated pasture is not calibrated in DAYCENT, we assume that nitrogen losses for this crop are the same as those for alfalfa.[12]

Tables 9 and 10 show the environmental effects of the increase in nitrogen price for each crop on a per acre basis. These tables make clear that intensive margin adjustments always have the intended effect on the environmental outcomes of interest: for each crop, a reduction in nitrogen intensity is associated with a decrease in both nitrate leaching and N_2O emissions. In addition, the attendant environmental effects can be significant. For instance, there seems to be a sharp reduction in nitrate leaching for corn and sunflower. Changes in field emissions of N_2O on a crop-by-crop basis appear to be more modest, except maybe for corn.

Table 9: Nitrate leaching change for each crop due to intensive margin adjustments (%)

Crop	Increase in nitrogen price			
	4 ¢/lb N	8 ¢/lb N	12 ¢/lb N	16 ¢/lb N
Alfalfa	-2.07	-3.29	-4.06	-4.56
Corn	-8.42	-15.28	-19.84	-22.43
Pasture (irrigated)	-2.07	-3.29	-4.06	-4.56
Rice	-0.91	-1.73	-2.32	-2.78
Safflower	-4.13	-7.90	-10.42	-11.37
Sunflower	-12.55	-17.52	-20.50	-22.45
Processing tomato	-2.65	-4.41	-5.72	-6.76
Wheat	-4.24	-7.19	-9.27	-10.78

However, the story is more nuanced when looking at aggregate regional effects. Table 11 reports the total environmental outcomes at the regional scale, taking into account

[12]This is hardly a satisfactory assumption. We were not able to find measures of nitrate leaching or N_2O emissions for pasture in the literature. However, we note that since the acreage change for irrigated pasture is extremely small, the contribution of this crop to changes in nitrogen applied regionally, and attendant environmental outcomes, is likely negligible, at least under our maintained fixed-proportion assumption for this crop.

Table 10: N_2O emissions change for each crop due to intensive margin adjustments (%)

Crop	Increase in nitrogen price			
	4 ¢/lb N	8 ¢/lb N	12 ¢/lb N	16 ¢/lb N
Alfalfa	-0.61	-1.08	-1.37	-1.52
Corn	-5.23	-9.47	-12.69	-14.56
Pasture (irrigated)	-0.61	-1.08	-1.37	-1.52
Rice	-0.96	-1.81	-2.45	-2.97
Safflower	-3.81	-7.85	-10.48	-11.32
Sunflower	-6.21	-8.84	-10.47	-11.56
Processing tomato	-1.39	-2.48	-3.30	-3.95
Wheat	-3.01	-5.53	-7.39	-8.69

all margins of adjustment, while table 12 is constructed assuming that leaching and N_2O emissions per acre and per crop are fixed at their pre-tax values, so that the only changes in environmental indicators stem from the observed crop reallocation pattern. Assuming away changes in nitrogen and water application, it appears that the acreage reallocation effect does little for mitigating nitrogen pollution, especially at lower tax levels. However, as tax levels rise and intensive margin adjustments level out, acreage reallocation among crops begins to play a more significant role in the environmental response. At the highest tax level considered here, the extensive margin effect accounts for about 45% of the total effect for N_2O emissions, and 30% for nitrate leaching.

Still, at all tax levels, total effects for both environmental outcomes are sizable, thanks to relatively strong intensive margin adjustment effects, as is clear from table 11. The induced reductions in nitrogen and water application rates appear to have a particularly strong effect on nitrate leaching. Overall, the tax scheme seems more effective at reducing nitrate leaching than field emissions of N_2O.

4 Conclusion

The present study demonstrates the usefulness of combining information obtained from observed economic behavior (input and output allocation, estimates of crop supply elasticities) with information simulated by a calibrated biophysical model, to infer the environmental effects of a policy that is likely to have effects both at the extensive and intensive margins.

The novelty of the approach presented here lies in the use of agronomic information, in the form of crop yield responses to water and nitrogen, to calibrate economic

Table 11: Aggregate environmental outcomes, total effect

Scenarios	Nitrate leaching		N_2O flux	
	Quantity (tonne N/yr)	% Change from base case	Quantity (tonne N/yr)	% Change from base case
Base case	4659.66	-	166.00	-
4 ¢/lb N	4433.82	-4.85	162.28	-2.24
8 ¢/lb N	4294.50	-7.84	159.37	-3.99
12 ¢/lb N	4164.28	-10.63	156.06	-5.99
16 ¢/lb N	4029.96	-13.51	152.21	-8.31

