Testing for complementarity between the use of continuous no-till and cover crops: an application of Entropy approach

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Abstract

The benefits of no-till farming are fully-realized only when no-till is used continuously over numbers of years. Research shows that most US farmers do not use the practice continuously. One of the commonly suggested reasons for the intermittent tillage is the risk of significant yield penalty during the first several years after converting to continuous no-till. Agronomic research suggests that that cover crops can be both economical and biological answer to the risk of yield reduction associated with the use of continuous no-till as cover crops accelerate the processes of converting and storing nitrogen in the soil, and improve soil structure and water infiltration. However, whether farmers consider the complementary benefits of continuous no-till and cover crops is largely unknown. The objective of this study is to evaluate the relationship between the uses of the two conservation practices in Indiana. We develop a dynamic model of farmers' decision-making and estimate the probabilities of moving from one tillage/cover crops category to another. We apply a combination of Quadratic Programming and Cross-Entropy methods to the data from Conservation Tillage Information Center and Indiana Tillage and Cover Crops Transect, spanning 1992-2016. We find that there is no evidence in favor of the complementarily between the use of continuous no-till and continuous cover crops in Indiana. We also find that the use of continuous cover crops in the state is growing steadily at a rate of approximately 30% during 2011-2016 whereas the share of land allocated to continuous no-till increases slightly in the same period. The novelty of our contribution relates to both econometric methodology and data used. We introduce a novel approach for estimating dynamic models of farmers' yearly choices. We also demonstrate the possibility of testing for complementarity of farmers' choices with very limited – aggregated and missing – data. The latter novelty also opens possibilities for utilizing other aggregate, e.g., county-level, data collected and reported by the US Department of Agriculture.

1. Introduction

No-till (NT) is defined as a tillage system under which soil is left with minimum disturbance (CTIC, 2017). NT provides multiple on-farm and off-farm benefits: improving soil resilience and soil productivity, water quality (Derpsch, Friedrich, Kassam, & Li, 2010; Rittenburg et al., 2015). One of the most promising benefit of NT is carbon sequestration. NT increases the soil organic carbon (SOC) when compared with other tillage systems (T) (i.e., mulch, ridge and conventional tillage systems), and thus can contribute to reduction in greenhouse gas emissions (Lal, 2011). In 2015, USDA announced 10 building blocks consisting of wide range of technologies and practices that aim to reduce greenhouse gas emissions (https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdafiles/State-Offices/Michigan/newsreleases/pdfs/climate-smart-fact-sheet.pdf). The first building block is to improve soil resilience and increase soil productivity by promoting conservation practices such as conservation tillage (CT) and NT systems. However, the benefits CT and/or NT are only fully realized when the practices are used continuously over a period of year (USDA-NRCS, 2014). Even a single tillage event can release all carbon gained back to atmosphere (Conant, Easter, Paustian, Swan, & Williams, 2007; VandenBygaart, 2016).

Existing literature show that most farmers till their land every now and then (Derpsch, Friedrich, Kassam, & Li, 2010; Hill, 2001); only a small percentage of farmers in the US realizes the benefits of continuous NT (CNT) (Gelfand et al., 2011). Using Agricultural Resource Management Service (ARMS) data, Claassen and Ribaudo (2016) reported that only 21% of fields that grew wheat in 2009, corn in 2010 and soybeans in 2012 used NT in all 4 years. Horowitz, Ebel, and Ueda (2010) analyzed data from National Resource Inventory-Conservation Effect Assessment Project (NRI-CEAP) and ARMS, and showed that only 13% acres planted corn and soybeans in Upper Mississippi River Basin (UMRB) was in CNT in all 3 years surveyed. Hill (2001) tracked the use of CNT in Illinois, Indiana, and Minnesota during the period 1994-1999, and reported that on average, less than 2% field was in CNT in all 6 years surveyed. Profit-maximizing farmers are reluctant to adopt CNT because of the potential high yield penalty associated with NT, particularly, with cool, wet spring time weather (Wilhelm & Wortmann, 2004), and thus incentives may be needed to promote CNT (Claassen & Ribaudo, 2016).

Recent data show that cover crops (CR) increase corn and soybeans yields by 2.1%, and 4.2% respectively (http://www.ctic.purdue.edu/Cover%20Crops/). CR accelerate the process of converting and storing nitrogen in the soil, and improve soil structure and water infiltration (Amado et al., 2006; Delgado & Gantzer, 2015; Kaspar & Bakker, 2015; Villamil, Bollero, Darmody, Simmons, & Bullock, 2006). Using CR and NT on the same farm/field increase the benefits of the use of CNT exponentially (Snapp et al., 2005; USDA, 1996). Long term research shows that the economic benefit of NT can be fully realized after some seven years of CNT (Hoorman, Islam, Sundermeier, & Reeder, 2009). In these transition years, adoption of CR and NT simultaneously can improve the soil productivity and minimize the yield loss or even eliminate the loss associated with CNT (Hoorman et al., 2009; Le, 2017). Overall, agronomic evidences in favor of complementarily between the use of continuous CR (CCR) and CNT, but only limited number of farmers have adopted bundled conservation practices such as NT and CR (Wade, Claassen, & Wallander, 2015). The complementarity between use of CNT and CCR is largely unknown because panel CR and tillage data are limited and often unavailable to researchers.

