International Soil and Water Conservation Research 7 (2019) 109–118

Contents lists available at ScienceDirect

International Soil and Water Conservation Research

journal homepage: www.elsevier.com/locate/iswcr

Original Research Article

Persistence in tillage decisions: Aggregate data analysis

Dat Q. Tran [a, b, *], Lyubov A. Kurkalova [c, d]

[a] University of Arkansas at Fayetteville, AR 72701, Department of Agricultural Economics and Agribusiness, USA
[b] Can Tho University, Department of Hydraulic Engineering, Vietnam
[c] 1601 E. Market St., Greensboro, NC, 27411, North Carolina A&T State University, Department of Economics, USA
[d] 1601 E. Market St., Greensboro, NC, 27411, North Carolina A&T State University, Department of Energy and Environmental Systems, USA

ARTICLE INFO

Article history:
Received 22 August 2018
Received in revised form
3 March 2019
Accepted 20 March 2019
Available online 23 March 2019

Keywords:
Aggregate data
Continuous conservation tillage
Markov chain model
Crop rotations
Highly erodible land

ABSTRACT

The Emission Gap Report 2013 from the United Nations Environment Program showed that adopting conservation tillage such as no-till, as an alternative to conventional tillage, contributes significantly to climate change mitigation through carbon sequestration. However, substantial amounts of soil carbon are lost when farmers interrupt continuous use of conservation tillage with conventional tillage. Conservation tillage is spreading, but little is known about the behavioral persistence in tillage decisions. To address the gap in the literature, we estimate county-specific Markov models of tillage-crop choices, and use the predicted probabilities of alternative two- and three-year tillage rotations to evaluate spatial variation and temporal persistence in conservation tillage adoption for the state of Iowa (U.S). We find that the county-average probabilities of continuous conservation tillage range between 0.133 and 0.295, and vary significantly among crop rotations. We also find a statistically strong positive effect of the incidence of the highly erodible land on the county-average use of continuous conservation tillage. Our results underscore the importance of dynamic modeling for understanding behavioral persistence in tillage decisions, and the interdependence between farmers' crop and tillage rotations.

1. Introduction

Conservation tillage (CT) has been a subject of considerable research because, when compared to conventional tillage (VT), it provides numerous environmental benefits and could play a major role in climate change mitigation (Knowler & Bradshaw, 2007; Mangalassery et al., 2014; Prokopy, Floress, Klotthor-Weinkauf, & Baumgart-Getz, 2008; UNEP, 2013; Wade & Claassen, 2017). While both CT and VT are umbrella terms encompassing multiple tillage systems, the delineations used in the U.S. most commonly follow the ones by the Conservation Technology Information Center (CTIC), which defines CT (VT) as any tillage system that leaves at least 30% (less than 30%) of the soil covered with crop residue after planting. Under these definitions, CT encompasses no-till/strip-till, mulch-till and ridge-till, and VT - reduced-till and/or intensive-till with involvement of moldboard plowing and/or multiple tillage trips (CTIC, 2018).

Controlled experiments conducted under a wide range of soil and climatic conditions show that continuous CT (CCT), i.e., CT used continuously over a number of years, contributes to protection of soil from erosion, enhances beneficial microbial activity, and sequesters carbon, when compared to continuous conventional tillage (CVT), i.e., VT practiced continuously over the same number of years (Busari, Kukal, Kaur, Bhatt, & Dulazi, 2015; Lal, 2004, 2014; Sainju, Senwo, Nyakatawa, Tazisong, & Reddy, 2008; Uri, 2001). Alternating CT (ACT), i.e., the practice under which CT is alternated with VT in some years, has received less attention in the literature. Nevertheless, it has been shown that the many environmental benefits of CT are lost with the reversal back to VT even for a single year (Conant, Easter, Paustian, Swan, & Williams, 2007; Grace et al., 2011; Six et al., 2004). Specifically, climate change mitigation benefits of CT and its most stringent version, no-till (NT), are fully realized only when the practices are used continuously over a period of years, as CCT or continuous NT (CNT) (Grandy, Robertson, & Thelen, 2006; USDA-NRCS, 2015; VandenBygaart, 2016).

Because of the associated environmental benefits, CCT use has been promoted by multiple U.S. agricultural conservation programs (Bowman, Wallander, & Lynch, 2016; Claassen, Cattaneo, & Johansson, 2008; Duriancik et al., 2008; USDA-NRCS, 2015). Although the planning, monitoring, and evaluation of such conservation programs requires historical data on land use and CT

* Corresponding author. University of Arkansas at Fayetteville, AR 72701, Department of Agricultural Economics and Agribusiness, USA
E-mail addresses: datquoct@uark.edu (D.Q. Tran), lakurkal@ncat.edu (L.A. Kurkalova).

https://doi.org/10.1016/j.iswcr.2019.03.002
2095-6339/

Abbreviations

CT	conservation tillage
VT	conventional tillage
ACT	alternating conservation tillage
CCT	continuous conservation tillage
CVT	continuous conventional tillage
CC and CCC	corn after corn and corn after corn after corn rotations, respectively
CS	corn after soybeans or soybeans after corn rotations
CCS	corn after corn after soybeans
CSC	corn after soybeans after corn
SCC	soybeans after corn after corn
SCS	soybeans after corn after soybeans
HEL	highly erodible land

(Gallant, Sadinski, Roth, & Rewa, 2011; Jackson-Smith, Halling, de la Hoz, McEvoy, & Horsburgh, 2010; Lobb, Huffman, & Reicosky, 2007; Osmond et al., 2012; Tomer et al., 2014), the spatial patterns of CCT, CVT and ACT remain poorly understood. Prokopy et al. (2008) reviewed 25 years of literature focused on the adoption of conservation practices and concluded that much of the literature on tillage adoption utilizes cross-sectional data and use static approaches. Therefore, little is known about persistence in tillage decisions. Similarly, Claassen and Ribaudo (2016) noted that disadoption is an issue for conservation programs and only a few studies have examined the persistence of cropland conservation practices. Most recently, Dayer, Lutter, Sesser, Hickey, and Gardali (2017) meta-analysis of private landowner conservation behavior argued that persistence in the adoption of easily reversible conservation practices should not be assumed to be the outcome, and that empirical research to examine whether and why landowners continue with conservation practices is urgently needed.

