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The net carbon benefits value of adopting cover crops

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We model an agricultural production technology that integrates agricultural revenue, carbon sequestration, and greenhouse gas (GHG) emissions. The model accommodates cover crop and non-cover crop practices. We calculate carbon sequestration and GHG emissions shadow prices by quantifying the willingness to accept to increase sequestration and to reduce GHG emissions further. Our findings are based on a nonparametric data envelopment analysis (DEA) and a sample of corn fields in Illinois. We find that cover crop fields exhibit superior carbon benefits, valued at USD 27.30 per acre, compared to non-cover crop fields. This value falls within the higher range of payments for cover crop adoption in voluntary carbon markets available to Midwest farms, limiting broader adoption of cover crops.

Key words: cover crops; DEA; GHG emissions; net carbon footprint; shadow price

1. Introduction

In 2021, agriculture represented about 10% of the total US greenhouse gas (GHG) emissions of 6,340.2 million metric tons of carbon dioxide equivalent (MMT CO_2 eq., Environmental Protection Agency - EPA 2023). US net emissions, factoring in carbon sequestration, amounted to 5,586 MMT CO_2 eq., with agricultural cropland contributing 2.5% to sequestration (18.9 MMT CO_2 eq.). The main GHGs generated by crop production are nitrous oxide (N_2O), methane (CH_4), and CO_2 that result from nitrogen (N) fertilizers, soil management, and energy use. N_2O is especially harmful. It has 273 times the warming potential of CO_2

over a 100-year period. The EPA estimates that N fertilizers are responsible for 75% of the US N_2O emissions and half of the agricultural GHG emissions.

Growing concerns about climate change and the incentives offered by carbon markets have led farmers to adopt more sustainable agricultural practices (for example, IL-Corn 2023, ISA 2023). Agriculture offers two pathways to reduce its net carbon footprint: adopt management practices that reduce GHG emissions, and store carbon in the soil (Freibauer et al. 2004, Smith 2004). Both involve cost.

The complex relationship between agricultural inputs, intended and unintended outputs (crop production and carbon sequestration, and GHG emissions) makes assessing the cost of reducing agriculture's net carbon footprint challenging. We use management-science and operations-research tools to investigate these costs and to derive shadow prices for carbon sequestration and GHG emissions. These shadow prices measure the private costs of sequestration-enhancing and GHG reduction practices. The GHG emissions reduction strategies include careful use of N fertilizers, minimum mechanized field work, and adoption of extensive production practices. The sequestration-enhancing practices include growing cover crops. Because adopting cover crops reduces agriculture's carbon footprint, we pay especial attention to studying the value of adoption from agriculture's perspective. This facilitates assessing the compensation that carbon markets can offer to fields when converting to cover crops.

We develop an agricultural production technology model that integrates agricultural revenue, carbon sequestration, and greenhouse gas (GHG) emissions. The model accommodates cover crop and non-cover crop agricultural practices. We derive the shadow prices for sequestration and GHG emissions using the production technology and a non-parametric approach. Specifically, we develop an innovative data envelopment analysis (DEA) representation to model the intersection between agriculture and the environment while using the marginal-value approach of Podinovski et al. (2016) to obtain shadow prices.

Previous research has provided shadow prices for outputs that lack market prices (Färe et al. 1993, 2012, Matsushita and Yamane 2012, Murty et al. 2006, Wang et al. 2021). While the estimation of industrial-pollution shadow prices is widespread, less attention has been directed to agricultural pollution (see Färe et al. 2006, Tang et al. 2016, Khataza et al. 2017 and Bierkens et al. 2019 for a few exceptions). Although some studies have addressed shadow pricing of agricultural GHG emissions, to our knowledge, none have derived agricultural sequestration shadow prices. Wu et al. (2018) utilize a non-parametric directional distance function to obtain the shadow price of agricultural carbon emissions in 30 provinces in China. De Cara and Jayet (2000) focus on shadow pricing of net agricultural GHG emissions from the French agricultural sector using a maximum revenue linear programming model. Njuki and Bravo-Ureta (2015) derive the shadow price of GHG emissions from the US dairy industry using a parametric directional output distance function. These studies model GHG emissions abatement using a reduced-form representation of the production technology that cannot account for the interdependence between inputs, intended outputs, and by-products (see, for example, Murty et al. 2012 and Chen 2014).

Murty et al. (2012) model pollution and intended production to capture the salient features of by-production. These include the inability to reduce by-products when inputs and intended outputs remain constant and the interdependence between changes in inputs, intended outputs, and by-products. We follow their framework and define an agricultural production technology set as the intersection of a carbon sequestration sub-technology that generates agricultural revenue and carbon sequestration and a GHG emissions sub-technology. We calculate shadow prices for agricultural carbon sequestration and GHG emissions using a unique data set collected in 2021 among Illinois corn growers, offering field-level estimates.

To the best of our knowledge, our study is the first to model agricultural revenue, carbon sequestration, and GHG emissions jointly while considering the interdependence between these agricultural outputs. For the first time, we provide shadow prices for both carbon sequestration and GHG emissions. Using agricultural land as the numeraire, we calculate carbon sequestration shadow prices for each field in our sample by measuring the field's willingness to accept an additional increase in carbon sequestration. Similarly, for GHG emissions shadow prices, we quantify the willingness to accept a small reduction in GHG emissions. By comparing cover crop and non-cover crop fields, we provide the value of the superior carbon services provided by cover crop fields and compare it against current voluntary carbon market payments.[1]

Our results suggest that cover crop fields can sequester carbon at a lower marginal cost than non-cover crop fields, highlighting the benefits of cover crops for carbon sequestration. However, non-cover crop fields exhibit lower marginal costs in reducing GHG emissions, attributable to their more intensive nitrogen use and increasing marginal costs of mitigating GHG emissions. We summarize the various shadow values into a single price that reflects the marginal value of the total carbon benefits of cover crop relative to non-cover crop fields, expressed in USD per acre. The findings suggest that cover crop fields exhibit higher carbon benefits, valued at USD 27.30 per acre, compared to non-cover crop fields.

Our results allow us to assess the potential farmer participation in carbon markets by estimating the private costs of providing carbon offsets. Carbon markets are becoming a popular market-based policy to reduce GHG emissions. In a carbon market, sequestered carbon and/or avoided or reduced GHG emissions may generate carbon offsets that can be certified, registered, and traded. Enterprises contributing to carbon sequestration and GHG emissions reduction represent the market's supply side. The demand side should include enterprises that intend to reduce upstream and downstream emissions and those that find buying carbon offsets from the market cheaper than reducing their carbon footprint.

Despite the absence of a compliance carbon market for Illinois farms, some voluntary carbon markets compensate farmers for the adoption of practices that reduce fields' carbon footprint. Programs such as the "Farmers for Soil Health" (PCM 2024a) initiative and the "New PepsiCo Incentive Payment Program" (PCM 2024b) offer payments ranging from USD 10 to USD 25 per acre for the adoption of cover crops. Carbon benefits from cover crops valued at USD 27.30 per acre exceed this upper limit. This suggests that current compensation from voluntary markets may not fully cover adoption costs for several fields in our sample. The implications of our results extend beyond the agricultural community, offering valuable insights for policymakers aiming to encourage sustainable farming practices and navigate the complexities of carbon markets. Results are also relevant for firms seeking to reduce their carbon footprint, as our values serve as guidelines to stimulate an increased supply of carbon offsets.

2. Methodology

This section describes our methods to derive shadow prices for carbon sequestration and GHG emissions. We first present a general discussion of the agricultural production technology and how shadow values can be generated using a functional representation of the technology. We then define the DEA formulation of the functional representation of this technology.