Recent NT and CR data covering large regions are rarely available to researchers. Conservation Tillage Information Center (CTIC) collected nationwide tillage data annually for 1989-1998, biannually for 2000-2004, and for selected counties and states for 2006-2008 (CTIC, 2017). CTIC relied on road transect survey method to gather tillage and crop management systems but did not track the same farms/fields. Thus, CTIC data are not useful to assessing the extent of CNT. In addition, the CTIC data are only available at county level. ARMS and NRI-CEAP indicate that the use of NT is growing, though neither data set estimates the use of CNT either (Horowitz, Ubel, & Ueda, 2010). Moreover, ARMS and NRI-CEAP data are confidential and thus they are only available to researchers in aggregate forms – at a county or state level. Recently, CR and NT data became available through The Census of Agriculture. However, the data are only available for the year 2012 and do not provide a separation of CT adoption rates by crop. Finally, remote sensing techniques show promising potential in collecting crop residue covers data (Sharma et al., 2016; Sullivan, Strickland, & Masters, 2008), but significant improvement is needed to provide a reliable estimation of crop residue covers (Quemada & Daughtry, 2016; Zheng, Campbell, Serbin, & Galbraith, 2014).

One notable exception in terms of NT and CR data is Indiana. The Indiana Conservation Partnership (ICP) has been collecting and reporting county-level NT and CR adoption rates using road transect survey method. NT adoption rates are available for 1990, 1993, 1997, 2000, 2004, 2009, 2011, 2013, 2015 and 2016. ICP has also gathered and reported the CR adoption rates for 2011, 2013, 2014, 2015 and 2016. Similar to the CTIC, ARMS and NRI-CEAP data, ICP does not provide the information on the levels of the use of CCR and CNT.

The data limitations above described do not let us test for the complementarity between the use of CNT and CCR using the method introduced by Perry, Moschini, and Hennessy (2016).

To overcome our data restrictions – aggregated data with some years missing – we use a combination of Quadratic Programming (QP) and Cross-Entropy (CE) approach – a non-parametric approach (Golan, Judge, & Miller, 1996) – to infer the probabilities of farmers' year-to-year NT and CR choices. We then use the Bayes' theorem to test for complementarity between the use of CNT and CCR in Indiana. The novelty of our contribution relates to both the data used and econometric methodology that we apply. We introduce a novel approach for estimating dynamic models of farmers' yearly NT and CR choices and for testing for complementarity of farmers' choices with very limited – aggregated and/or missing – data. The novelty not only extends the recently introduced approached of Perry et al. (2016), who rely heavily on field-scale, panel data, but also opens up the possibilities for utilizing other aggregate, e.g., county-level, data reported by USDA.

Our estimated results indicate that there is no evidence in favor of the complementarity between the use of CNT and CCR in Indiana during 2011-2016. We find that neither the use CCR increases the probability of adopting CNT nor the use of CNT increased the probability of adopting CCR. We also find that the use of CCR in the state is growing steadily at a rate of 30% during 2011-2016 whereas the use of CNT increases slightly during the same period.

The rest of the paper proceeds as follows. We first present the data and the model to be estimated, beginning with an exposition on the challenges associated with the econometric analysis of dynamics of farmers' NT and CR choices with only aggregate and missing data. We then specify the model and present the econometric procedure for estimation of the use of CNT and CCR. We follow with the presentation and discussion of the empirical results. The paper concludes with a discussion of policy implications and possible extensions of the study.

2. Methodology

In this section, we present the data followed by the statistical model. We applied a combination of QP and CE approaches to estimate Markov transition probabilities of farmers' NT and CR choices. The QP is used to estimate prior information for the CE method. In addition, due to missing data, we use Maximum Entropy (ME) to recover missing data. We then use ME to estimate the joint and conditional probabilities of CNT and CCR adoptions based on estimated transition probabilities. To test for complementarity between the use of CNT and CCR, we apply Bayes' theorem.