Table 12: Aggregate environmental outcomes, extensive margin effect only

Scenarios	Nitrate leaching		N_2O flux	
	Quantity (tonne N/yr)	% Change from base case	Quantity (tonne N/yr)	% Change from base case
Base case	4659.66	-	166.00	-
4 ¢/lb N	4638.26	-0.46	165.37	-0.38
8 ¢/lb N	4618.57	-0.88	164.75	-0.76
12 ¢/lb N	4564.30	-2.05	162.98	-1.82
16 ¢/lb N	4474.22	-3.98	160.03	-3.60

production functions that explicitly allow for input substitution. This feature of our model necessitates the addition of crop-specific shadow prices for water and nitrogen to the generalized CES model proposed by Mérel et al. (2011). These shadow factor prices, very much like the calibration duals first introduced by Howitt (1995b), reflect "hidden" costs or benefits of input application that are not captured by the agronomic response functions, but instead are revealed by the observed economic behavior.

The calibration approach was implemented on a simplified model of crop agriculture for Yolo County, California, to investigate the economic and environmental effects of a nitrogen tax. Results suggest that even with a moderate value for the elasticity of substitution between inputs, intensive margin adjustments are likely to constitute a very significant part of the behavioral response to nitrogen price increases at lower tax levels. As tax levels increase and reductions in input application rates start to level out due to yield effects, extensive margin adjustments start to play a more significant role in the reduction of nitrogen employment at the regional scale.

Environmental effects are not perfectly correlated with behavioral outcomes. Over the range of taxes considered here, intensive margin adjustments are responsible for the bulk of the environmental benefits from the policy. This is because nitrogen-saving crops are not necessarily the ones with the lowest leaching and N_2O emissions factors, so that crop reallocation, even when it works towards a reduction of regional nitrogen application, may not contribute significantly to reductions in leaching and/or field emissions.

Overall, these results suggest the need to better account for variability in input use in models of agricultural supply, especially when modeling the effects of agri-environmental policies that are likely to influence the intensive margins. The coupling of biophysical process models with economic information obtained at a more aggregate level represents a promising avenue in this respect. The integration of the agricultural sector into climate change mitigation efforts worldwide represents an important and timely policy issue, the study of which could benefit from the approach proposed in this paper.