2.1. The technology

Our sample fields produce corn, and we tailor the production technology to these fields by allowing for two intended outputs: corn revenue y and carbon sequestration s, and one unintended output - GHG emissions e. The intended and unintended outputs are produced by non-polluting inputs $x \in \mathbb{R}_+^K$, including land x_1 and other inputs x_{-1}, along with polluting inputs such as nitrogen n and power costs p that generate GHG emissions. The corn production technology is defined by

$$T = \{(x,n,p,y,s,e) \in \mathbb{R}_+^{K+5} : (x,n,p) \text{ can produce } (y,s,e)\}.$$

Following Murty et al. (2012), we model T as the intersection of two distinct sub-technologies: the *carbon sequestration technology*, T^S, that generates revenue from corn and carbon sequestration and the *GHG emissions technology*, T^E, that generates GHG emissions. The two sub-technologies share the polluting inputs n and p. We write:

$$T^S = \{(x,n,p,y,s,e) \in \mathbb{R}_+^{K+5} : (x,n,p) \text{ can produce } (y,s)\}, \tag{1}$$

and

$$T^E = \{(x,n,p,y,s,e) \in \mathbb{R}_+^{K+5} : (x,n,p) \text{ can produce } e\} \tag{2}$$

with T as their intersection.

$$T = T^S \cap T^E.$$

We assume that land is freely disposable. That is

$$(x_1, x_{-1}, n, p, y, s, e) \in T \implies (x_1', x_{-1}, n, p, y, s, e) \in T \text{ for } x_1' \geq x_1.$$

In words, if one can produce (y,s,e) from (x_1, x_{-1}, n, p), then one can also produce (y,s,e) from (x_1', x_{-1}, n, p), where $x_1' \geq x_1$. Given other inputs, this implies that increasing land use is consistent with nondecreasing revenue, sequestration, and constant GHG emissions. We assume T is closed and nonempty. By our assumptions of closedness, nonemptiness, and free disposability of land, the following holds

$$X(x_{-1}, n, p, y, s, e) \leq x_1 \iff (x_1, x_{-1}, n, p, y, s, e) \in T, \tag{3}$$

where

$$\begin{aligned} X(x_{-1}, n, p, y, s, e) &= \inf\{x_1 : (x_1, x_{-1}, n, p, y, s, e) \in T\} \\ &= \inf\{x_1 : (x_1, x_{-1}, n, p, y, s, e) \in T^S \wedge (x_1, x_{-1}, n, p, y, s, e) \in T^E\}. \end{aligned} \tag{4}$$

$X(x_{-1}, n, p, y, s, e)$ [hereafter, $X(.)$] in expression (3) is a *function representation* of T. Thus, knowing $X(.)$ is equivalent to knowing T. It gives the minimum land required to produce (y, s, e) given some (x_{-1}, n, p).

Define $X^S(x_{-1}, n, p, y, s)$ and $X^E(x_{-1}, n, p, e)$ as

$$X^S(x_{-1}, n, p, y, s) = \inf\{x_1 : (x_1, x_{-1}, n, p, y, s, e) \in T^S\} \tag{5}$$

and

$$X^E(x_{-1}, n, p, e) = \inf\{x_1 : (x_1, x_{-1}, n, p, y, s, e) \in T^E\}. \tag{6}$$

$X^S(x_{-1}, n, p, y, s)$ [hereafter, $X^S(.)$] and $X^E(x_{-1}, n, p, y)$ [hereafter, $X^E(.)$] give the minimum amount of land to produce (y, s) and e, given other netputs. Under the assumptions that T^S and T^E are closed and nonempty and x_1 is freely disposable, the following holds,

$$X^S(x_{-1}, n, p, y, s) \le x_1 \iff (x_1, x_{-1}, n, p, y, s, e) \in T^S, \tag{7}$$

$$X^E(x_{-1}, n, p, e) \le x_1 \iff (x_1, x_{-1}, n, p, y, s, e) \in T^E. \tag{8}$$

The free disposability of x_1 ensures $X^S(.)$ and $X^E(.)$ are complete function representations of sub-technologies T^S and T^E, respectively. Thus, from (4), (5) and (6) we have

$$X(x_{-1}, n, p, y, s, e) = \max\{X^S(x_{-1}, n, p, y, s), X^E(x_{-1}, n, p, e)\}. \tag{9}$$

2.2. Shadow prices for carbon sequestration and GHG emissions

For a smooth technology, shadow values are obtained as derivatives of the function representation of the technology. We derive the function representation of our technology using DEA, which results in a polyhedral frontier. Efficient fields can form the kink of the frontier where shadow values are not unique. Thus, we obtain carbon sequestration and GHG emissions shadow prices in land units using the one-sided derivatives (marginal values) of $X(.)$ (Chambers and Färe 2008, Podinovski et al. 2016). One-sided derivatives of $X(.)$ at s for a small movement λ with respect to a vector v are

$$X_s'(x_{-1}, n, p, y, s, e; v) = \lim_{\lambda \to 0^+} \left(\frac{X(x_{-1}, n, p, y, s + \lambda v, e) - X(x_{-1}, n, p, y, s, e)}{\lambda} \right) \tag{10}$$

and

$$-X_s'(x_{-1}, n, p, y, s, e; v) = \lim_{\lambda \to 0^-} \left(\frac{X(x_{-1}, n, p, y, s + \lambda v, e) - X(x_{-1}, n, p, y, s, e)}{\lambda} \right). \tag{11}$$

Equation (10) is the right-hand derivative of $X(.)$ with respect to s, which gives the willingness to accept a small unit increase in s. Equation (11) is the left-hand derivative of $X(.)$ and gives the willingness to pay for a small unit decrease in s. Both (10) and (11) are expressed in land units given all other netputs fixed (Chambers and Färe 2008, Chambers et al. 2014). One-sided derivatives of $X(.)$ at e for a small movement α with respect to vector v are

$$X_e'(x_{-1},n,p,y,s,e;v) = \lim_{\alpha\to 0^+}\left(\frac{X(x_{-1},n,p,y,s,e+\alpha v)-X(x_{-1},n,p,y,s,e)}{\alpha}\right) \tag{12}$$

and

$$-X_e'(x_{-1},n,p,y,s,e;v) = \lim_{\alpha\to 0^-}\left(\frac{X(x_{-1},n,p,y,s,e+\alpha v)-X(x_{-1},n,p,y,s,e)}{\alpha}\right). \tag{13}$$

Equation (12) is the right-hand derivative of $X(.)$ with respect to e, which gives the willingness to pay for a small unit increase in e. Equation (13) is the left-hand derivative of $X(.)$ and gives the willingness to accept a small unit decrease in e. Both (12) and (13) are expressed in land units given all other netputs fixed.

Function $X(.)$ is convex thus, for $\lambda \in [0,1]$ and two points s and s',

$$X(s)+\lambda[X(s')-X(s)] \geq X(s+\lambda(s'-s))$$

where $X(s)$ is a simplified notation of $X(x_{-1},n,p,y,s,e)$ and $X(s+\lambda(s'-s))$ is a simplified notation of $X(x_{-1},n,p,y,s+\lambda(s'-s),e)$. If a direction v is defined by $s'-s$, then,

$$X(s)+\lambda[X(s')-X(s)] \geq X(s+\lambda v)$$

Rearranging, we get,

$$X(s')-X(s) \geq \frac{X(s+\lambda v)-X(s)}{\lambda}$$

Taking the limit $\lambda \to 0^+$ on the right-hand side gives

$$X(s')-X(s) \geq \lim_{\lambda\to 0^+}\left(\frac{X(s+\lambda v)-X(s)}{\lambda}\right)$$

From (10), it implies

$$X(s')-X(s) \geq X_s'(s;v)$$

The subdifferential of $X(.)$ at s is given by

$$\partial_s X(s) = \{q \in \mathbb{R} : X(s') \geq X(s) + q'(s'-s), \forall s' \in \mathbb{R}\} \tag{14}$$

where $X(s)+q'(s'-s)$ gives the approximation of the linear change in $X(.)$ when we move from s to s' for all $s' \in \mathbb{R}$. Geometrically, it consists of all the possible hyperplanes tangent to $(s, X(s))$. Define s' a point after a small movement λ from s in the direction $v = 1$. From (14), we get

$$\frac{X(s+\lambda)-X(s)}{\lambda} \geq q', \tag{15}$$

which implies, from Rockafellar (1970, chap. 23), Theorem 23.4,

$$X'_s(s;1) = \max\{q' : q \in \partial_s X(s)\} = \max\{\partial_s X(s)\} \tag{16}$$

Now defining s' a point after a small movement λ from s in the direction $v = -1$, we get

$$\begin{aligned} & X'_s(s;-1) = \max\{-q' : q \in \partial_s X(s)\} = -\min\{q' : q \in \partial_s X(s)\} \\ \implies & -X'_s(s;-1) = \min\{\partial_s X(s)\} \end{aligned} \tag{17}$$

In terms of e we get

$$X'_e(e;1) = \max\{q' : q \in \partial_e X(e)\} = \max\{\partial_e X(e)\} \text{ and} \tag{18}$$

$$-X'_e(e;1) = \min\{q' : q \in \partial_e X(e)\} = \min\{\partial_e X(e)\} \tag{19}$$

Considering the intended nature of carbon sequestration, we calculate its shadow prices using equation (16). Given the unintended nature of GHG emissions, we calculate their shadow prices by relying on (19).

2.3. Corn production technology and DEA representation

Table 1 provides the netputs, their notations, and units of measurement for the corn production technology. Inputs are factors that produce or boost corn grain yield or prevent yield drag. Some contribute directly or indirectly to carbon sequestration and GHG emissions. Plants utilize atmospheric CO_2 to produce glucose molecules during photosynthesis simultaneously sequestering and storing the carbon in their biomass and soil (Hutchinson et al. 2007, Lorenz 2013). Thus, inputs that boost corn production or prevent yield drag contribute to carbon sequestration (s). Synthetic N fertilizer (n) boosts crop yield (and thus s). However, it contributes to GHG emissions (e) by generating N_2O.[2] The more fertilizer applied, the greater the danger of fertilizer loss due to gaseous emissions. Power costs (p) include costs related to mechanized fieldwork such as corn and cover crop planting, corn harvest, and cover crop termination associated with CO_2 emissions. GHG emissions are estimated

Table 1 Netputs in the corn production technology.