2.1. Data

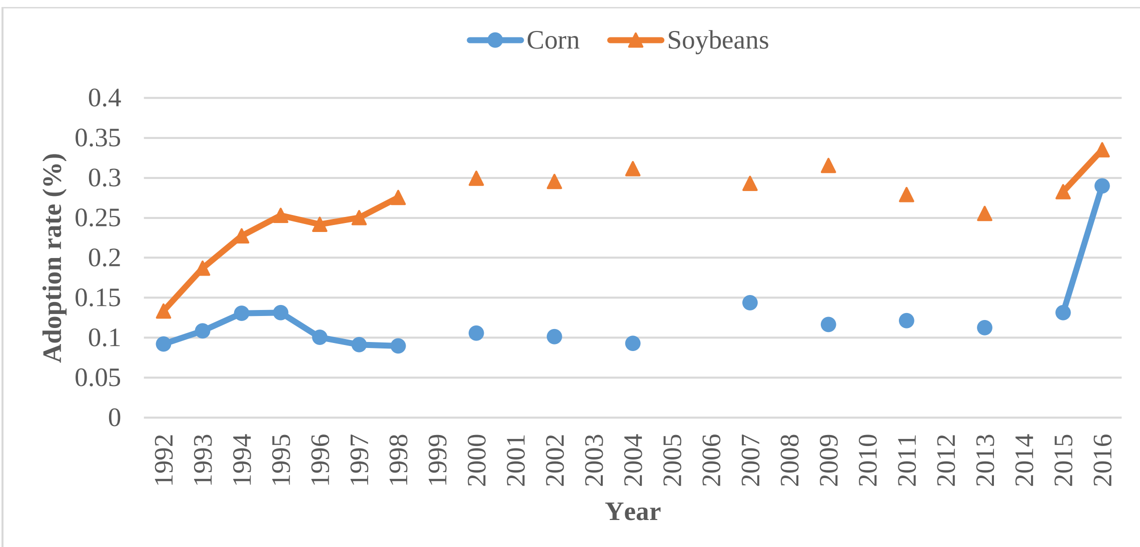

Figure 1. No-till adoption rates, 1992-2016, Indiana.

In this study, we use data from two sources. We use CTIC tillage data for 1992-1997, 2000, 2002 and 2004[1], whereas the ICP tillage and CR are used for 2007, 2009, 2011 and 2013-2016. We also use the USDA Census of Agriculture NT and CR data to test the models' performance.

[1] The difference between the CTIC- and the ICP-reported NT adoption rates for 1993, 1997, 2000 and 2004 is negligible.

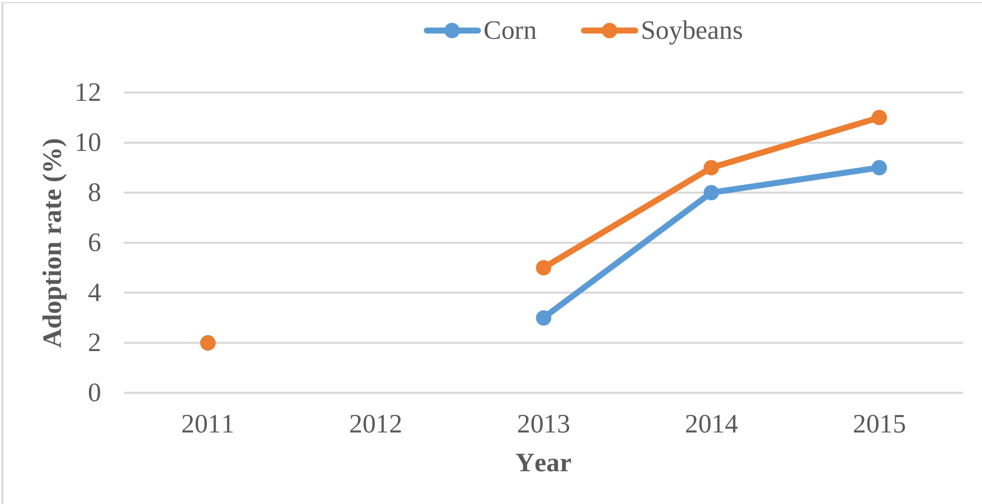

Figure 2. Cover crops adoption rates, 2011-2016, Indiana.

2.2. Statistical model

We use combination of QP and Generalized Cross Entropy (GCE) estimate 1st order Markov nonstationary transition matrices for the use NT and CR. The GCE techniques, which are founded on the directed divergence or minimal discriminability principles of Kullback (1959), were introduced by Golan et al. (1996). The GCE Markov problem can be formulated for a given t as follows:

$$\min I(\mathbf{p_{ij}(t)}, \mathbf{u_{jm}(t)}) = \sum_i \sum_j \mathbf{p_{ij}(t)} * \ln\left(\frac{\mathbf{p_{ij}(t)}}{\mathbf{q_{ij}(t)}}\right) + \sum_j \sum_m \mathbf{u_{jm}(t)} * \ln\left(\frac{\mathbf{u_{jm}(t)}}{\mathbf{w_{jm}(t)}}\right) \quad (1)$$

Subject to

$$\mathbf{s(t+1)} = \mathbf{s(t)} * \mathbf{p_{ij}(t)} + \mathbf{e_j(t)} \quad \forall i, j = 1, 2, 3, 4 \quad (2)$$

$$\sum_j \mathbf{p_{ij}(t)} = 1 \quad \forall i = j = 1, 2, 3, 4 \quad (3)$$

$$\sum_n \mathbf{u_{jm}(t)} = 1 \quad \forall j = 1, 2, 3, 4, m = 1, 2, 3 \quad (4)$$

$$\mathbf{e_j(t)} = \sum_j \sum_n \mathbf{u_{jm}(t)} * \mathbf{v_m} \quad \forall j = 1,2,3,4, m = 1,2,3 \tag{5}$$

And

$$\mathbf{p_{ij}(t)} \geq 0 \quad \forall i, j \text{ and } \mathbf{u_{jm}(t)} \geq 0 \quad \forall j = 1,2,3,4, m = 1,2,3 \tag{6}$$