Identification of tillage data through remote sensing remain challenging (Zheng, Campbell, Serbin, & Galbraith, 2014; Sharma et al., 2016; Bégué et al., 2018), and the known tillage dynamics estimates come from field-level surveys. The surveys conducted in selected regions of the U.S. Corn Belt showed that NT was commonly alternated with other tillage practices in the 1990s (Hill, 1998, 2001; Napier & Tucker, 2001) and in 2004–2007 (USDA-NRCS, 2012). More recently, a national survey of famers growing corn, soybeans and wheat in the U.S. in 2009 and 2010 found that out of 622 farmers surveyed in the Corn Belt, which includes Illinois, Indiana, Iowa, Missouri, and Ohio, some 55% used CT on all crops in both years, 14% used VT on all crops in both years, and the remaining part of the sample used ACT (Andrews, Clawson, Gramig, & Raymond, 2013).

Exclusive reliance on farmer surveys for understanding of the spatial patterns of CCT, CVT, and ACT has several downsides. The high cost of conducting the surveys often results in relatively small samples, which limit the ability to make statistically reliable inferences. The detailed survey results could be inaccessible to researchers because of confidentiality concerns, resulting in the availability of the tillage time pattern estimates aggregated to the state or even multi-state regions only.[1] Finally, the tillage persistence patterns discerned from survey-based studies conducted in specific regions and on specific cropping patterns are not immediately transferable to other regions and/or cropping patterns because no explanation of the spatial variation in observed rates of CCT or ACT has been attempted (Knowler & Bradshaw, 2007; Knowler, Bradshaw, & Holmes, 2014; Prokopy et al., 2008; Baumgart-Getz, Prokopy, & Floress, 2012).

To address the need for alternative approaches to quantification of persistence in tillage decisions, our study evaluates the use of CCT and ACT using an explicitly dynamic Markov chain approach. Unlike static models, such as logistic regression, that focus on one-time choice, Markov chain is a probabilistic model that describes sequential processes - in our case, sequential choices of tillage. The method relies not on farmer surveys, but on time-ordered spatially aggregated data (Kurkalova & Tran, 2017; Lee, Judge, & Takayama, 1965).

A variety of past studies on the use of CT provided useful insights about the factors that are likely to affect the tillage adoption decisions (Knowler & Bradshaw, 2007; Prokopy et al., 2008; Baumgart-Getz at al., 2012; Knowler et al., 2014; Carlisle, 2016; Adusumilli & Wang, 2018); however, most of previous tillage studies used static models to study tillage decisions (Wallander, Bowman, Beeson, & Claassen, 2018). The use of the CT has been shown to vary by crops (Ding, Schoengold, & Tadesse, 2009; Horowitz, Ebel, & Ueda, 2010). The link between CT use and cropping sequences (crop rotations) has been suggested (Choi & Sohngen, 2010; Hill, 1998; Lewandrowski et al., 2004; Robertson et al., 2014; Torre Ugarte, Hellwinckel, & Larson, 2004), but barely explored. This is most likely because the majority of CT use studies used a static (one year at a time) as opposed to a dynamic (year to year transitions) settings, and tended to focus on analyzing the differences between one-year CT adopters versus one-year CT non-adopters (Claassen & Ribaudo, 2016; Wallander et al., 2018). To preview the results of our analysis, we show that in fact, the time patters of farmers' tillage and crop choices are highly interrelated.

We also gain insights into the relation between CCT and ACT, and soil erodibility. CT is the conservation practice that is used most widely among the practices aimed at combatting soil erosion on actively cropped Iowa land (Secchi et al., 2007; USDA-NRCS, 2012). Recent analysis of field-level, 2010 corn and 2012 soybean U.S. national survey found that designation of land as highly erodible land (HEL) increases the probability of NT alternated with other tillage practices and, to a greater extent, the probability of CNT (Wade & Claassen, 2017). To the best of our knowledge, our study is the first one to employ a dynamic framework to analyze the use of CCT.

The study has three interrelated objectives: to evaluate the spatial variability of CCT and ACT across the 99 counties, to analyze whether the variation in tillage dynamics is related to crop rotations, and to test whether the variability in CT persistence could be explained by a spatial variability in soil erodibility for a major U.S. crop production region, state of Iowa. The resulting improved understanding of both (a) the extent of CCT and ACT and (b) the factors associated with their spatial variability is likely to be helpful in improving the assessment of the environmental effects of alternative tillage systems.

2. Data and methods

The analysis involves two major steps. In step one, we estimate the matrices describing the transitions among alternative tillage-crop choices for each of the 99 counties in Iowa, and calculate the county-specific probabilities of CCT and ACT. To reveal the spatial pattern of CT persistence, we map the probabilities. In the step two, we study how CCT and ACT probabilities vary with crop rotations

[1] For example, the Agricultural Resource Management Survey (ARMS) estimate of NT adoption for corn following corn in Iowa is statistically unreliable due to a low sample size (USDA-ERS, 2018). Likewise, the National Resources Inventory-Conservation Effects Assessment Project (NRI-CEAP) estimates of CNT are based on a low sample size and currently available only for a limited sets of geographic regions, each encompassing multiple states (Horowitz et al., 2010).

and soil erodibility in the study area. The following subsections detail the study area, statistical model, data, computation of CCT and ACT probabilities, and the measurement of the dependency between the estimated probabilities of alternative tillage rotations, crop rotations, and soil erodibility.

2.1. Study area

Our study is conducted for the state of Iowa (U.S), where row cropping is dominated by two crops, corn and soybeans, the combined share of which in Iowa harvested cropland was 91, 92, 93, and 94 percent in 1992, 1997, 2002, and 2007, respectively (USDA, 2019). The two crops are usually alternated in consecutive years i.e., corn after corn, corn after soybeans and soybeans after corn (Plourde, Pijanowski, & Pekin, 2013; Sahajpal, Zhang, Izaurralde, Gelfand, & Hurtt, 2014; Secchi, Kurkalova, Gassman, & Hart, 2011; Stern, Doraiswamy, & Raymond, 2012). While many possible delineations of tillage systems exist (CTIC, 2018), we focus on the two commonly considered alternatives, CT and VT.