Input - (Unit)	Output - (Unit)
(n) Nitrogen (lbs.)	(y) Revenue (\$)
(p) Power costs (\$)	(s) Sequestration (tCO_2 eq.)
(x_1) Land (acres)	(e) GHG emissions (tCO_2 eq.)
(x_2) Corn seed cost (\$)	
(x_3) Phosphorus (lbs.)	
(x_4) Potassium (lbs.)	
(x_5) Pesticide cost (\$)	
(x_6) Organic matter (%)	
(c) Cover crop use (Cover crop and Non-cover crop)	

Note: Cover crop use is a categorical variable. Notation and units of measure are indicated in parentheses before and after the netput description, respectively. Netputs and units of measurement are conditioned by our dataset, which we discuss in the Data section.

measures of N_2O and CO_2 emissions mostly from N application and mechanized field works. Other inputs such as other fertilizers, pesticides and seeds can reduce GHG emissions by boosting crop yield, leading to increased N uptake, or prevent yield drag, avoiding decreased N uptake. A lack of phosphorus and potassium fertilizers might limit plant growth. When used appropriately, pesticides prevent yield from declining by controlling weeds and insects. Seeds are essential for crop growth and subsequent nitrogen uptake.

Our production technology includes a categorical variable, cover crop use, distinguishing between cover and non-cover crop practices. In addition to improving soil quality, cover crops contribute to carbon sequestration. Cover crops also reduce N_2O emissions by absorbing remnant N after the harvest of main crops (Behnke and Villamil 2019) mitigating denitrification and associated N_2O emissions from fields. A common approach to handling categorical variables in DEA modeling is to treat different categories as separate production processes within the technology (Førsund 2002). We use subscript c, where $c \in \{$*cover crop fields, non-cover crop fields*$\}$ to distinguish between the two production processes.

As discussed earlier, we use $X_c^S(.)$ to represent T_c^S and $X_c^E(.)$ to represent T_c^E. $X_c^S(.)$ provides the minimum amount of land x_1 to produce a given (y, s) holding all other netputs constant (Equation 20). $X_c^E(.)$ provides the minimum amount of land x_1 for a given e holding all other netputs constant (Equation 21). Fields with $X_c^S(.) = x_1$ are located on the frontier of the carbon sequestration technology. Fields with $X_c^E(.) = x_1$ are on the frontier of the GHG emissions technology. Fields on the frontiers are efficient, while fields not on the frontiers are inefficient. The DEA formulations for $X_c^S(.)$ and $X_c^E(.)$ are:

$$X_c^S(x_{-1},n,p,y,s)=\min_{\gamma_i}\left\{\begin{array}{l}\sum_i \gamma_i x_{i1}:\\ \forall k=2,\ldots,5, x_k=\sum_i \gamma_i x_{ik}, x_6\geq \sum_i \gamma_i x_{i6},\\ n=\sum_i \gamma_i n_i, p=\sum_i \gamma_i p_i, y\leq \sum_i \gamma_i y_i, s\leq \sum_i \gamma_i s_i,\\ \gamma_i\geq 0,\ \text{and}\ \sum_i \gamma_i=1\end{array}\right\} \tag{20}$$

and

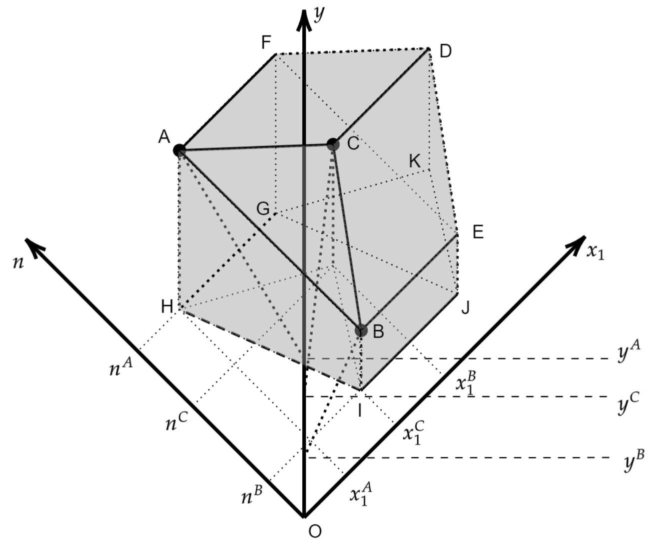
$$X_c^E(x_{-1},n,p,e)=\min_{\mu_i}\left\{\begin{array}{l}\sum_i \mu_i x_{i1}:\\ \forall k=2,\ldots,5, x_k=\sum_i \mu_i x_{ik}, x_6\geq \sum_i \mu_i x_{i6},\\ n=\sum_i \mu_i n_i, p=\sum_i \mu_i p_i, e=\sum_i \mu_i e_i,\\ \mu_i\geq 0,\ \text{and}\ \sum_i \mu_i=1\end{array}\right\}, \tag{21}$$

where $i=1,\ldots,I$, denotes the fields and γ_i and μ_i the weight of a particular field i in the linear combination of $X_c^S(.)$ and $X_c^E(.)$. We assume that our crop production technology exhibits variable returns to scale (VRS), which in DEA formulations is represented by the constraints $\sum_i \gamma_i=1$ and $\sum_i \mu_i=1$. The equality and inequality signs in the netput constraints denote weak and free disposability, respectively.

We assume free disposability of the intended outputs and weak disposability of the unintended output. It ensures that one can always produce less crop revenue and sequester less carbon from the atmosphere with the same inputs and GHG, but one cannot reduce GHG emissions maintaining the same inputs and intended outputs. Corn requires N for optimal growth, and applying N fertilizers based on soil N level can enhance crop yield (Nafziger 2017). However, applying too much N fertilizer can decrease corn yield (CORTEVA 2023, Vargas et al. 2015) and affect revenue. To allow for N congestion in corn production, we assume weak disposability of nitrogen (n) in T_c^S. This ensures increasing n while maintaining the other netputs constant is infeasible. We further allow for congestion in the use of power costs (p), potassium (x_4) and pesticides (x_5). In contrast, we assume that organic matter in soil (x_6) is freely disposable, as one can always increase organic matter in soil without altering corn revenue (y) and carbon sequestration (s).

As discussed, N fertilizers and power costs contribute to N_2O and CO_2 emissions (Hassan et al. 2022), which suggests that using excess N fertilizers and power costs for a fixed e is infeasible. Thus, we assume weak disposability of n and p in T_c^E. This is consistent with

Figure 1 **Approximation of the convex technology using hypothetical points and freely and weakly disposable netputs.**



the weak disposability of e, as GHG emissions can only be increased (decreased) with an increase (decrease) in N fertilizers and/or power costs. Formally, nitrogen (n) and emissions (e) are weakly disposable if

$$(x,n,p,y,e)\in T^E \implies (x,\lambda n,p,y,\lambda e)\in T^E, \lambda \geq 1 \text{ and}$$
$$(x,n,p,y,e)\in T^E \implies (x,\theta n,p,y,\theta e)\in T^E, \theta \in [0,1],$$

which implies that we can increase or decrease e and n in tandem. Also, this is true between power costs (p) and emissions (e). Organic matter in soil (x_6) is freely disposable in T_c^E as one can always increase soil organic matter without altering e given other fixed inputs. All inputs that are weakly disposable in T_c^S are also weakly disposable in T_c^E as overuse of these inputs can harm the intended outputs and increase GHG emissions, given a fixed amount of other netputs.

In Figure 1, we illustrate the shape of $X_c^S(.)$ in (x_1,n,y) space. We select three hypothetical points A, B and C. The plane ABC represents the convex technology among three combinations of inputs and output. Free disposability of x_1 is illustrated by planes $ACDF$, $BCDE$, and $ABEF$ moving in the direction of x_1 infinitely and forming a convex hull $ABCDEF$. Input n is weakly disposable. Thus, $ACDF$ and $AFGH$ are bounding hyperplanes in the direction of n, implying that the shadow price sign for n is unrestricted. Free disposabilty of y implies all points below the convex hull ABC are in the feasible region. Jointly imposing free disposability of x and y ensures all points below $ABCDEF$ are in the feasible region (i.e., points on and in the region $ABCDEF$ plus $ABEFGHIJ$).