The minimization of function (1) subjects to constraints (2)-(6) is run one transition matrix at a time. Here, *s(t)* is the one-by-four vector of tillage-crop shares in time *t*, corresponding to NT corn, tillage (T) corn, NT soybeans, and T soybeans for NT model[2] and CR corn, no CR (NC) corn, CR soybeans, and NC soybeans for CR model; p_{ij}(t) are the elements of transition matrix that represent the probabilities of moving from one crop-tillage/cover crops category, i, to another crop-tillage/cover crops category, j, in time t. $q_{ij}(t)$ is the prior information for $p_{ij}(t)$. The error includes two components: error weight, u and error support, v (Golan et al., 1996). Equation (1) represents the GCE criterion, which minimizes the distance between the prior distribution (q_{ij}) and transition matrix (p_{ij}). Simultaneously, the distance between error weights (u_{jm}) and their prior information (w_{jm}) is also minimized. Equation (2) is the Markov data consistency constraint. Equation (4) represents set of additivity constraints for the required Markov row constraint, while equation (5) does so for the proper probabilities of the reparametrized error. All proper transition probabilities and errors are required to be nonnegative ($p_{ij}, u_{ij} \geq 0$). The prior information on the error weights is uniformly distributed with $w = 1/m$, $m = 3$ $(m \geq 2)$ because further increases in m are shown to have little effect on the mean-square-error of estimates (Golan et al., 1996). The support bound are set to $v = [-MAE, 0, MAE]$, with MAE being the Mean Absolute Error of QP method.

[2] In this study, NT include NT and strip-till. Other tillage practices (mulch, ridge and conventional tillage practices) are included in the tillage category.

2.2.1. Estimation of prior information using Quadratic Programming

The prior information plays a significant role in the success of GCE technique (Aurbacher & Dabbert, 2011; Golan et al., 1996; Howitt & Reynaud, 2003; You, Wood, & Wood-Sichra, 2009). We apply QP to estimate stationary transition matrix during 1992-1997[3] (Kelton, 1994; Kurkalova & Tran, 2017; Lee, Judge, & Takayama, 1965; Lee, Judge, & Zellner, 1970; Tran & Kurkalova, 2016) to estimate prior transition matrix (q_{ij}). The fit of QP technique is evaluated via MAE, which is defined for each year n by

$$MAE^{n} = \frac{1}{4}\sum_{j=1}^{4}\left|s_j^n - \hat{s}_j^n\right| \tag{7}$$

$$\mathbf{s(t+1)} = \mathbf{s(t)} * \mathbf{q} + \boldsymbol{\varepsilon}, \tag{8}$$

where ε is the vector of random errors. The stationary transition matrix p^{st} is estimated by minimizing the quadratic form

$$\min_{q}(\mathbf{s(t+1)} - \mathbf{s(t)} * \mathbf{q})' * (\mathbf{s(t+1)} - \mathbf{s(t)} * \mathbf{q}) \tag{9}$$

Subject to

$$0 \le \mathbf{q_{ij}} \le 1, \quad i, j = 1,\ldots,4 \tag{10}$$

$$\sum_{j=1}^{4}\mathbf{q_{ij}} = 1, \quad i = 1,\ldots,4. \tag{11}$$

In this study, we assume that all the transition probabilities from soybeans to soybeans are equal to zero. In many parts of the northern Midwest, soybeans-soybeans rotation is very unlikely choice (Hennessy, 2006; Sahajpal, Zhang, Izaurralde, Gelfand, & Hurtt, 2014; Secchi, Kurkalova, Gassman, & Hart, 2011; Stern, Doraiswamy, & Akhmedov, 2008; Stern,

[3] QP is only applicable when the number of data point is greater than the number of state and transition matrix is stationary.

Doraiswamy, & Raymond Hunt, 2012). Thus, we restricted the four transition probabilities from soybeans to soybeans to zero:

$$\mathbf{p_{ij}} = 0, \quad i, j = 3, 4.$$

2.2.2. Recovering missing data

Another problem in this study is missing data. As mentioned above, CTIC has collected CRM data annually from 1989 to 1997 and biannually from 1998 to 2004, and ICP has been collecting NT adoption rates of 1990, 1993, 1997, 2000, 2004, 2009, 2011, 2013, 2015 and 2016. Thus, when we combine the two data sources, we do not have the data for 1999, 2001, 2003, 2005, 2006, 2007, 2008, 2010, 2012 and 2014. And ICP has been gathering the CR adoption rates for 2011, 2013, 2014, 2015 and 2016. We recover the missing data by treating them as unknown parameters in the GCE. To this end, Generalized Maximum Entropy (GME) is specified to let the aggregate crop-tillage shares in year t determine the most likely aggregate crop-tillage shares in year t+1 as well as the transition matrix for that period. For example, transition matrix for 1998-1999 and the tillage-crop shares for 1999 will be derived from the crop-tillage shares in 1998 and the prior information estimated from 1997-1998. The GME specified is:

$$\begin{aligned}\min I(\mathbf{p_{ij}(t), s(t), u_{jm}(t)}) &= \sum_i \sum_j \mathbf{p_{ij}(t)} * \ln\left(\frac{\mathbf{p_{ij}(t)}}{\mathbf{q_{ij}(t)}}\right) + \sum_k \mathbf{s_k(t+1)} * \ln\left(\frac{\mathbf{s_k(t+1)}}{\boldsymbol{\varphi}_\mathbf{k}\mathbf{(t+1)}}\right) \\ &+ \sum_j \sum_n \mathbf{u_{jm}(t)} * \ln\left(\frac{\mathbf{u_{jm}(t)}}{\mathbf{w_{jm}(t)}}\right) + \sum_k \sum_m \boldsymbol{\delta}_\mathbf{km}\mathbf{(t)} * \ln\left(\frac{\boldsymbol{\delta}_\mathbf{km}\mathbf{(t)}}{\boldsymbol{\gamma}_\mathbf{km}\mathbf{(t)}}\right)\end{aligned} \tag{12}$$

Subject to

$$\mathbf{s(t+1)} - (\mathbf{s(t)} * \mathbf{p_{ij}(t)} + \mathbf{e_j(t)} + \boldsymbol{\eta}_\mathbf{j}\mathbf{(t)}) = 0 \quad \forall i, j = 1, \ldots, 4 \tag{13}$$

$$\sum_j \mathbf{p_{ij}(t)} = 1 \quad \forall i, j = 1, \ldots, 4 \tag{14}$$

$$\sum_{m} \mathbf{u_{jm}(t)} = 1 \quad \forall j = 1,\ldots 4, m = 1,2,3 \tag{15}$$

$$\mathbf{e_j(t)} = \sum_{j}\sum_{m} \mathbf{u_{jm}(t)} * \mathbf{v_m} \quad \forall j = 1,\ldots 4, m = 1,2,3 \tag{16}$$

$$\sum_{k} \mathbf{s(t+1)} = 1 \quad \forall k = 1,\ldots,4 \tag{17}$$

$$\sum_{m} \boldsymbol{\delta}_{\mathbf{km}}\mathbf{(t)} = 1 \quad \forall k = 1,\ldots 4, m = 1,2,3 \tag{18}$$

$$\boldsymbol{\eta}_{\mathbf{j}}\mathbf{(t)} = \sum_{k}\sum_{m} \boldsymbol{\delta}_{\mathbf{km}}\mathbf{(t)} * \vartheta_{\mathbf{m}} \quad \forall k = 1,\ldots 4, m = 1,2,3 \tag{19}$$

and

$\mathbf{p_{ij}(t)} \geq 0 \quad \forall i, j = 1,\ldots,4$, $u_{jm}(t) \geq 0 \quad \forall k = 1,\ldots 4, m = 1,2,3$, $s_k(t) \geq 0 \quad \forall k = 1,\ldots,4$ and

$$\boldsymbol{\delta}_{\mathbf{jm}}\mathbf{(t)} \geq 0 \quad \forall k = 1,\ldots 4, m = 1,2,3 \tag{20}$$

Equation (13) represents data consistency constraints, and η_j are the errors of crop-tillage shares estimated, with δ_{km} and ϑ_m being the error weights and supports, respectively. Both prior information for shares (φ) and their errors (γ) are assumed uniformly distributed.

The objective function (12) is minimized subject to constraints (13)-(20), providing the estimates of transition matrices and missing data.

2.3. Evaluating models' performance

We compute MAE to evaluate the fit of QP approach. For the GCE and GME approaches, the normalized entropy (s_p) measures the amount of information in the estimated coefficients, corresponding to a pseudo $R^2 = 1 - s_p$ $(0 \leq s_p \leq 1)$ (Golan et al., 1996):

$$S_p = \frac{-\sum_{i}\sum_{j} p_{ij} * \ln(p_{ij})}{k * \ln(k)} \tag{21}$$

2.4. Bayes' theorem for testing complementarity

Consider two events: (1) Event CNT occurs when an acre of Indiana is adopted CNT and (2) event CCR when an acre of Indiana is adopted CCR. When the two events are not independent, Bayes' theorem states that the conditional probability of event CNT occurring given that event CCR has occurred, $P(CNT / CCR)$, is equal to the joint probability of the two events, $P(CNT \cap CCR)$, divided by the marginal probability if even CCR occurring, $P(CCR)$. Similarly, conditional probability of event CCR occurring given that event CNT has occurred, $P(CCR / CNT)$:

$$P(CNT / CCR) = \frac{P(CNT \cap CCR)}{P(CCR)} \tag{22}$$

$$P(CCR / CNT) = \frac{P(CNT \cap CCR)}{P(CNT)} \tag{23}$$

Thus, we have

$$\frac{P(CNT)}{P(CCR)} = \frac{P(CNT / CCR)}{P(CCR / CNT)} \tag{24}$$

We compute $P(CCR)$ and $P(CNT)$ based on estimated transition matrices and crop-tillage/cover crops shares, and then use the estimated $P(CCR)$ and $P(CNT)$ to estimate $P(CNT / CCR)$ and $P(CCR / CNT)$ using GME. The main constraint in the second step is stated as equation (24). Then, we compute the joint probabilities.