2.2. Markov chain model of tillage-crop choices

The first-order, Markov chain model of tillage-crop choices starts with the assumption that all cropland in a given county k in year t is allocated to one of four mutually exclusive tillage-crop uses: 1 (CT corn), 2 (VT corn), 3 (CT soybeans), and 4 (VT soybeans) (Howard, 1971; Kurkalova & Tran, 2017; Lee et al., 1965). The model postulates that present year tillage-crop choices depend on previous year decisions and the probabilities of transition. Specifically, let p_{ijk} be the probability of tillage-crop choice j in the current year following tillage-crop use i in the year before in county k, where i, $j = 1, \ldots 4$; $k = 1, \ldots, K$, and $K = 99$ is the total number of counties considered. Then s_{jk}^{t+1}, the proportion of the county k's land in tillage-crop j in year $t + 1$, is equal

$$s_{jk}^{t+1} = \sum_{i=1}^{4} p_{ijk} s_{ik}^{t} + \varepsilon_{jk}^{t+1}, \quad j = 1, \ldots, 4; \quad k = 1, \ldots, K, \tag{1}$$

where s_{ik}^{t} is the proportion of the county k's land in tillage-crop i in year t (previous year), ε_{jk}^{t+1} is a random error, and $\sum_{j=1}^{4} p_{ijk} = 1, \quad i = 1, \ldots 4; \quad k = 1, \ldots, K$.

Because of the multiple diseases associated with planting soybeans after soybeans under Iowa soil and climatic conditions (Mueller, Robertson, Sisson, & Tylka, 2010), the practice is very rare in the state and the corresponding probabilities, p_{ijk}, $i,j = 3,4$, are postulated to be zero. The remaining probabilities of tillage-crop choices can be estimated using the restricted least squares (RLS) method if four or more years of the land proportion data are available (Kurkalova & Tran, 2017).

2.3. Data

We estimate models (1), one for each Iowa county, using the data on the proportions of land in the four tillage-crop uses that come from the National Crop Residue Management (CRM) survey by CTIC (CTIC, 2018). As a complete, county-level, national coverage survey, CRM has been the backbone of numerous studies of alternative tillage systems (Ding et al., 2009; Ogle et al., 2010; Baker, 2011; Panagopoulos et al., 2015, 2017). The CRM records are based on a combination of county conservation experts' opinions and the roadside transect method that requires visual assessment of tillage systems while driving a set course through the county. The accuracy of the data has been regarded adequate (Baker, 2011; Gassman, Secchi, Jha, & Kurkalova, 2006). The periodicity of the survey was reduced from every year (1989–1998) to every other year (1998–2004), and the later data were collected only for selected counties in selected states (2006–2008) (CTIC, 2018). Fig. 1 shows the summary of the data.

We estimate the county-specific models (1) using the six year of data, t = 1992, …,1997, leaving 1998, 2000, 2002 and 2004 for out-of-sample evaluation of model performance. We chose the 1992 to 1997 period for estimation because it is the longest time span for which the data fluctuate annually without a significant increasing or decreasing trend – the fluctuations consistent with the stationary Markov model (Lee et al., 1965). Note that although annual data are available 1989–1991, they do not display the zigzag pattern consistent with the model, and in consequence are not used for model estimation. Also of note is the fact that the six-year time span of the data is sufficient for estimating a four-state Markov model (Lee et al., 1965).

To investigate whether the use of continuous and/or alternating CT is affected by soil erodibility, we focus on the HEL. USDA Natural Resource Conservation Service (NRCS) classifies cropland as HEL if the potential of a soil to erode, considering the physical and chemical properties of the soil and climatic conditions where it is located, is eight times or more the rate at which the soil can sustain productivity (USDA/NRCS, 2002). To match the spatial resolution of

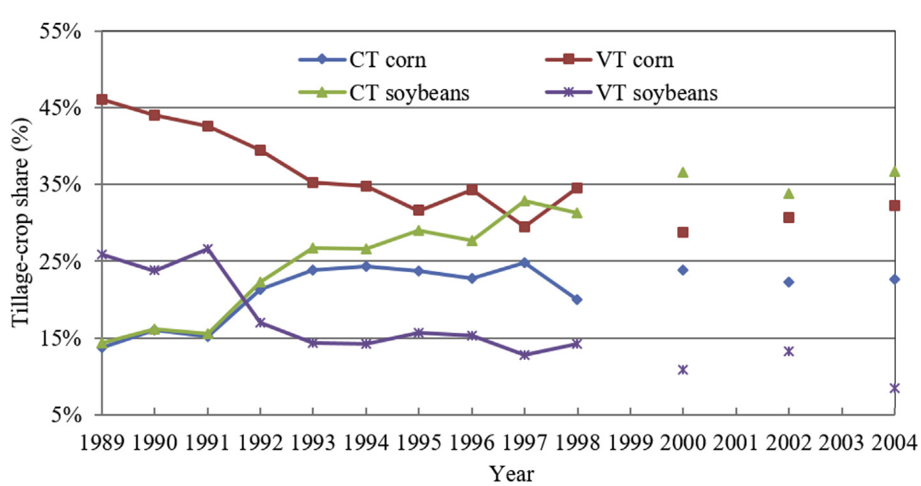

Fig. 1. Shares of alternative tillage-crop areas in the combined corn and soybeans total area, Iowa. Source: CTIC data (CTIC, 2018). CT = conservation tillage and VT = conventional tillage.

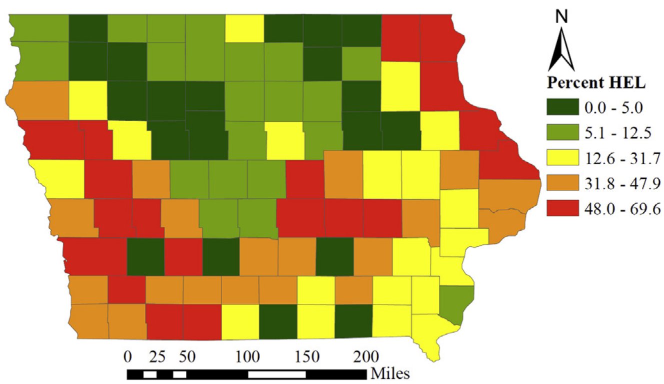

Fig. 2. Percentage of cropland classified as highly erodible land (HEL code of 1, highly erodible), by county, Iowa.