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Appendix

A. Yield responses to water

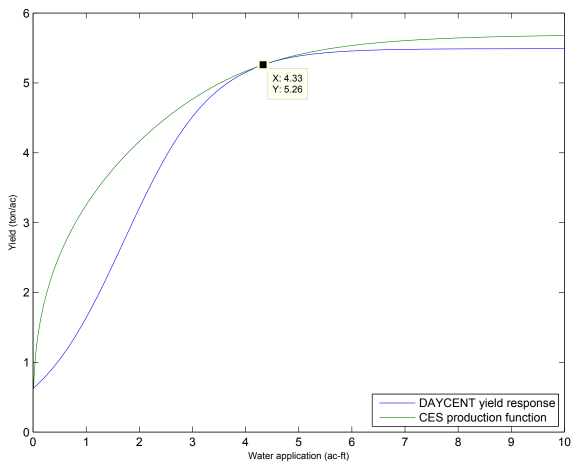

Figure 1: Corn

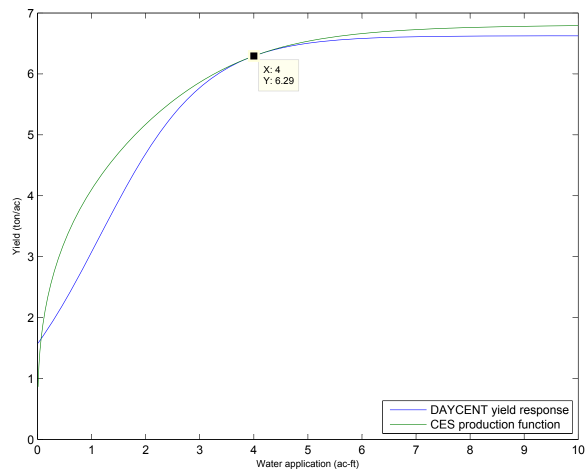

Figure 2: Alfalfa

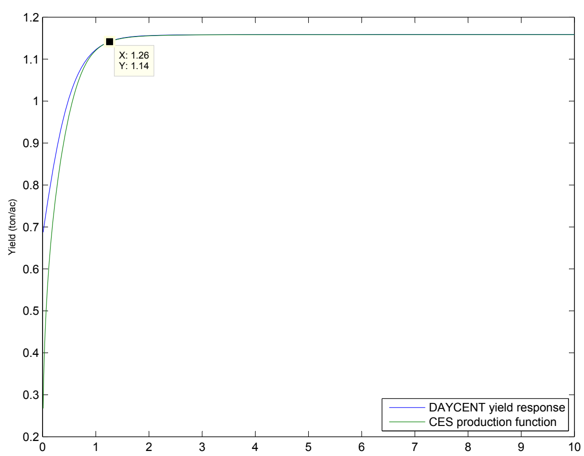

Figure 3: Safflower

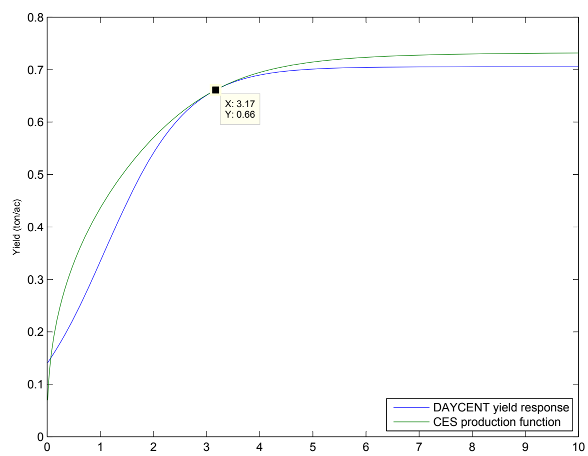

Figure 4: Sunflower

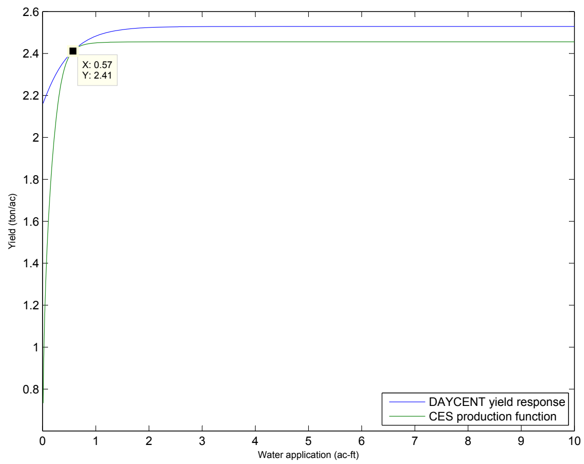

Figure 5: Wheat

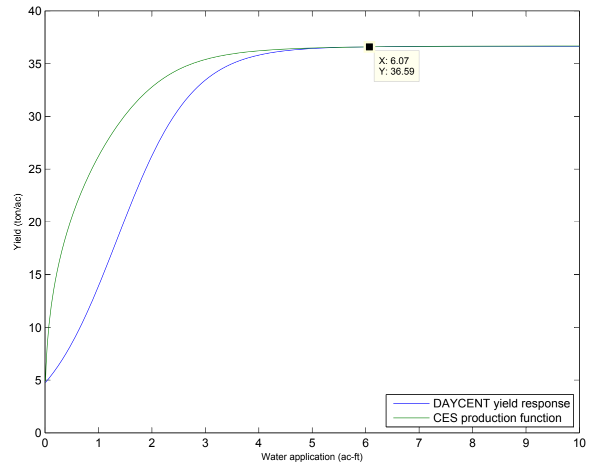

Figure 6: Tomato

B. Yield responses to nitrogen

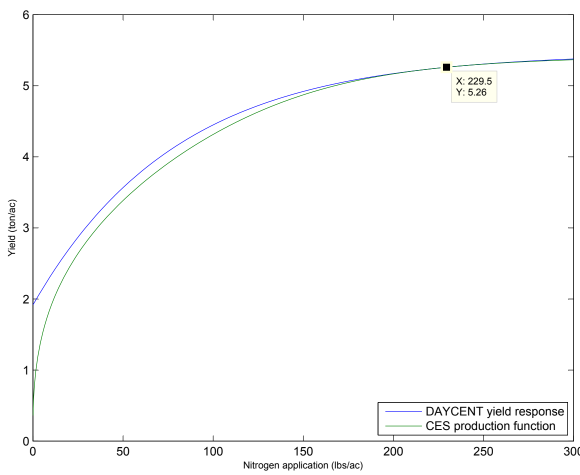

Figure 7: Corn

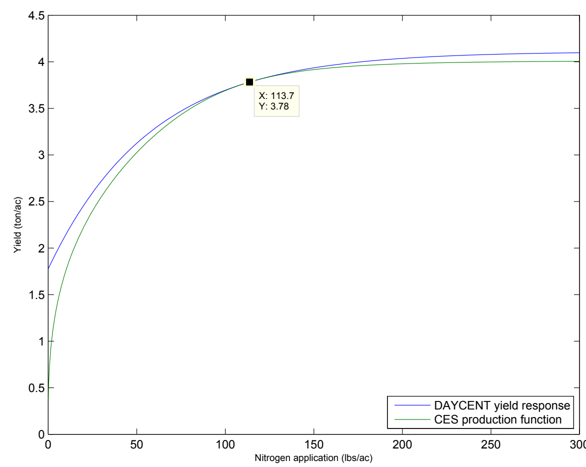

Figure 8: Rice

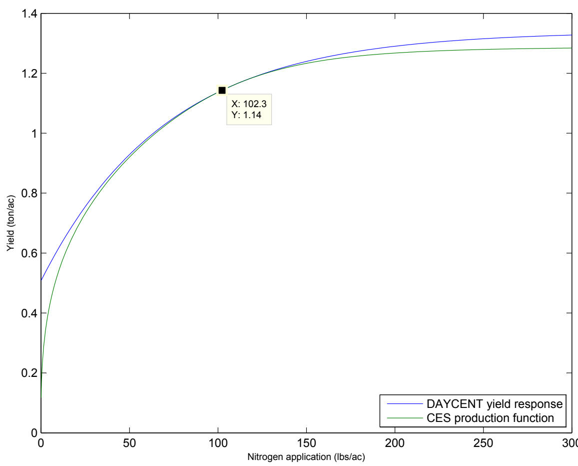

Figure 9: Safflower

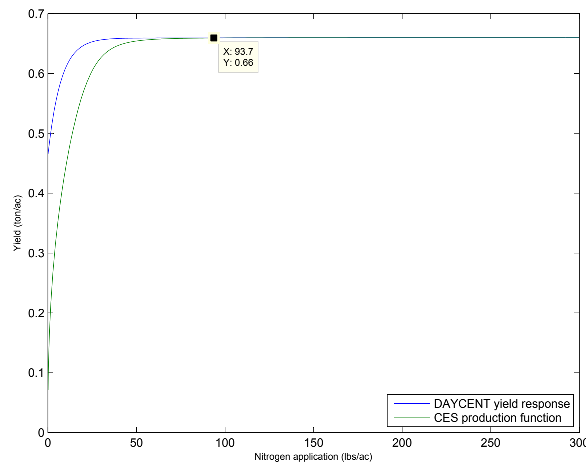