To test for complementarity between CNT and CCR, we estimate two probabilities: the event CNT occurring given that the complement of event CCR has occurred, $P(CNT / \overline{CCR})$, and the event CCR occurring given that the complement of event CNT has occurred, $P(CCR / \overline{CNT})$.

$$P(CNT / CCR) = \frac{P(CCR / CNT) P(CNT)}{P(CCR)} = \frac{P(CCR / CNT) P(CNT)}{P[(CCR \cap CNT) \cup (CCR \cap \overline{CNT})} \tag{25}$$

$$P(CCR/\overline{CNT}) = \frac{P(CCR) - P(CNT \cap CCR)}{1 - P(CNT)} \quad (26)$$

$$P(CNT/\overline{CCR}) = \frac{P(CNT) - P(CNT \cap CCR)}{1 - P(CCR)} \quad (27)$$

If $P(CNT/CCR) > P(CNT/\overline{CCR})$, the adoption of CCR has increased the probability of adopting CNT. If, $P(CCR/CNT) > P(CCR/\overline{CNT})$, the adoption of CNT has increased the probability of adopting CCR.

3. Results and discussions

3.1. The performance of the models

We first evaluate the models performance based on MAE and S_p values. MAE for both CR and NT dynamics models are considerably small (less than 2%). The normalized Entropy values are ranging from 0.30 to 0.55 for NT model and from 0.15 to 0.27 for CR model. We also compare our estimates and observed data. Regarding the CR model, the observations come from two sources: ICP and the 2012 Census of Agriculture. Similarly, CTIC and ICP NT data are used for the NT model. The comparison between the observed and measured CR and NT rates is presented in figures 3 and 4, respectively. It is worth noting that the 2012 Census of Agriculture estimates are considerable higher than that of ICP for both CR and NT. For instance, according to ICP, NT rates are 40% and 37% in 2011 and 2013, respectively, whereas the Census of Agriculture NT rates are estimated at 48% in 2012.

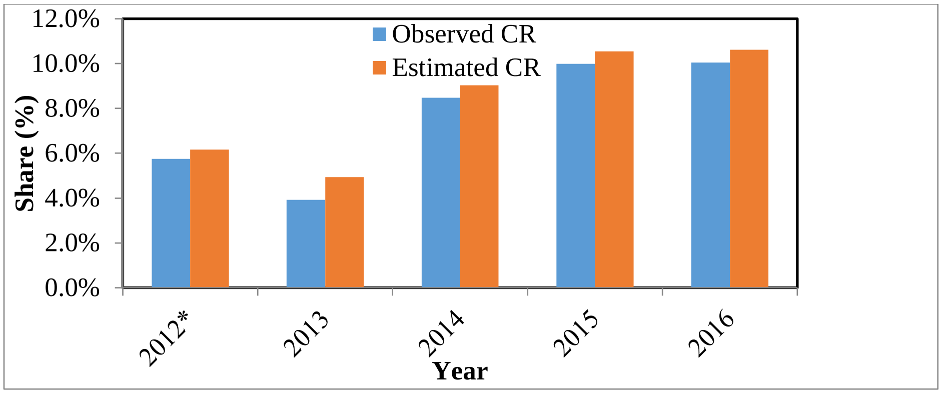

Figure 3. Estimated versus measured percentage of cover crops in Indiana

Notes: The observed data come from ICP for all years except 2012. The 2012 data are from the Census of Agriculture.

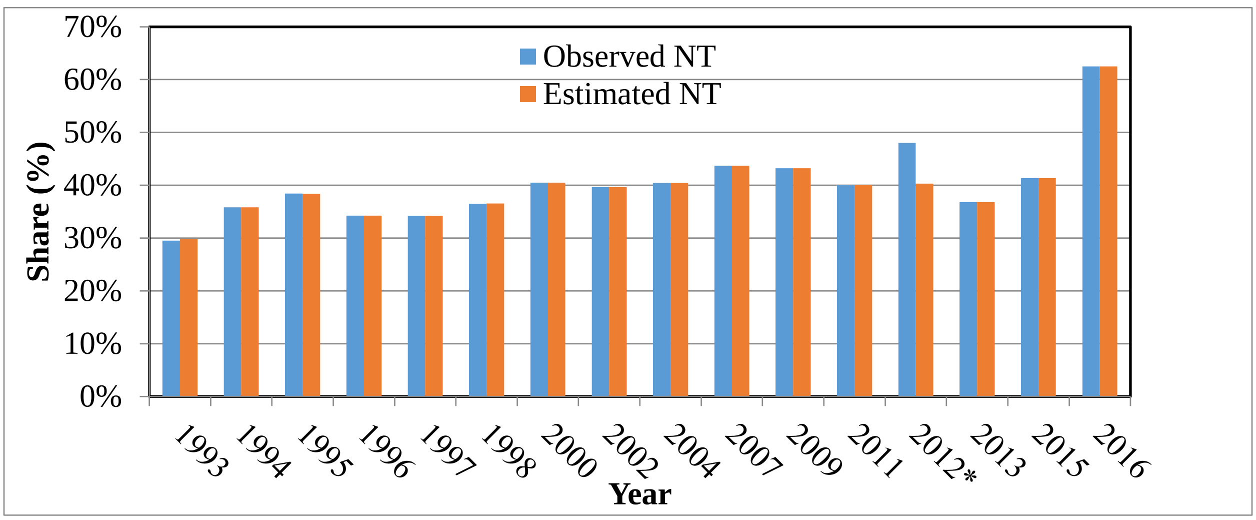

Figure 4. Estimated versus measured percentage of NT in Indiana

Notes: *the observed data come from ICP for all years except 2012. The 2012 data are from the Census of Agriculture.