CRM, which is reported at the county level, we use the county k average percentage of cropland designated as HEL, HEL_k, as a measure of county-average soil erodibility.

The data for the HEL acreage come from the Iowa Soil Properties and Interpretations Database (ISPAID) version 7.1 (ISU, 2004), in which the HEL code has three possible values: 1, if a given map unit if highly erodible, 2, if the map unit is potentially highly erodible, and 3, if the map unit is not highly erodible. + the HEL code value of 1 only. Following previous crop production studies that use county-level data (Claassen et al., 2017; Ding et al., 2009; Zimmermann & Heckelei, 2012), we calculate HEL_k as the percentage of the county's cropland with the HEL code value of 1 in the total county's cropland. Fig. 2 shows the spatial variation of the county-average percentage of cropland classified as HEL, HEL_k, k = 1, …,99, on the map of Iowa.

2.4. Extent of CCT and ACT

Once the models (1) are estimated, we test several hypotheses about the extent of CCT and ACT. In line with the most common crop rotations in Iowa, which are either biannual or triannual, corn-soybeans, continuous corn, and corn-corn-soybeans (Plourde et al., 2013; Sahajpal et al., 2014; Secchi et al., 2009, 2011), we focus on two- and three-year tillage rotations.

We use the estimates of the transition probabilities in model (1) to estimate the probabilities of (or shares of cropland in) alternative tillage and crop rotations. When only two years of tillage-crop choices are considered, the probability of CCT in any given year is the probability that tillage is CT in both the current and the previous years, i.e., the sum of the probabilities of CT corn after CT corn, CT corn after CT soybeans, and CT soybeans after CT corn. The probabilities of CCT are computed for all the five two-year sequences within the time period of our data, i.e., for 1992–93, 1993–94, 1994–95, 1995–96, 1996–97; we use the five-year average as a single, county-level measure of the extent of two-year CCT, $P_{k,CCT-2}$:

$$P_{k,CCT-2} = \frac{1}{5}\sum_{t=1992}^{1996}\left(p_{11k}s_{1k}^{t} + p_{31k}s_{3k}^{t} + p_{13k}s_{1k}^{t}\right) \tag{2}$$

The computation of the three-year probabilities of CCT follows the same logic as for the two-year counterparts, except we average over the four three-year sequences within the time period of our data, i.e., for 1992–94, 1993–95, 1994–96, and 1995–97:

$$\begin{aligned} P_{k,CCT-3} = \frac{1}{4}\sum_{t=1992}^{1995}\big(&p_{11k}p_{11k}s_{1k}^{t} + p_{11k}p_{13k}s_{1k}^{t} + p_{13k}p_{31k}s_{1k}^{t} \\ &+ p_{31k}p_{13k}s_{3k}^{t} + p_{31k}p_{11k}s_{3k}^{t}\big). \end{aligned} \tag{3}$$

The average probabilities of two- (three-) year ACT, $P_{k,ACT-2}$ ($P_{k,ACT-3}$), are computed similarly; they are detailed in the Appendix.

In addition to the unconditional probabilities of alternative tillage rotations, we compute the probabilities conditional on alternative crop rotations. Specifically, the probability of county k, two-year CCT on land that is in continuous corn (corn after corn), CC, rotation is measured as the five-year average of the probability of CCT conditional on CC rotation, $P_{k,CCT-2|CC}$. Similarly, the extent of county k, two-year CCT on land that is in corn-soybeans rotation (corn after soybeans or soybeans after corn), CS, is measured as the five-year average of the probability of CCT conditional on CS, $P_{k,CCT-2|CS}$ (Howard, 1971):

$$\begin{aligned} P_{k,CCT-2|CC} &= \frac{1}{5}\sum_{t=1992}^{1996}\left(\frac{p_{11k}s_{1k}^{t}}{p_{11k}s_{1k}^{t} + p_{21k}s_{2k}^{t} + p_{12k}s_{1k}^{t} + p_{22k}s_{2k}^{t}}\right) \\ P_{k,CCT-2|CS} &= \frac{1}{5}\sum_{t=1992}^{1996}\left(\frac{p_{31k}s_{3k}^{t} + p_{13k}s_{1k}^{t}}{p_{31k}s_{3k}^{t} + p_{41k}s_{4k}^{t} + p_{32k}s_{3k}^{t} + p_{42k}s_{4k}^{t} + p_{13k}s_{1k}^{t} + p_{23k}s_{2k}^{t} + p_{14k}s_{1k}^{t} + p_{24k}s_{2k}^{t}}\right) \end{aligned} \tag{4}$$

For the sake of brevity, the formulas for the five-year-average conditional probabilities of two-year ACT conditional on CC rotation, $P_{k,ACT-2|CC}$; and ACT conditional on CS, $P_{k,ACT-2|CS}$, are provided in the Appendix. The Appendix also details the four-year-average probabilities of three-year CCT and ACT, conditional on three years of corn, CCC ($P_{k,CCT-3|CCC}$and $P_{k,ACT-3|CCC}$); two years of corn in a three-year cropping pattern, CCS/CSC/SCC ($P_{k,CCT-3|CCS}$and $P_{k,ACT-3|CCS}$); and one year of corn in a three-year cropping pattern, SCS ($P_{k,CCT-3|SCS}$and $P_{k,ACT-3|SCS}$).

We use the probabilities of alternative tillage rotations conditional on crop rotations to test the following hypotheses:

H1. The probability of CCT differs between crop rotations.

H2. The probability of ACT differs between crop rotations.

We test each hypothesis using both the two- and the three-year estimates. To test hypothesis H1 with the two-year estimates, we use the analysis of variance (ANOVA) F-test (Casella & Berger, 2002) to test the null hypothesis of equal means for $\overline{P}_{CCT-2|CC}$ and $\overline{P}_{CCT-2|CS}$. Here and throughout the rest of the paper the "bar" over notation means that the estimate is averaged over county estimates, i.e., for example, $\overline{P}_{CCT-2|CC} = \sum_k P_{k,CCT-2|CC}/K$. If the F-test rejects the null hypothesis, we conclude that the probabilities of a two-year CCT differ between crop rotations.