Figure 10: Sunflower

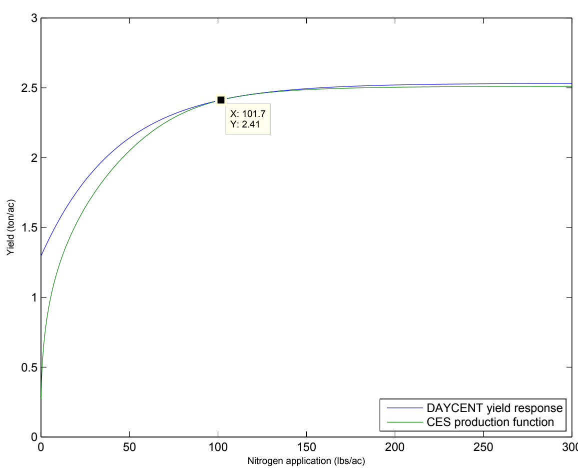

Figure 11: Wheat

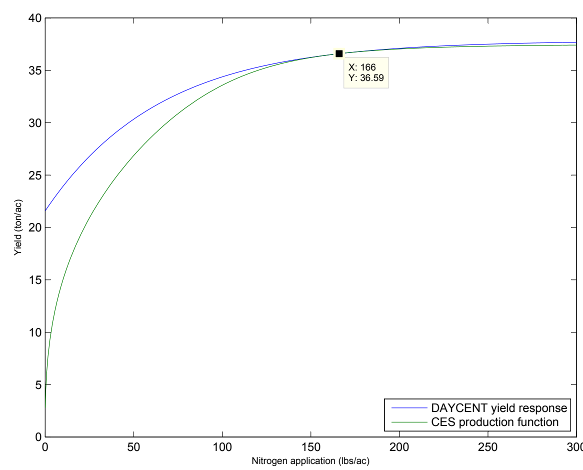

Figure 12: Tomato

C. Derivation of expression (9)

We drop the crop index to alleviate notation. Denote $\bar{c}_1 = c_1 + \bar{\lambda} + \lambda_1$, $\bar{c}_2 = c_2 + \lambda_2$ and $\bar{c}_3 = c_3 + \lambda_3$. Thus, the $\bar{c}_j$s represent the full factor costs, inclusive of all shadow components. The first-order conditions for optimization of the profit from a given crop are

$$p\mu\delta \left(\sum_l \beta_l {x_l}^{\rho} \right)^{\frac{\delta}{\rho}-1} \beta_j {x_j}^{\rho-1} = \bar{c}_j \quad \forall\, j = 1, \dots, 3. \tag{10}$$