3.2. Dynamics of no-till

Figure 5 presents the comparison between the observed percentage of NT and estimated percentage of CNT. The estimated CNT strongly suggest that farmers often alternate NT with tillage practices. We estimate that only approximately 30% of land classified as NT is actually under CNT. The estimated CNT also indicates the potential effect of the change in corn and soybeans prices on the use of CNT. The percentage of CNT decreased during the period of 2008-2014, corresponding to the increase in the prices for corn and soybeans. The use of CNT increase after 2014. It is estimated that 12% of Indiana cropland in 2014 is under CNT compared with 26% in 2016 (table 1).

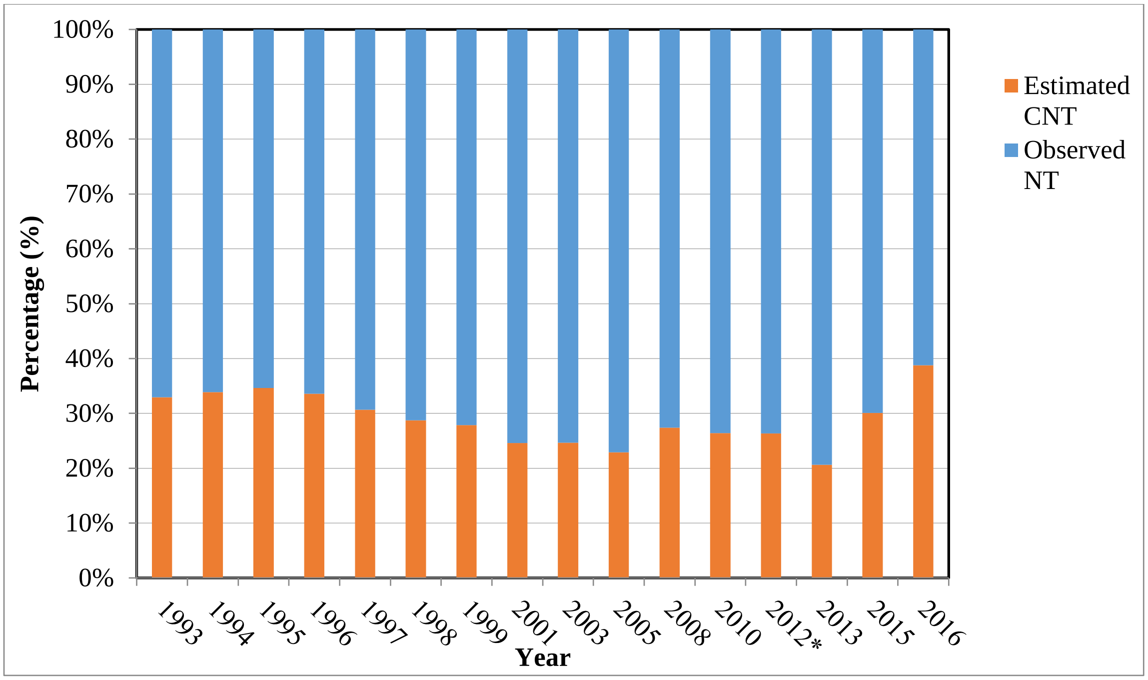

Figure 5. Estimated CNT versus observed percentage of NT in Indiana

Table 1. The change in the use of CNT, 2008-2016

Tillage regime	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016
CNT	19%	15%	16%	14%	15%	12%	16%	26%
Continuous T	28%	29%	33%	34%	37%	39%	36%	25%
Rotational NT	53%	55%	51%	52%	48%	49%	48%	49%