For the three-year estimates, we begin with the ANOVA to test the null hypothesis of equal means for $\overline{P}_{k,CCT-3|CCC}$, $\overline{P}_{k,CCT-3|CCS \text{ or } CSC \text{ or } SCC}$ and $\overline{P}_{k,CCT-3|SCS}$. If we cannot reject this null hypothesis, we conclude that the three-year probability of CCT does not differ by crop rotation. If we reject this null hypothesis, we follow with the Fisher's Least Significant Difference (LSD) test (Schlotzhauer & Littell, 1997) to identify the conditional probabilities that are different from the rest of the group. Hypothesis H2 is tested following similar procedures.

Finally, we use the unconditional probabilities of alternative tillage rotations to test the following hypotheses:

H3. The greater the percentage of land classified as HEL the greater the use of CCT.

H4. The greater the percentage of land classified as HEL the greater the use of ACT.

As with the hypotheses H1 and H2, we use both two- and three-year probabilities to ascertain the effect of HEL on CCT and ACT. To test hypothesis H3, we fit a simple linear regression of the probability of CCT ($P_{k,CCT-2}$ or $P_{k,CCT-3}$) on HEL_k, $k = 1, \ldots, 99$. If the estimated slope coefficient is positive and statistically different from zero, then we conclude that the data support the hypothesis. Hypothesis H4 is tested similarly, with the probability of CCT replaced by the probability of ACT.

3. Results and discussion

3.1. Estimated models and probabilities of alternative tillage rotations

The results of estimating the 99 county-specific models (1) are summarized in Table 1.

Evaluation of fit of the county-specific models (1) is based on the comparison of the observed versus predicted tillage-crop shares. The Mean Absolute Error (MAE), calculated as the year- and county-specific average of the difference between observed and estimated tillage-crop shares, is relatively small. The in-sample MAEs are less than 5% for the majority of counties (92 out of 99), and no county has the MAE greater than 10%. The out-of-sample model prediction are likewise reasonable: the average MAE is equal 6, 9, 8 and 9 percent with standard deviation of 4, 5, 4 and 4 percent for 1998, 2000, 2002 and 2004, respectively. Another measure of model fit, the estimated coefficients of correlation between the observed shares and simulated shares, also suggests that the model fits well with the data (Table 2).

The average probability of adopting CT when prior tillage decision was CT ranges from 0.098 to 0.51. When farmers use CT on soybeans, they more often than not rotate the practice with VT: only 44% of CT soybean fields remain in CT the next year. In contrast, more than 60% of the fields remain in CT the year after using CT on corn (Table 1). We also find that the use of ACT is widespread in Iowa: for two-year tillage-crop sequences, the average probability of being ACT is almost equal to the sum of the average probabilities of CVT and CCT, whereas on average 70% hectares are in ACT for three-year tillage-crop sequences, an increase by 21% after one year (Fig. 3).

We find that CT and VT are practiced continuously to approximately the same extent: the acreage-weighted average probabilities of CCT and CVT are equal 0.269 vs. 0.242 after two years, and 0.161 and 0.139 after three years (Fig. 3). The same consistency shows in the comparison across counties. The counties with the higher VT rates tend to have higher two- and three-year CVT rates: the coefficients of determination between average VT rate and the average probabilities of two- and three-year CVT are 0.400 and 0.294. Similarly, the coefficients of determination between average CT rate and the average probabilities of two- and three-year CCT are 0.416 (Fig. 4a) and 0.305 (Fig. 4b). However, it must be noted that

Table 2
Estimated correlation between the observed and simulated shares.

Year	Tillage-crop share			
	CT corn	VT corn	CT soybeans	VT soybeans
1993	0.824	0.875	0.796	0.769
1994	0.783	0.802	0.781	0.653
1995	0.828	0.810	0.808	0.850
1996	0.836	0.813	0.819	0.857
1997	0.836	0.743	0.687	0.725

Note: p-values are smaller than 0.0001 for all correlation coefficients. CT = conservation tillage and VT = conventional tillage.

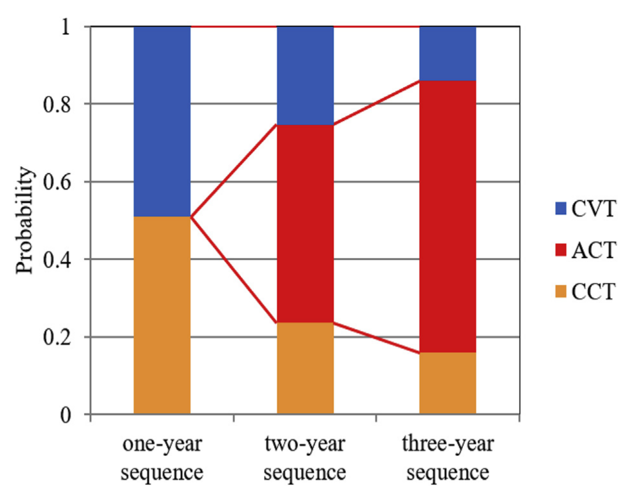

Fig. 3. Estimated average probability of continuous conservation tillage (CCT), continuous conventional tillage (CVT) and alternating conservation tillage (ACT). The one-year sequence is the county- and 1992–1997 average of the observed data. The average two-year probabilities are $\overline{P}_{CCT-2}$, $\overline{P}_{ACT-2}$, and $\overline{P}_{CVT-2} = 1 - \overline{P}_{CCT-2} - \overline{P}_{ACT-2}$; and the average three-year probabilities are $\overline{P}_{CCT-3}$, $\overline{P}_{ACT-3}$, and $\overline{P}_{CVT-3} = 1 - \overline{P}_{CCT-3} - \overline{P}_{ACT-3}$, for CCT, ACT, and CVT, respectively.

Table 1
Estimated average probabilities $\overline{p}_{ij}$ with the corresponding standard errors.