The dual versions of the linear problems (20) and (21) are

$$H_c^S(x_{-1},n,p,y,s) = \max_w \left\{ \begin{array}{l} \phi + w_y y + w_s s - (w_n^y - w_n^{'y})n - (w_p^y - w_p^{'y})p \\ - \sum\limits_{k=2,\ldots,5} (w_k^y - w_k^{'y})x_k - w_6^y x_6 : \\ \phi + w_y y_i + w_s s_i - (w_n^y - w_n^{'y})n_i - (w_p^y - w_p^{'y})p_i \\ - \sum\limits_{k=2,\ldots,5} (w_k^y - w_k^{'y})x_{ik} - w_6^y x_{i6} \leq x_{i1} \\ \forall i = 1,\ldots,I \end{array} \right\} \tag{22}$$

$$H_c^E(x_{-1},n,p,e) = \max_w \left\{ \begin{array}{l} \theta + (w_e - w_e')e - (w_n^e - w_n^{'e})n - (w_p^e - w_p^{'e})p \\ - \sum\limits_{k=2,\ldots,5} (w_k^e - w_k^{'e})x_k - w_6^e x_6 : \\ \theta + (w_e - w_e')e_i - (w_n^e - w_n^{'e})n_i - (w_p^e - w_p^{'e})p_i \\ - \sum\limits_{k=2,\ldots,5} (w_k^e - w_k^{'e})x_{ik} - w_6^e x_{i6} \leq x_{i1} \\ \forall i = 1,\ldots,I \end{array} \right\} \tag{23}$$

where ϕ and θ are the dual variables to VRS constraints in (20) and (21), respectively and w's in (22) and (23) are marginal (shadow) values of netputs of the carbon sequestration and the GHG emissions technologies. These marginal values are fields' private netput shadow prices at their private optimal level of outputs and are derived using equations (24) and (25).

$$\max\{\partial_s H_c^S(.)\} = \max_w \left\{ \begin{array}{l} w_s : \\ \phi + w_y y + w_s s - (w_n^y - w_n^{'y})n - (w_p^y - w_p^{'y})p \\ - \sum\limits_{k=2,\ldots,5} (w_k^y - w_k^{'y})x_k - w_6^y x_6 = H_c^S(.), \\ \phi + w_y y_i + w_s s_i - (w_n^y - w_n^{'y})n_i - (w_p^y - w_p^{'y})p_i \\ - \sum\limits_{k=2,\ldots,5} (w_k^y - w_k^{'y})x_{ik} - w_6^y x_{i6} \leq x_{i1} \\ \forall i = 1,\ldots,I \end{array} \right\} \text{ and} \tag{24}$$

$$\min\{\partial_e H_c^E(.)\} = \min_w \left\{ \begin{array}{l} w_e - w_e' : \\ \theta + (w_e - w_e')e - (w_n^e - w_n'^e)n - (w_p^e - w_p'^e)p \\ - \sum_{k=2,\ldots,5} (w_k^e - w_k'^e)x_k - w_6^e x_6 = H_c^E(.), \\ \theta + (w_e - w_e')e_i - (w_n^e - w_n'^e)n_i - (w_p^e - w_p'^e)p_i \\ - \sum_{k=2,\ldots,5} (w_k^e - w_k'^e)x_{ik} - w_6^e x_{i6} \leq x_{i1} \\ \forall i = 1, \ldots, I \end{array} \right\}. \tag{25}$$

The first constraints in (24) and (25) give the solutions to (22) and (23) for all fields, both efficient and inefficient.[3] For efficient fields, the solution to $H_c^S(.)$ and $H_c^E(.)$ is x_1. Thus, the first constraints in (24) and (25) for efficient fields are:

$$\phi + w_y y + w_s s - (w_n^y - w_n'^y)n - (w_p^y - w_p'^y)p - \sum_{k=2,\ldots,5} (w_k^y - w_k'^y)x_k - w_6^y x_6 = x_1$$

and

$$\theta + (w_e - w_e')e - (w_n^e - w_n'^e)n - (w_p^e - w_p'^e)p - \sum_{k=2,\ldots,5} (w_k^e - w_k'^e)x_k - w_6^e x_6 = x_1.$$

For inefficient fields, shadow values are derived as slopes at their projections on the frontier (Podinovski 2019). The first constraints in (24) and (25) give the projection on the frontier for any inefficient fields.

The shadow prices of carbon sequestration and GHG emissions are real prices as they are in units of land per unit of GHG emissions, i.e., acres per tCO_2 eq. The $\max\{\partial_s H_c^S(.)\}$ is the additional farm area farmers would require to increase carbon sequestration by a tCO_2 eq. for a particular year. The $\min\{\partial_e H_c^E(.)\}$ represents the area farmers would need to add to reduce GHG emissions by a tCO_2 eq. for a particular year. To facilitate comparison with carbon market payment structures, expression (26) transforms real shadow prices into nominal values, in USD per tCO_2 eq. per year, by using N applied per acre and N price.

$$\begin{aligned} &\text{Nominal shadow price} \left(\frac{USD}{tCO_2\ eq.} \right) \\ &= \text{Real shadow price} \left(\frac{acre}{tCO_2\ eq.} \right) \times \text{N applied} \left(\frac{lbs.}{acre} \right) \times \text{N price} \left(\frac{USD}{lbs.} \right). \end{aligned} \tag{26}$$

3. Data

The data for this study come from Precision Conservation Management (PCM), a farmer-led program aimed at developing conservation strategies that address environmental challenges while remaining financially viable (PCM 2023). PCM collects data at the field level on input and output quantities, costs, and returns from participating Illinois corn and soybean growers. In collaboration with Cool Farm Tool (CFT), PCM provides estimates of carbon sequestration and GHG emissions for each field based on the netputs used. PCM is pivotal in enabling farmers to participate in carbon markets.

The 2021 PCM data comprises 793 fields from 159 Illinois corn growers that manage 51,708 acres of farmland in 46 of the 102 Illinois counties. Figure 2 shows that most sample acres are concentrated in central and northern Illinois. Corn fields in our sample represent less than 1% of the 11 million acres of corn for grain planted in Illinois in 2021 (NASS 2023). Sample average corn yield is 215 bushels per acre, about 6% higher than the average state corn yield in 2021 (202 bushels per acre, NASS 2023). Differences in yields and the small percentage of corn land covered by our sample farms call for caution when extrapolating our results. More than 90% of the sample fields follow a corn-soybean rotation system. While corn is a N intensive crop, little or no nitrogen is applied in soybean farming because the crop can fix nitrogen on its own. We focus on corn in our analysis, as it poses more challenges for carbon sustainability than soybeans.

Following the methods section, we define 12 variables – three outputs and nine inputs. These include revenue from corn grain production in USD (y); carbon sequestration in tCO_2 eq. (s); gross GHG emissions in tCO_2 eq. (e); nitrogen fertilizer in pounds (n); power costs in USD (p); land area in acres (x_1); corn seed costs in USD (x_2); phosphorus fertilizer in pounds (x_3); potassium fertilizer in pounds (x_4); pesticide costs in USD (x_5); organic matter percent in soil (x_6); and cover crop use (c) as a categorical variable. PCM estimates s and e based on Cool Farm Tool and produces x_6 based on the USDA Web Soil Survey.[4] All netputs are expressed on a per-field basis, the unit of observation in the PCM dataset. Information on cover crops is limited and of a qualitative nature. We categorize observations as cover crop fields if they use either winter-killed cover crops or winter-hardy cover crops and non-cover crop fields if they don't use any.

Table 2 displays netput summary statistics by cover crop use on a per-acre basis for comparability. Appendix B complements summary statistics at the field level. Out of 793 fields, 120 (15%) plant cover crops and 673 (85%) do not. The median gross revenue per acre for cover crop fields is $1,105.12, approximately 4% less than for non-cover crop fields ($1,155.00). The median carbon sequestration per acre in cover crop fields (0.55 tCO_2 eq.)

Figure 2 Distribution of sample acres in Illinois.

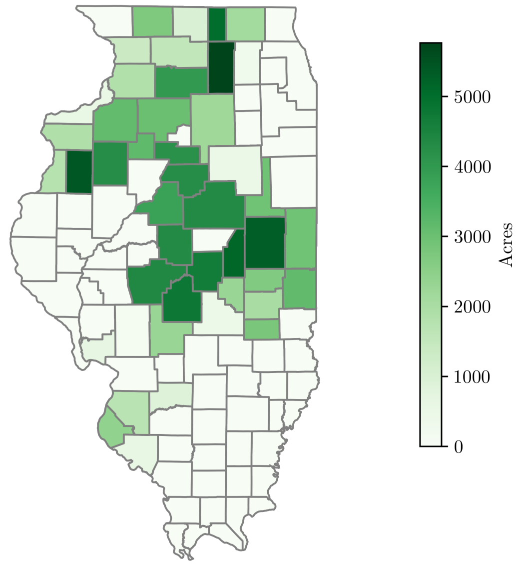


Table 2 Summary statistics of variables used in the analysis by cover crop use on a per-acre basis.