Therefore, x_2 and x_3 can be expressed as functions of x_1: $x_2 = \left(\frac{\beta_1}{\beta_2}\frac{\bar{c}_2}{\bar{c}_1}\right)^{\frac{1}{\rho-1}} x_1$ and $x_3 = \left(\frac{\beta_1}{\beta_3}\frac{\bar{c}_3}{\bar{c}_1}\right)^{\frac{1}{\rho-1}} x_1$. Plugging these expressions back into the first-order condition with respect to x_1 and defining $\beta_1' = \beta_1 + \beta_2 \left(\frac{\beta_1}{\beta_2}\frac{\bar{c}_2}{\bar{c}_1}\right)^{\frac{\rho}{\rho-1}} + \beta_3 \left(\frac{\beta_1}{\beta_3}\frac{\bar{c}_3}{\bar{c}_1}\right)^{\frac{\rho}{\rho-1}}$, we obtain:

$$p\mu\delta \left(\beta_1'(\bar{c}_3)\right)^{\frac{\delta}{\rho}-1} \beta_1 x_1^{\delta-1} - \bar{c}_1 = 0 \tag{11}$$

where we have made explicit the fact that $\bar{c}_3$ appears in the expression of β_1'. The derivative $\frac{\partial x_1}{\partial \bar{c}_3}$ can be obtained as

$$\begin{aligned}
\frac{\partial x_1}{\partial \bar{c}_3} &= -\frac{p\mu\delta\beta_1 x_1^{\delta-1}\left(\frac{\delta}{\rho}-1\right)(\beta_1')^{\frac{\delta}{\rho}-2}\beta_3\left(\frac{\beta_1}{\beta_3\bar{c}_1}\right)^{\frac{\rho}{\rho-1}}\left(\frac{\rho}{\rho-1}\right)(\bar{c}_3)^{\frac{\rho}{\rho-1}-1}}{p\mu\delta(\beta_1')^{\frac{\delta}{\rho}-1}\beta_1(\delta-1)x_1^{\delta-2}} \\
&= -\frac{x_1\left(\frac{\delta}{\rho}-1\right)\left(\frac{\rho}{\rho-1}\right)\beta_3^{-\frac{1}{\rho-1}}\beta_1^{\frac{\rho}{\rho-1}}(\bar{c}_1)^{-\frac{\rho}{\rho-1}}(\bar{c}_3)^{\frac{1}{\rho-1}}}{\beta_1'(\delta-1)} \\
&= -\frac{(\delta-\rho)\sigma\beta_1\left(\frac{\beta_1}{\beta_3}\frac{\bar{c}_3}{\bar{c}_1}\right)^{\frac{1}{\rho-1}}x_1}{(1-\delta)\beta_1'\bar{c}_1} \\
&= -\frac{(\delta-\rho)\sigma\beta_1 x_3}{(1-\delta)\beta_1'\bar{c}_1} \\
&= -\frac{(\delta-\rho)\sigma\beta_1 x_3}{(1-\delta)p\mu\delta(\beta_1')^{\frac{\delta}{\rho}}\beta_1 x_1^{\delta-1}} \\
&= -\frac{(\delta-\rho)\sigma x_3}{(1-\delta)pq\delta x_1^{-1}} \\
&= \frac{\sigma x_1 x_3}{pq\delta} - \frac{x_1 x_3}{pq\delta(1-\delta)}
\end{aligned}$$

where we have made use of $\sigma = \frac{1}{1-\rho}$ and $q = \mu(\beta_1')^{\frac{\delta}{\rho}} x_1^{\delta}$. Evaluated at the reference allocation, this derivative becomes

$$\frac{\partial x_1}{\partial \bar{c}_3} = \frac{\sigma b}{\delta}\frac{\bar{x}_3}{\bar{x}_1} - \frac{b}{\delta(1-\delta)}\frac{\bar{x}_3}{\bar{x}_1}$$

where we have used $b = \frac{\bar{x}_1^2}{p\bar{q}}$. Equation (9) follows.