Previous year tillage-crop choice	Current year tillage-crop choice			
	CT corn	VT corn	CT soybeans	VT soybeans
CT corn	0.098 ± 0.017	0.125 ± 0.017	0.510 ± 0.031	0.267 ± 0.028
VT corn	0.120 ± 0.016	0.149 ± 0.020	0.475 ± 0.023	0.256 ± 0.019
CT soybeans	0.440 ± 0.029	0.560 ± 0.029	0	0
VT soybeans	0.397 ± 0.038	0.603 ± 0.038	0	0

Notes: The probabilities of transition from soybeans to soybeans were postulated to be zero. CT = conservation tillage and VT = conventional tillage.

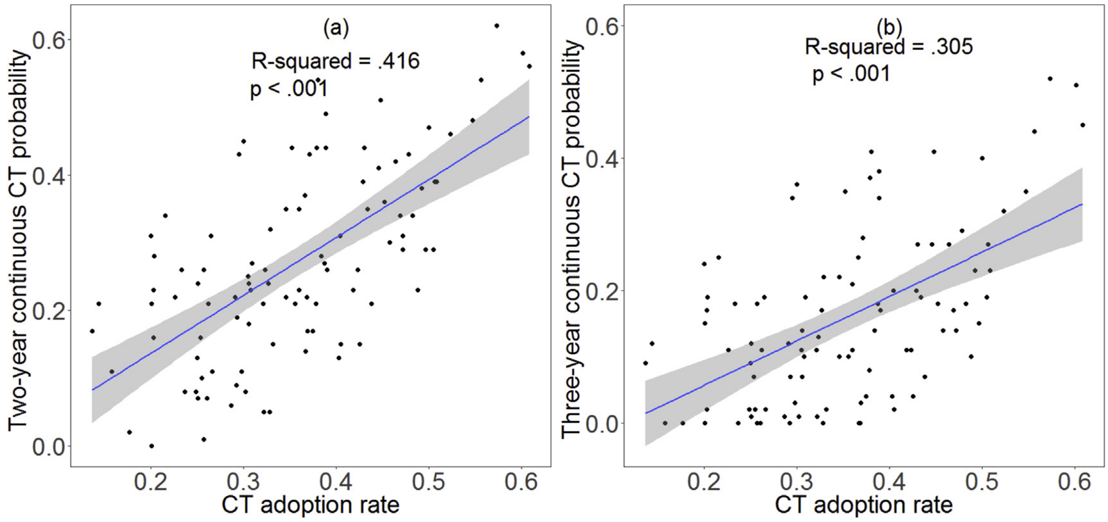

Fig. 4. Average probability of continuous conservation tillage (CCT) for two-year cropping sequence (Fig. 4a) and three-year cropping sequence (Fig. 4b) as a function of conservation tillage (CT) adoption rate. Scatterplots of two and three-year CCT by CT adoption rate are overlaid with the fit lines, 95% confidence bands are shaded.

the coefficients of determination are notably less than one. These findings imply that neither one-year rate of CT is an accurate measure of the CCT, nor one-year rate of VT is an accurate measure of the CVT.

In addition, our findings support to the concerns in the recent literature that argue that the CT's contribution to climate change mitigation is likely to be overstated because a sizable portion of CT is not in this practice permanently (Powlson et al., 2014; VandenBygaart, 2016). A noteworthy extension of our work would be a revision of the estimates of the current rate of carbon sequestration in the Iowa and/or U.S. Midwest agricultural soils taking into consideration the degree and the spatial patterns of the persistence in tillage decisions.

3.2. Hypotheses testing: CCT and crop rotations

The transition matrices estimated suggest that the choices of tillage and crop rotations are indeed bundled, i.e., the tillage time patterns differ significantly between crop rotations. On average, the probability of CT corn following CT corn is just 0.098, compared to 0.440 and 0.510 for the CT corn after CT soybeans and CT soybeans after CT corn, respectively (Table 1). The null hypothesis of the three mean probabilities being equal, $\overline{p}_{11} = \overline{p}_{13} = \overline{p}_{31}$ was rejected because the ANOVA F-test resulted in a p-value of less than 0.0001. The between-crop rotation difference is statistically strong: using the Fisher's LSD test at a 5% level of significance, we failed to reject the hypothesis $\overline{p}_{13} = \overline{p}_{31}$ and rejected the hypotheses of $\overline{p}_{11} = \overline{p}_{13}$ and $\overline{p}_{11} = \overline{p}_{31}$. These findings support hypothesis H1; they imply that land in continuous corn is less likely to be in CCT that the land in corn-soybean rotation.

The same general conclusion about the tight connections between CCT and crop rotations emerges from the comparison of the probabilities of CCT conditional on crop rotations (Table 3a and Table 3b). For two-year rotations, we find a strong support to hypothesis H1, because the average probabilities of CCT are statistically different between the two rotations considered, continuous corn and corn-soybeans. When three-year rotations considered, the support for hypothesis H1 is not as strong because two of the three considered probabilities are not statistically different. Nevertheless, we find that the average probabilities of CCT are lower for corn-heavy three-year rotations (continuous corn and corn-corn-soybeans) than rotations with only one year of corn.

Table 3a
Estimated average probabilities of two-year tillage rotations conditional on two-year crop rotation.

Rotation	Tillage-crop choice	
	CCT	ACT
CC	0.171 [a]	0.481 [c]
CS	0.295 [b]	0.504 [c]

Note: Within-column means followed by the same letter are not significantly different using Fisher's LSD at a 5% significance. We exclude estimated probabilities of nine counties since the probability of corn after corn is equal zero. CC = corn after corn rotation, CS = corn after soybeans and soybeans after corn rotations, CCT = continuous conservation tillage, and ACT = alternating conservation tillage.

Table 3b
Estimated average probabilities of three-year tillage rotations conditional on three-year crop rotation.

Rotation	Tillage-crop choice	
	CCT	ACT
CCC	0.151 [a]	0.525 [c]
CCS/CSC/SCC	0.133 [a]	0.739 [d]
SCS	0.212 [b]	0.710 [d]

Note: Within-column, means followed by the same letter are not significantly different using Fisher's LSD at a 5% significance. We exclude estimated probabilities of nine counties since the probability of corn after corn after corn is equal zero. CCC = corn after corn after corn rotation, CCS = corn after corn after soybeans rotation, CSC = corn after soybeans after corn rotation, SCC = soybeans after corn after corn rotation, and SCS = soybeans after corn after soybeans rotation.