3.3. Dynamics of cover crops

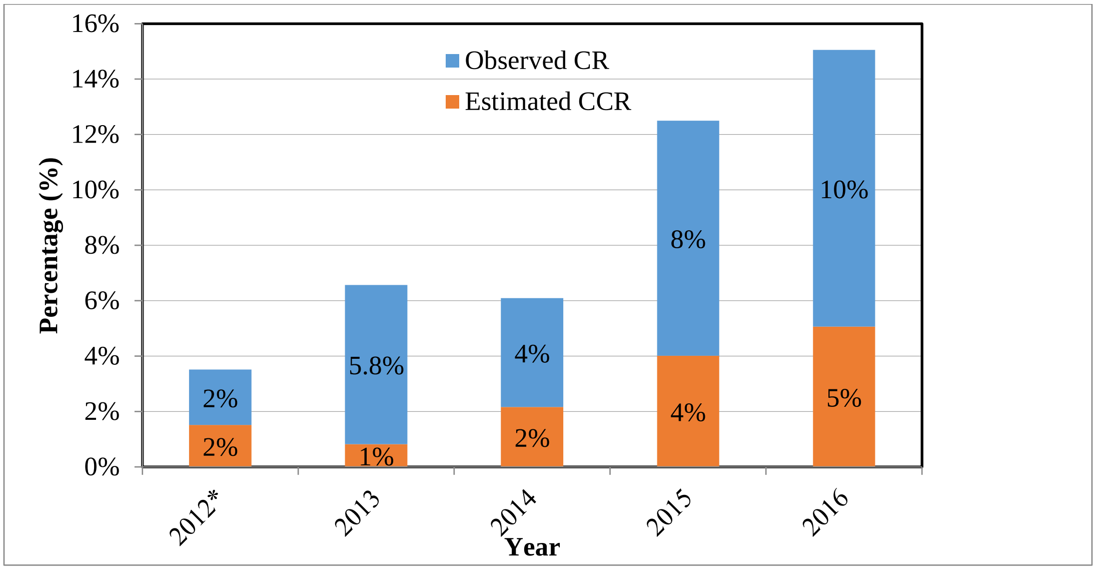

Figure 6. Estimated CNT versus observed percentage of NT in Indiana

Figure 6 shows the dynamics of the use of CCR. Similar to the use of CNT, we estimate that on average, only half of land under CR remains under CR after one year. Even though the use of CCR increased significantly during 2013-2016, the CCR is still used on less than 5% of total cropland in Indiana in 2016. Given the use of CNT in the state is almost 30% in the same period, the low use of CCR suggests that only a small fraction of Indiana farmers adopt CCR and CNT on the same farms/fields.

3.4. Complementarity between the use of CNT and CCR

Table 2. The use of CCR and CNT for 2011-2016, Indiana

Probability	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016
CCR	0.015	0.008	0.022	0.040	0.051
CNT	0.143	0.151	0.125	0.160	0.262
P(CNT/CCR)	0.00912	0.00347	0.00108	0.00037	0.00014
P(CCR/CNT)	0.00096	0.00019	0.00019	0.00009	0.00003
$P(CNT/\overline{CCR})$	0.136	0.148	0.126	0.166	0.275
$P(CCR/\overline{CNT})$	0.017	0.010	0.025	0.048	0.069

Estimated shares and conditional probabilities of Indiana CCR and CNT for 2011 through 2016 are presented in table 2. In all years, the conditional probability of using CNT given CCR, *P(CNT/CCR*), is lower than the conditional probability of using CNT given the probability of not using CCR, $P(CNT/\overline{CCR})$, indicating that the use of CCR does not increase the probability of adopting CNT. Similarly, the conditional probability of using CCR given alternating NT or continuous conventional tillage, $P(CCR/\overline{CNT})$, is higher than the conditional probability of using CCR given CNT, $P(CCR/CNT)$, indicating that the use of CNT would not affect the Indiana farmers' decision to adopt CCR. It is worth noting that the gap between the *P(CNT/CCR*) and $P(CNT/\overline{CCR})$ does not narrow over time, indicating that even though the use of CCR is on the rise in the state, the increasing adoption of CCR does not improve the year-to-year probability of using CNT. In conclusion, the Bayes' theorem results reject the hypothesis of complementarity between the use of CNT and CCR in Indiana.

4. Conclusions

Soil is one of the most important resources worldwide. Agronomic evidence indicates that the benefits of CNT to the soil health and water quality are enhanced if CNT is used simultaneous with CCR. However, only very small portion of farmers adopt CNT and CCR on the same farms/fields. Using a combination of QP and Entropy approaches, we find that there is no evidence in favor of the complementarily between the use of CNT and CCR in Indiana during 2011-2016. This finding is in line with the only previous study that looked into simultaneous use of these two practices. Wade, Claassen, and Wallander (2015) used national ARMS data collected in the 2010 and 2011 surveys to show that the CR and NT adoption rates were less than 2% and 40%, respectively, indicating that US farmers have not customarily used NT and CR on the same fields to take advantage of complementarity of the two practices. We also find that the use of CCR in the Indiana is growing steadily at a rate of 30% during 2011-2015 whereas the use of CNT adoption rates increase only slightly in the same period.

Our study contributes to the literature in both methodology and data leveraged. First, we introduce a novel approach for estimating dynamic models of farmers' yearly choices with very limited – aggregated and missing – data. Second, we demonstrate the possibility of testing for complementarity of farmers' choices with aggregated and incomplete data. The latter novelty not only extends the recently introduced approached of Perry et al. (2016), who rely heavily on field-scale – panel data – but also opens up possibilities for utilizing other aggregate, e.g., county-level, data reported by USDA.

One of potential policy implications of this study is that even though agronomic studies strongly support the use of CNT and CCR simultaneously, promoting the use of CR might not be an effective approach to increase the use of CNT and subsequently accelerate amount of carbon sequestered.

An important question remains unanswered relates to the effect of natural conditions on the use of CNT and CCR. Future research could investigate the variability of CNT and CCR adoption by taking into consideration of heterogeneity of natural conditions (e.g., soil types, variability of weather). Our framework could be potentially extended to by treating the transition matrices as a functions of natural resources and economic conditions, thus allowing for testing for the complementarity between the use of CCR and CNT at farm/field level.

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