Netputs	Cover crop field N = 120			Non-cover crop field N = 673		
	Median	p25	p75	Median	p25	p75
(y) Revenue (\$/acre)	1105.12	960.75	1207.50	1155.00	1050.00	1249.50
(s) Sequestration (tCO_2 eq./acre)	0.55	0.40	0.55	0.12	0.12	0.26
(e) GHG emissions (tCO_2 eq./acre)	0.24	0.21	0.27	0.25	0.22	0.29
(n) Nitrogen (lbs./acre)	194.66	176.00	218.14	206.80	188.89	223.30
(p) Power costs (\$/acre)	137.30	128.50	147.62	120.75	109.80	129.85
(x_1) Land (acres)	42.52	25.83	69.21	67.00	38.28	82.31
(x_2) Corn seed cost (\$/acre)	120.31	118.59	120.31	120.31	113.44	120.31
(x_3) Phosphorus (lbs./acre)	53.52	40.00	78.00	71.22	52.00	89.83
(x_4) Potassium (lbs./acre)	80.00	60.00	90.00	75.00	58.20	120.00
(x_5) Pesticide cost (\$/acre)	74.00	55.00	77.00	74.00	63.00	85.00
(x_6) Organic matter (%)	0.08	0.04	0.17	0.08	0.05	0.98

Note: p25 and p75 denote the first and third quartiles, respectively. Notation and units of measure are indicated in parentheses before and after the netput description, respectively. Source - PCM dataset.

is 358% higher than in non-cover crop fields (0.12 tCO_2 eq.). Non-cover crop fields emit 4% more greenhouse gas (GHG) emissions per acre (0.25 tCO_2 eq.) than cover crop fields (0.24 tCO_2 eq.). The median nitrogen applied is 194.66 and 206.80 lbs. per acre for cover and non-cover crop corn fields.

The University of Illinois recommends using N fertilizer based on the Corn Nitrogen Rate Calculator (CNRC). CNRC provides the Maximum Return to Nitrogen (MRTN) rate and the Most Profitable Nitrogen Range (MPNR) based on current nitrogen and corn prices for different regions in the state (CNRC 2023). Using a N price of \$0.38 per pound and a corn price of \$5.25 per bushel, both obtained from the PCM dataset,[5] we derive the MRTN and MPNR rates for our sample. For the northern, central, and southern regions of Illinois, MRTN is 194, 193, and 215 lbs. of N per acre, while the MPNR is 178-208, 180-207, and 200-231 lbs. of N per acre. Appendix C offers the distribution of corn fields across different categories of N use based on the MRTN and the MPNR. The appendix shows that the percentage of corn fields applying above the university-recommended N (MRTN and MPNR) is higher among non-cover crop fields than among cover crop fields, consistent with relatively higher GHG emissions from non-cover crop fields.

The median power cost for cover crop fields is higher than that for non-cover crop fields (\$137.30 vs. \$120.75 per acre). This reflects the extra tillage and planting operations required by cover crop fields. The median land area of cover crop and non-cover crop fields is 42.52 and 67.00 acres, respectively. The median corn seed cost per acre is the same for both types of fields (\$120.31). Cover crop fields exhibit a lower phosphorus fertilizer cost per acre (\$53.52) than non-cover crop fields (\$71.22). The potassium cost per acre is slightly higher in cover crop (\$80.00) than in non-cover crop fields (\$75.00). Both field types have the same median pesticide cost per acre (\$74.00). The estimated median organic matter content in soil is also the same across field types (0.08%). Following Sarkis (2007), we estimate our DEA model using normalized netputs to reduce dispersion in magnitudes and for computational efficiency. We normalize each netput by dividing its observations by its mean.

4. Results

We calculate $X_c^S(.)$ in (20), $X_c^E(.)$ in (21), and the technology $X_c(.) = \max\{X_c^S(.), X_c^E(.)\}$. Given some fixed level of other inputs, $X_c(.)$ gives the maximum between the minimum land required for given agricultural revenue and carbon sequestration and the minimum land required for given GHG emissions. We identify fields with $X_c^S(.) \geq X_c^E(.)$ and call them *carbon sequestration technology fields*. We call fields with $X_c^S(.) \leq X_c^E(.)$ as *GHG emissions technology fields*. Carbon sequestration technology fields use land to produce intended outputs at least as efficiently as to generate GHG emissions. GHG emissions technology fields use land to generate GHG emissions at least as efficiently as to produce the intended outputs.

Figure 3 **Technologically feasible space of T in $(x_1, (x_{-1}, n, p))$ space.**

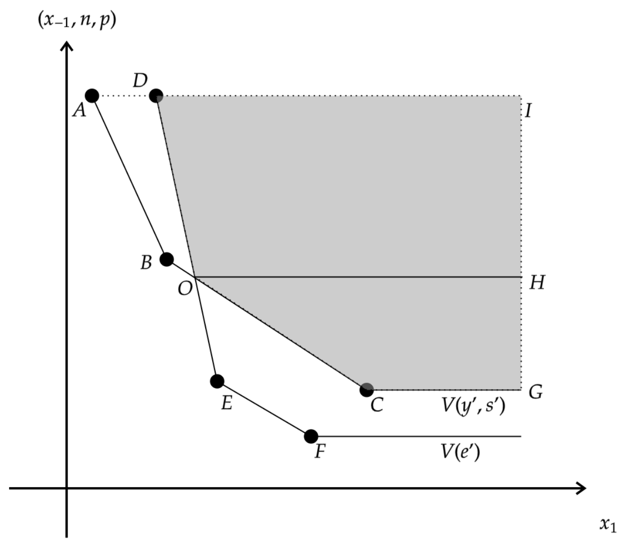


Figure 3 illustrates the technologically feasible space of T in $(x_1, (x_{-1}, n, p))$ space and regions for carbon sequestration and GHG emissions technology fields. Let the piece-wise linear frontier through A, B, and C belong to the isoquant for y' and s', and the piece-wise linear frontier through D, E, and F belong to that for e'. All input bundles due east of the frontier ABC can produce y' and s'. All input bundles due east of the frontier DEF can produce e'. The input bundles that can produce y', s', and e' fall in the intersection of these two sets, points due east of the piece-wise linear DOC. Fields in $OCGH$ are carbon sequestration technology fields, and fields in $DOHI$ are GHG emissions technology fields. The equality signs denoting carbon sequestration and GHG emissions technology fields represent fields in OH. These fields use land to produce intended outputs and reduce GHG emissions with equal efficiency.

Table 3 illustrates the distribution of sample fields into carbon sequestration and GHG technology fields by cover crop use. We find that 71% of cover crop fields are carbon sequestration technology fields, while 65% are classified as GHG emissions technology fields. The two percentages do not add up to 100% as they include the intersection between the two sub-technologies. Non-cover crop fields have a larger proportion (58%) of GHG emissions technology fields than carbon sequestration technology fields (49%). Differences between cover crop and non-cover crop fields reflect cover crop fields' ability to sequester more carbon per acre compared to non-cover crop fields. The non-trivial presence of cover and non-cover

Table 3 Distribution of carbon sequestration and GHG emissions technology fields by cover crop use.

	Cover crop field N = 120	Non-cover crop field N = 673
Carbon sequestration technology fields	85 (71%)	330 (49%)
GHG emissions technology fields	79 (65%)	388 (58%)

Note: Carbon sequestration technology fields are fields with $X_c^S(.) \geq X_c^E(.)$ and GHG emissions technology fields are fields with $X_c^S(.) \leq X_c^E(.)$. The total percentages in carbon sequestration and GHG emissions technology fields do not add up to 100% for cover and non-cover crop fields because of the presence of fields belonging to both carbon sequestration and GHG emissions technology fields. The intersection, i.e., 44 (36% of) cover crop and 45 (7% of) non-cover crop fields, uses land equally efficiently to produce intended outputs and reduce GHG emissions.

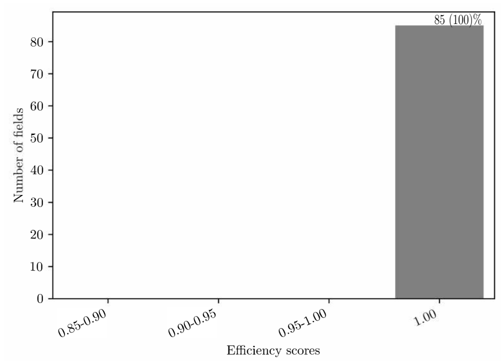
crop fields in the GHG emissions technology category reflects that a significant proportion of sample fields apply nitrogen above recommended rates. Appendix C reveals that 52.5% and 68.80% of cover crop and non-cover crop fields apply nitrogen above MRTN. This facilitates fields to be classified as GHG emissions technology fields, indicating their relative ease in reducing GHG emissions.