Unlike for CCT, our estimation results suggest only weak interactions between ACT and crop rotations (Table 4). Hypothesis H2 is rejected when two-year rotations are considered, and is weakly supported when three-year rotations are considered. We find that the probability of ACT is lower for the continuous corn when compared to the three-year rotations that include soybeans.

To our knowledge, this is the first study that quantifies the interdependence of farmers' choices of crop and tillage rotations in a major U.S. crop production region, Iowa. We find that the crop rotations associated with greater incidence of corn are associated with lower use of CCT, and possibly, with lower use of ACT. These results are important for two reasons. First, these findings may help explain the inconsistent statistical significance of the impact of crop

Table 4
Summary of hypotheses testing.

Hypothesis	Transition matrix estimates	Two-year probabilities	Three-year probabilities
H1 - supported	The probability of transition from CT to CT is higher for corn-soybeans rotation than for continuous corn	CCT use is lower on continuous corn than on corn-soybeans rotation	CCT use is lower for rotations with two or three years of corn versus rotations with only one year of corn
H2 - supported partially	N/A	No statistical evidence that ACT use differs between continuous corn and corn-soybeans rotation	ACT use is lower on continuous corn versus rotations that include soybeans
H3 - supported	N/A	HEL status increases the probability of CCT	HEL status increases the probability of CCT
H4 - rejected	N/A	HEL is not a significant predictor of ACT use	HEL is not a significant predictor of ACT use

Note: N/A means not applicable. CCT = continuous conservation tillage, ACT = alternating conservation tillage and HEL = highly erodible land.

rotations on the CT use noted in previous research. For example, Fuglie (1999) found an insignificant effect of crop rotation on CT adoption, but the results of Wu and Babcock (1998) and Torre Ugarte et al. (2004) implied that rotating crops positively affects the use of CT. However, these previous studies employed a static framework that dealt with a one-year CT use only. Our findings imply that a dynamic framework is imperative when assessing and explaining CT use.

Second, the recent past has seen an increase in continuous corn at the expense of corn-soybean rotation throughout the U.S. Midwest (Plourde et al., 2013; Stern et al., 2012). If the connections between crop and tillage rotations that we have quantified using the 1992–2004 data hold for later years, then the shift toward corn monoculture has also affected tillage intensity. An important topic for future research is then to analyze the environmental implications of this combined change in rotations and tillage intensity.

3.3. Hypotheses testing: CCT and HEL

The estimated slope coefficient from the regression of $P_{k,CCT-2}$ on HEL_k is 0.0019 with the p-value of 0.006, and that of $P_{k,CCT-3}$ on HEL_k is 0.0013 with the p-value of 0.036. These estimates provide a strong support to the hypothesis H3. Indeed, the spatial distribution of the average probability of three-year CCT (Fig. 5) is reasonably similar to the spatial distribution of the percentage of cropland in HEL (Fig. 2). However, we find no statistically significant impact of HEL_k on $P_{k,ACT-2}$ or $P_{k,ACT-3}$, thus rejecting hypothesis H4.

While previous studies acknowledged the possible relationship between CT adoption and HEL, they commonly utilized static frameworks (e.g., Logit model) and cross-sectional data, and in consequence, did not analyze the potential link between the persistence of CT use and HEL. A study of Wade and Claassen (2017) is an exception. Using a unique, four-year panel coming from farmers' survey, ARMS data, Wade and Claassen (2017) found that HEL designation could be the single important factor influencing the use of continuous no-till by the U.S. corn and soybean producers. Unfortunately, such ideal data to study CT persistence in large geographic regions, i.e., panel farmer survey (or remote sensing) data on tillage systems, is presently technologically challenging and/or expensive to collect (Sharma et al., 2016; Bégué et al., 2018). In the absence of the ideal tillage data, the method we use offers a viable alternative, complementing approach that relies on only aggregate, county-average, time ordered data.

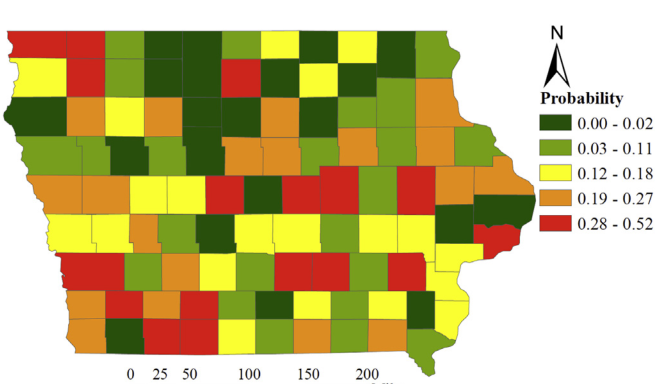

Fig. 5. Average probability of three-year continuous conservation tillage (CCT), by county, Iowa.

The statistically strong positive effect of HEL on the use of CCT and no effect of HEL on the use of ACT that we find could contribute to resolving another inconsistency in previous research. As the soil erosion prevention contribution of CT is well recognized by farmers (Andrews et al., 2013; Cooper, 1997; Fuglie, 1999; Perry, Moschini, & Hennessy, 2016; Tomer, Moorman, James, Hadish, & Rossi, 2008), researchers have been puzzled on why a wider use of CT on the land that is prone to erosion did not always show as statistically significant (Knowler & Bradshaw, 2007; Lambert, Sullivan, Claassen, & Foreman, 2007; Ding et al., 2009). The inability to find the differences in CT use on HEL vs. non-HEL land in these studies has been attributed to small sample size, the insufficient incentives provided by the conservation compliance, the policy that penalizes for intensive farming on HEL (Claassen et al., 2017), and/or insufficient monitoring of conservation compliance. Our findings about the differentiated impact of HEL on the use of CCT versus ACT contribute to this discussion by pointing to another possible explanation: the impact of HEL on CT use varies depending on whether the practice is used continuously or intermittently.