We recalculate both $X_c^S(.)$ and $X_c^E(.)$ using carbon sequestration and GHG emissions technology fields, respectively, and identify the efficient and inefficient fields. The carbon sequestration technology efficiency scores are calculated as $\lambda^S = X_C^S(.)/x_1$, the minimum land area ratio to actual land area. The GHG emissions technology efficiency scores are derived as $\lambda^E = X_C^E(.)/x_1$. When $\lambda^S(\lambda^E) = 1$, fields are fully efficient in their land use given their intended outputs (GHG emissions). When $\lambda^S(\lambda^E) < 1$, fields do not minimize land area, given their intended outputs (unintended GHG emissions).

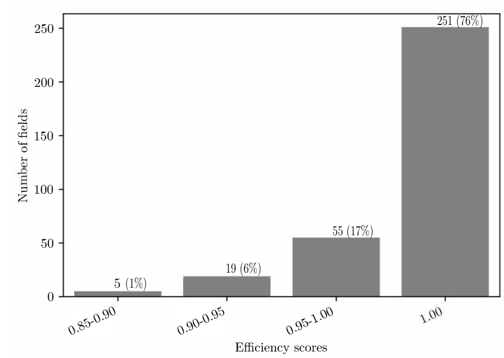
We show the distribution of λ^S and λ^E for our sample fields by cover crop use in Figure 4. A 100% and 76% of cover crop and non-cover crop crop carbon sequestration technology fields are efficient (Figure 4, panel A). While cover crop fields have lower median revenue per acre than non-cover crops, their efficiency in the carbon sequestration technology is likely driven by superior carbon sequestration. This results in average carbon sequestration technology efficiency scores for cover and non-cover crop fields of 1.000 and 0.990. Percentage-wise 97% and 76% of the cover crop and non-cover crop GHG emissions technology fields are efficient (Figure 4, panel B), resulting in average efficiency scores of 0.998 (0.991). These results suggest that cover crop fields more closely adhere to MRTN than non-cover crop fields. In summary, cover crop fields use land more efficiently for both intended and unintended outputs, consistent with their greater carbon benefits compared to non-cover crop fields.

Figure 4 **Distribution of the carbon sequestration technology (λ^S) and the GHG emissions technology (λ^E) efficiency scores by cover crop use.**

Panel A: Carbon sequestration technology efficiency scores (λ^S)

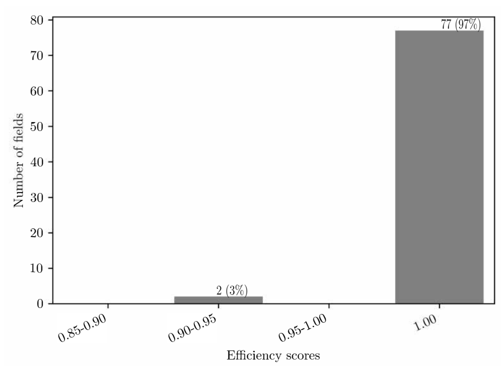


(a) Cover crop fields

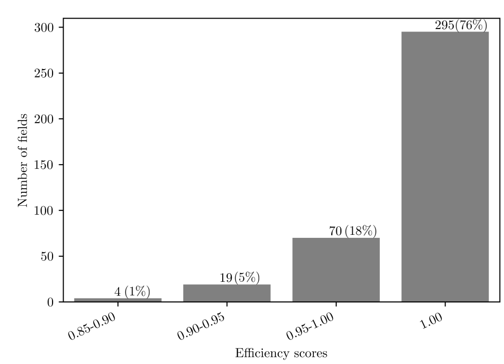


(b) Non-cover crop fields

Panel B: GHG emissions technology efficiency scores (λ^E)



(c) Cover crop fields



(d) Non-cover crop fields

We calculate shadow prices for efficient and inefficient fields. As discussed, shadow prices for efficient fields are the frontier's slope at their specific positions. Shadow prices for inefficient fields are the slope at their projection on the frontier. This ensures that land use inefficiencies are not factored into shadow prices. The focus is on compensating fields for carbon sequestration and GHG emissions mitigation rather than, for instance, unnecessary land rental costs.

To retrieve carbon sequestration and GHG emissions shadow prices, we run the linear programs (24) and (25), for both cover and non-cover crop fields. The optimization can result in unbounded solutions (Podinovski and Førsund 2010) when a marginal increase in sequestration or reduction in emissions, holding other netputs fixed, leads outside of the feasible technology. This is a consequence of the weak disposability assumptions on most netputs, which restricts the extrapolation outside the convex combination of the observed data. Shadow prices are undefined for the unbounded solutions. Thus, we only report bounded solutions.

Because we use mean-normalized data, shadow values $\max\{\partial_s H_c^S(.)\}$ ($\min\{\partial_e H_c^E(.)\}$) are expressed as ratios of mean-normalized land to mean-normalized carbon sequestration (GHG emissions). We transform $\max\{\partial_s H_c^S(.)\}$ to acres of land per tCO_2 eq. by multiplying by the sample mean land area to the sample mean sequestration ratio. We convert $\min\{\partial_e H_c^E(.)\}$ to acres of land per tCO_2 eq. by multiplying by the sample mean land area to the sample mean GHG emissions ratio.

Table 4 presents carbon sequestration and GHG emissions shadow values for efficient fields by cover crop use in panels A and B, respectively. Columns labeled (1) report real values (in acres per tCO_2 eq.). Columns labeled (2) report nominal values (in USD per tCO_2 eq.) based on equation (22). Carbon sequestration shadow values are reported for 36 cover crop and 204 non-cover crop carbon sequestration technology fields, accounting for 42.35% and 81.27% of total efficient fields, respectively. As a consequence of our disposability assumptions, shadow prices are undefined for 57.65% efficient cover crop and 18.73% efficient non-cover crop carbon sequestration technology fields because they cannot increase their sequestration further, given their netputs.

The median real sequestration shadow prices are 0.93 acres per tCO_2 eq. for efficient cover crop fields and 1.33 acres per tCO_2 eq. for efficient non-cover crop fields. This suggests that carbon sequestration can be increased by a tCO_2 eq. by adding an additional 0.93 (1.33) acres of cover crop (non-cover crop fields). These correspond to approximately 2% of the median land area for both field types. Shadow prices for non-cover crop fields are 43.01% higher than cover crop fields given the absence of carbon sequestration-enhancing practices in non-cover crop fields.

While real shadow prices are helpful, nominal shadow prices provide insight when compared with prevailing carbon market prices. We use equation (26) to convert real shadow prices into nominal ones, measured in USD per tCO_2 eq. The equation relies on the N used per acre and N prices in the crop year. The median nominal sequestration shadow prices for efficient cover and non-cover crop fields are USD 75.60 and 98.33 per tCO_2 eq. for 2021. This suggests efficient cover crop fields would incur a marginal cost of USD 75.60 to increase

Table 4 Summary of carbon sequestration and GHG emissions shadow values for efficient fields in acres of land per tCO_2 eq. and USD per tCO_2 eq. by cover crop use.

Panel A: Carbon sequestration shadow prices

	Cover crop field N = 36 $\max\{\partial_s H^S(.)\}$		Non-cover crop field N = 204 $\max\{\partial_s H^S(.)\}$	
	(1)	(2)	(1)	(2)
Median	0.93	75.60	1.33	98.33
p25	0.46	39.89	0.58	43.70
p75	1.33	107.89	2.82	209.50

Panel B: GHG emissions shadow prices

	Cover crop field N = 17 $\min\{\partial_e H^E(.)\}$		Non-cover crop field N = 124 $\min\{\partial_e H^E(.)\}$	
	(1)	(2)	(1)	(2)
Median	-1.48	-90.47	-0.69	-50.78
p25	-1.98	-181.32	-2.04	-164.71
p75	-0.28	-23.88	0.01	0.61

Note: Column (1) indicates shadow values in acres per tCO_2 eq. (real shadow values) and column (2) indicates shadow values in USD per tCO_2 eq. (nominal shadow values). Nominal shadow values are obtained by multiplying the real values by N applied per acre and N price. p25 and p75 denote the first and third quartiles, respectively.

carbon sequestration by an additional tCO_2 eq. The marginal cost for efficient non-cover crop fields is USD 98.33, a 30.02% larger. In summary, carbon sequestration shadow prices suggest that non-cover crop fields face higher marginal costs for increasing carbon sequestration compared to cover crop fields.

Our assumption that certain netputs are weakly disposable limits our ability to extrapolate beyond the observed data. Hence, GHG emissions shadow prices are reported for 17 cover crop and 124 non-cover crop fields. The median real GHG emissions shadow prices for efficient cover crop and non-cover crop fields are -1.48 and -0.69 acres per tCO_2 eq. (Table 4, panel B, columns (1)). The negative values result from the unintended nature of GHG emissions and indicate the additional land area is required to reduce emissions marginally. For example, crop fields need to expand the farmed area by an additional 1.48 acres to reduce their GHG emissions by one tCO_2 eq. Notice that the rest of the netputs are maintained constant, which implies an extensification of production methods. Real GHG emissions shadow prices for cover crop fields are 114.49% higher than for non-cover crop fields due to increasing private marginal costs of mitigating GHG emissions. Because cover crop fields better adhere

Table 5 Summary of carbon sequestration and GHG emissions shadow values for inefficient non-cover crop fields in acres of land per tCO_2 eq. and USD per tCO_2 eq.

Panel A: Carbon sequestration shadow prices		
	Non-cover crop field N = 79 $\max\{\partial_s H^S(.)\}$	
	(1)	(2)
Median	0.00	0.00
p25	0.00	0.00
p75	0.15	11.91
Panel B: GHG emissions shadow prices		
	Non-cover crop field N = 93 $\min\{\partial_e H^E(.)\}$	
	(1)	(2)
Median	-0.44	-37.35
p25	-1.19	-107.27
p75	0.322	22.73

Note: Column (1) indicates shadow values in acres per tCO_2 eq. (real shadow values) and column (2) indicates shadow values in USD per tCO_2 eq. (nominal shadow values). Nominal shadow values are obtained by multiplying the real values by N applied per acre and N price. p25 and p75 denote the first and third quartiles, respectively.

to MRTN, they face larger marginal costs. The median real GHG emissions shadow prices for efficient cover crop and non-cover crop fields represent approximately 3.5% and 1% of their respective median land areas.

We convert real GHG emissions shadow prices to nominal values using N applied per acre and N price and present results in Table 4, panel B, column (2). Cover crop fields incur a marginal cost of USD 90.47, while non-cover crop fields incur USD 50.78 for an additional unit decrease in GHG emissions. GHG emissions shadow prices for cover crop fields are 77.91% higher than those for non-cover crop fields, implying increasing marginal costs to reduce GHG emissions. This suggests that the latter can reduce GHG emissions at a lower cost compared to fields that use conservation practices.

Table 5 provides summary statistics of carbon sequestration and GHG emissions shadow prices for inefficient non-cover crop fields. We do not report shadow prices for inefficient cover crop fields since all fields in the carbon sequestration technology (fields with $X_c^S(.) \geq X_c^E(.)$) are efficient, and only 2 fields in the GHG emissions technology (fields with $X_c^S(.) \leq X_c^E(.)$) are inefficient. The median carbon sequestration shadow price for inefficient non-cover crop fields is 0.00 acre per tCO_2 eq. This suggests that at least half of these inefficient fields operate in the region where the marginal cost of increasing carbon sequestration is zero. Hence, inefficient non-cover crop fields operate as if they were not compensated for sequestering carbon. This is consistent with carbon market payments targeting the adoption of cover crops to enhance carbon sequestration. The median GHG emissions shadow prices for inefficient non-cover crop fields are -0.44 acre per tCO_2 eq. and -USD 37.35 per tCO_2 eq. in real and nominal terms, respectively. Thus, these fields would incur a marginal cost of USD 37.35 to reduce GHG emissions by an additional tCO2 eq., which contrasts with efficient non-cover crop fields marginal costs of USD 50.78 per tCO_2 eq. Combined, the marginal costs faced by inefficient non-cover crop fields suggest less attention to carbon footprint relative to their efficient counterparts.

4.1. Comparison of shadow values to current carbon market prices

Compliance carbon markets have emerged in response to regulatory mandates in the United States. They function on a regional basis and cover only a small portion of the farmland. While none of the compliance carbon markets apply to our sample fields, voluntary carbon markets are available to all farms across the United States. Carbon markets may consist of inset markets, offset markets, or a blend. In inset markets, entities within the agribusiness sector serve as carbon buyers, while offset markets involve firms outside the agribusiness sector. While some of these programs pay for outcomes (e.g., per tCO_2 eq.), others pay by practice (e.g., per acre). The latter requires a change in farming practice, such as reducing N use or adopting cover crops.

Farms in our sample are paid by practice. The payment received depends on the program in which the farmer enrolls and the practice adopted. Payments for cover crop adoption range between USD 10 and USD 25 per acre and year ("Farmers for Soil Health," PCM (2024a); "New PepsiCo Incentive Payment Program," (PCM 2024b)). We investigate whether these payments compensate for the private value associated with the lower net carbon footprint of cover crop fields compared to non-cover crop fields. We first transform nominal shadow prices in Table 4 into USD per acre using equation (27), which relies on information regarding carbon sequestration and GHG emissions per acre for each field.

$$\begin{aligned}&\text{Nominal shadow price}\left(\frac{USD}{acre}\right)=\\&\text{Nominal shadow price}\left(\frac{USD}{tCO_2\ eq.}\right)\times\text{GHG emissions (Sequestration)}\left(\frac{tCO_2\ eq.}{acre}\right)\end{aligned}\tag{27}$$

Table 6 Summary of carbon sequestration and GHG emissions shadow prices for efficient fields in USD per tCO_2 eq. and in USD per acre by cover crop use.

Panel A: Carbon sequestration shadow prices

	Cover crop field N = 36 $\max\{\partial_s H^S(.)\}$			Non-cover crop field N = 204 $\max\{\partial_s H^S(.)\}$			Difference
	(1)	(2)	(3)	(1)	(2)	(3)	
Median	75.60	0.40	34.68	98.33	0.12	16.80	17.88
p25	39.89	0.40	10.55	43.70	0.12	5.95	4.60
p75	107.89	0.55	58.78	209.50	0.26	41.33	17.45

Panel B: GHG emissions shadow prices

	Cover crop field N = 17 $\min\{\partial_e H^E(.)\}$			Non-cover crop field N = 124 $\min\{\partial_e H^E(.)\}$			Difference
	(1)	(2)	(3)	(1)	(2)	(3)	
Median	-90.47	0.28	-23.35	-50.78	0.29	-13.93	-9.42
p25	-181.32	0.25	-51.97	-164.71	0.25	-46.69	-5.28
p75	-23.88	0.32	-8.30	-0.61	0.32	-0.18	-8.12

Note: Column (1) indicates shadow values in USD per tCO_2 eq. (nominal shadow values). These shadow prices are reported in this table from Table 4 for convenience. Column (2) reports carbon sequestration per acre in panel A and GHG emissions per acre in panel B. Column (3) reports shadow prices in USD per acre. Carbon sequestration (GHG emissions) shadow prices in USD per acre are calculated as the product of shadow prices in USD per tCO_2 eq. and sequestration (GHG emissions) per acre. Difference presents the difference in shadow prices (USD per acre, column 3) between cover crop and non-cover crop fields. p25 and p75 denote the first and third quartiles, respectively.

We present results in Table 6. Columns (1) replicate the nominal shadow prices (in USD per tCO_2) from Table 4 for convenience. Columns (2) report the carbon sequestration and GHG emissions per acre. Finally, columns (3) report the shadow price in USD per acre, which results from the product of columns (1) and (2). Although cover crop fields have a lower marginal cost of increasing sequestration by a ton of CO_2, their sequestration cost per acre exceeds that of non-cover crop fields. This discrepancy arises from the higher sequestration per acre in cover crop fields compared to non-cover crop fields (0.40 vs. 0.12). The difference in median sequestration shadow prices between our field categories is USD 17.88 per acre (USD 34.68 – USD 16.80), representing the compensation that cover crop fields should receive for their sequestration services. Likewise, the difference in median GHG emissions shadow prices between our field categories is USD 9.42 per acre (USD 23.35 - USD 13.93), providing an estimate of the compensation that cover crop fields should receive for their emissions mitigation services. Thus, for 2021, the total economic incentive for cover crop fields, considering carbon sequestration and GHG emissions reduction benefits of cover crops, should be USD 27.30 per acre (USD 17.88 + USD 9.42). This is above current cover crop adoption payments fluctuating between USD 10 - USD 25 per acre per year.

While cover crop adoption in the Midwest reached 7.2% in 2021, a significant increase from 1.8% a decade ago (Quinn 2022), the insufficient carbon payments may limit broader adoption of the agricultural practice. This underscores the significance of ecosystem service markets, where farmers receive payments for different environmental services, including carbon and water quality payments. Adopting cover crops can mitigate N runoff; thus, ecosystem service markets compensate cover crop fields for their reduced carbon and water pollution footprint. Since these payments can be stacked, they usually range between USD 25 and USD 50 per acre, averaging USD 35 per acre (Farmdoc 2023). Therefore, adopting cover crops becomes more appealing for farms through participation in ecosystem service markets.

5. Endnotes

[1]We do not consider compliance carbon markets as they currently have limited relevance for agriculture, covering only a small portion of the US farmland. At present, no compliance carbon market regulates Illinois fields.

[2]The main microbial processes that produce N_2O are nitrification and denitrification of available N in the soil (Robertson and Groffman 2007, Signor and Cerri 2013).

[3]These constraints eliminate the need to run linear problems (24) and (25) separately for efficient and inefficient fields.

[4]As a result, x_6 only reflects soil type but not soil management.

[5]We use the sample mean of N price whereas the corn price per bushel is the same across our sample fields.

6. Conclusions

We use management-science and operations-research methods to value the carbon benefits of cover crop fields compared to non-cover crop fields. To achieve this, we estimate the shadow prices of agricultural field-level carbon sequestration and GHG emissions, building upon the methodology proposed by Murty et al. (2012). This is the first article that offers shadow prices for carbon sequestration. We model the agricultural production technology as the intersection between the carbon sequestration sub-technology that generates crop revenue and sequesters carbon and the GHG emissions sub-technology.

We use the dual representation of the technology to calculate shadow prices, expressed relative to land, which serves as our numeraire. We model cover and non-cover crop fields as two separate production practices and report shadow values for each field type. Although we do not factor land inefficiencies into the calculation of shadow values, we report shadow prices for efficient and inefficient fields separately.

We use a unique field-level Illinois corn growers dataset that provides carbon sequestration and GHG emissions estimates. Median carbon sequestration shadow prices for efficient cover crop and non-cover crop fields are USD 75.60 and USD 98.33 per tCO_2 eq. The median GHG emissions shadow values for efficient cover crop and non-cover crop fields are USD 90.47 and USD 50.78 per tCO_2 eq. Our carbon sequestration shadow prices are consistent with the superior ability of cover crop fields to sequester carbon. GHG emissions' shadow prices are consistent with cover crop fields' superior compliance with the University of Illinois recommended nitrogen rates and with increasing marginal costs of GHG emissions mitigation. The shadow prices for inefficient fields are lower than for efficient fields, suggesting less attention to carbon footprint relative to their efficient counterparts. By comparing marginal costs between different field types, we establish that the net carbon benefit associated with cover crops relative to non-cover crops is valued at USD 27.30 per acre.

We compare this value with payments offered in voluntary carbon markets, which usually compensate farmers for adopting certain agronomic practices, especially cover crops. Our sample fields receive USD 10 to USD 25 per acre to cut their net carbon footprint ("Farmers for Soil Health" PCM (2024a); "New PepsiCo Incentive Payment Program" PCM (2024b)). This implies that only those fields at the higher payment range come close to covering the estimated USD 27.30 per acre, which suggests that these markets rarely offset the full cost of the practice. Ecosystem service markets have recently gained momentum as they offer payments for different environmental services. Since these markets allow stacking payments for different concepts, e.g., carbon and water quality payments, they offer a better incentive for adopting cover crops and increasing the supply of carbon offsets.

Our findings hold significant relevance for policymakers. We find that generating additional carbon offsets from Illinois fields may require higher payments, underscoring the importance of further promoting environmental service markets that enable farmers to capitalize on different environmental services. For businesses seeking sustainable and cost-effective strategies to offset their carbon footprint, agriculture emerges as a valuable supply source for additional carbon offsets. This may be particularly important for publicly traded companies if the Securities and Exchange Commission (SEC) implemented its climate change disclosure rulemaking, or if other states passed laws along the California's Climate Corporate Data

Accountability Act. Our results suggest further supply of offsets from agriculture could be generated, though the costs of acquiring these offsets may surpass current market values.

Information on actual carbon sequestration and GHG emissions from sample fields, as opposed to an estimation based on input use, would help refine our shadow values. Our results must be carefully interpreted, given that our sample of corn farms represents less than 1% of the 11 million acres of corn for grain planted in Illinois in 2021 (NASS 2023). Our research is also limited in the representativeness of our theoretical model. The latter relies only on the carbon sequestration and GHG emissions sub-technologies within the agricultural production technology while ignoring other by-products, such as soil erosion or water runoff. Including these sub-technologies by building a more complex multi-input, multi-output technology may allow for a better representation of the technology and estimation of shadow prices for other environmental services provided by agriculture. However, this would make the estimation of our model challenging, given the complex dynamics of such by-products within the agricultural production system.

Appendix

A. Dual tableau for linear problems $X_c^S(x_{-1}, n, p, y, s)$ and $X_c^E(x_{-1}, n, p, e)$

Panel A: Dual tableau for $X_c^S(x_{-1}, n, p, y, s)$

		γ_1	$\dots$	γ_i	$\dots$	γ_I	
$k \in \{2, \dots, 5, n, p\}$	w_k^y	$-x_{1k}$	$\dots$	$-x_{ik}$	$\dots$	$-x_{Ik}$	$-x_k$
$k \in \{2, \dots, 5, n, p\}$	$w_k^{'y}$	x_{1k}	$\dots$	x_{ik}	$\dots$	x_{Ik}	x_k
$k = 6$	$w_k^{'y}$	$-x_{1k}$	$\dots$	$-x_{ik}$	$\dots$	$-x_{Ik}$	$-x_k$
	w_y	y_1	$\dots$	y_i	$\dots$	y_I	y
	w_s	s_1	$\dots$	s_i	$\dots$	s_I	s
	ϕ	1	$\dots$	1	$\dots$	1	1
		x_{11}	$\dots$	x_{i1}	$\dots$	x_{i1}	

Panel B: Dual tableau for $X_c^E(x_{-1}, n, p, e)$

		μ_1	$\dots$	μ_i	$\dots$	μ_I	
$k \in \{2, \dots, 5, n, p\}$	w_k^e	$-x_{1k}$	$\dots$	$-x_{ik}$	$\dots$	$-x_{Ik}$	$-x_k$
$k \in \{2, \dots, 5, n, p\}$	$w_k^{'e}$	x_{1k}	$\dots$	x_{ik}	$\dots$	x_{Ik}	x_k
$k = 6$	$w_k^{'e}$	$-x_{1k}$	$\dots$	$-x_{ik}$	$\dots$	$-x_{Ik}$	$-x_k$
	w_e	e_1	$\dots$	e_i	$\dots$	e_I	e
	w'_e	$-e_1$	$\dots$	$-e_i$	$\dots$	$-e_I$	$-e$
	θ	1	$\dots$	1	$\dots$	1	1
		x_{11}	$\dots$	x_{i1}	$\dots$	x_{i1}	

B. Summary statistics of variables used in the analysis by cover crop use on a per-field basis.

	Cover crop field N = 120			Non-cover crop field N = 673		
	Median	p25	p75	Median	p25	p75
Revenue, (y)	46054.29	28777.82	73862.51	75274.50	41221.01	101717.07
Sequestration, (s)	23.62	10.97	34.11	9.22	5.07	18.03
GHG emissions, (e)	10.33	6.03	17.22	16.39	8.78	24.16
Nitrogen, (n)	8148.74	4720.19	13972.12	13417.24	7524.46	18222.92
Power costs, (p)	5780.62	3763.72	9634.43	7743.31	4343.51	10740.77
Land, (x_1)	42.52	25.83	69.21	67.00	38.28	82.31
Seed cost, (x_2)	5014.74	3107.91	8064.98	8043.60	4493.58	10003.49
Phosphorus, (x_3)	2401.68	1240.86	3682.12	3922.65	1945.80	6799.95
Potassium, (x_4)	3018.15	1523.58	4839.75	4727.40	2414.40	8248.41
Pesticide cost, (x_5)	2827.91	1718.10	4829.58	4352.00	2444.95	6944.64
Organic matter, (x_6)	0.08	0.04	0.17	0.08	0.05	0.98

Note: Source-PCM dataset. All netputs are expressed on a per-field basis. Revenue (y), power costs (p), seed cost (x_2) and pesticide cost (x_5) are expressed in USD, carbon sequestration (s) and GHG emissions (e) in tCO_2 eq., nitrogen (n), phosphorus (x_3) and potassium (x_4), in lbs., land (x_1) in acres, and organic matter (x_6) in percentage. p25 and p75 denote the first and third quartiles, respectively.

C. Percentage of corn farms in different categories based on maximum returns to N rate and most profitable N range by cover crop use.

	Cover crop field (%) N = 120	Non-over crop field (%) N = 673
Below MRTN	47.50	31.20
Above MRTN	52.50	68.80
Total	100.00	100.00
Below profitable range	34.17	14.86
Within profitable range	27.50	37.30
Above profitable range	38.33	47.85
Total	100.00	100.00

Note: Source- PCM dataset and own elaboration.

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