4. Conclusions

Most of previous tillage adoption research used static models to study tillage decisions (Wallander et al., 2018). Our study contributes to closing the gap in the understanding of the dynamics of tillage decisions in a major U.S. crop production region, Iowa. County-specific Markov chain models of tillage-crop transitions were estimated using the 1992–1997 CTIC data, with a good out-of-sample performance on the data through 2004. We showed that the probabilities of two- and three-year CCT and ACT are related to crop rotations, and the county-average use of CCT and ACT are affected by soil erodibility as measured by the county-average HEL proportion. We also find that there is a weak correlation between the use of CCT and CT adoption rate. This result implies that relying on conservation practices adoption rates to evaluate the success of conservation efforts might be misleading; an increase in adoption rates might be associated with increase in intermittent conservation practices rather than continuous conservation practices.

The better understanding of the persistence in tillage decisions could help refine the assessments of environmental ramifications from crop production and guide agri-environmental policies in the

U.S. Midwest, where corn and soybean commonly dominate crop production (USDA-NRCS, 2012). If data on other conservation practices of comparable time and spatial resolution become available, investigating how alternative crop-tillage rotations are related to the use of other conservation practices could further refine such assessments.[2]

The approach used in the study is not envisioned as a replacement for using field survey data to study the relationship between soil erodibility and the persistence in CT. Rather, our approach should be viewed as a complementary tool for an assessment of the relationship when multiple-year tillage survey data, which track the same fields over time, are not available.

Acknowledgements

This research was partially funded by the U.S Department of Agriculture (USDA) National Institute of Food and Agriculture (NIFA), award No. 2016-67024-24755. The funding source has no involvement in the study design, data collection and analysis, or any other aspects of the research or paper publication. The views expressed in this article are those of the authors and do not necessarily reflect the views or policies of the USDA.

Appendix. Details on computation of the probabilities of alternative crop and tillage rotations

Unconditional probabilities

The average probability of two-year ACT, $P_{k,ACT-2}$: $P_{k,ACT-2} = 1 - P_{k,CCT-2} - P_{k,CVT-2}$,

where $P_{k,CCT-2}$ is given in (2), and the average probability of two-year CVT,$P_{k,CVT-2}$, is given by

$$P_{k,CVT-2} = \frac{1}{5}\sum_{t=1992}^{1996}\left(p_{22k}s_{2k}^t + p_{42k}s_{4k}^t + p_{24k}s_{2k}^t\right).$$

The average probability of three-year ACT, $P_{k,ACT-3}$: $P_{k,ACT-3} = 1 - P_{k,CCT-3} - P_{k,CVT-3}$, where $P_{k,CCT-3}$ is given in (3), and the average probability of three-year CVT,$P_{k,CVT-3}$, is given by

$$P_{k,CVT-3} = \frac{1}{4}\sum_{t=1992}^{1995}\left(p_{22k}p_{22k}s_{2k}^t + p_{22k}p_{24k}s_{2k}^t + p_{24k}p_{42k}s_{2k}^t + p_{42k}p_{22k}s_{4k}^t + p_{42k}p_{24k}s_{4k}^t\right).$$

Conditional probabilities

Two-year conditional probabilities

The average probabilities of two-year ACT conditional on alternative rotations:

$$P_{k,ACT-2|CC} = \frac{1}{5}\sum_{t=1992}^{1996}\left(\frac{p_{21k}s_{2k}^t + p_{12k}s_{1k}^t}{p_{11k}s_{1k}^t + p_{21k}s_{2k}^t + p_{12k}s_{1k}^t + p_{22k}s_{2k}^t}\right),$$

$$P_{k,ACT-2|CS} = \frac{1}{5}\sum_{t=1992}^{1996}\left(\frac{p_{41k}s_{4k}^t + p_{32k}s_{3k}^t + p_{23k}s_{2k}^t + p_{14k}s_{1k}^t}{p_{31k}s_{3k}^t + p_{41k}s_{4k}^t + p_{32k}s_{3k}^t + p_{42k}s_{4k}^t + p_{13k}s_{1k}^t + p_{23k}s_{2k}^t + p_{14k}s_{1k}^t + p_{24k}s_{2k}^t}\right).$$

Three-year conditional probabilities

The average probabilities of three-year CCT conditional on alternative crop rotations:

$P_{k,CCT|CCC} = \frac{1}{4}\sum_{t=1992}^{1995}\left(\frac{p_{11k}p_{11k}s_{1k}^t}{P(CCC_k^t)}\right)$, where

$$P\left(CCC_k^t\right) = p_{11k}p_{11k}s_{1k}^t + p_{11k}p_{21k}s_{2k}^t + p_{21k}p_{12k}s_{1k}^t + p_{21k}p_{22k}s_{2k}^t + p_{12k}p_{11k}s_{1k}^t + p_{12k}p_{21k}s_{2k}^t + p_{22k}p_{12k}s_{1k}^t + p_{22k}p_{22k}s_{2k}^t. \tag{A.1}$$

$P_{k,CCT\ CCS\ \mathrm{or}\ CCS\ \mathrm{or}\ SCC} = \frac{1}{4}\sum_{t=1992}^{1995}\left(\frac{p_{11k}p_{31k}s_{3k}^t + p_{31k}p_{13k}s_{1k}^t + p_{13k}p_{11k}s_{1k}^t}{P(CCS_k^t)}\right)$,

where

$$\begin{aligned}P\left(CCS_k^t\right) = {} & p_{11k}p_{31k}s_{3k}^t + p_{11k}p_{41k}s_{4k}^t + p_{21k}p_{32k}s_{3k}^t \\ & + p_{21k}p_{42k}s_{4k}^t + p_{31k}p_{13k}s_{1k}^t + p_{31k}p_{23k}s_{2k}^t \\ & + p_{41k}p_{14k}s_{1k}^t + p_{41k}p_{24k}s_{2k}^t + p_{12k}p_{31k}s_{3k}^t \\ & + p_{12k}p_{41k}s_{4k}^t + p_{22k}p_{32k}s_{3k}^t + p_{22k}p_{42k}s_{4k}^t \\ & + p_{32k}p_{13k}s_{1k}^t + p_{32k}p_{23k}s_{2k}^t + p_{42k}p_{14k}s_{1k}^t \\ & + p_{42k}p_{24k}s_{2k}^t + p_{13k}p_{11k}s_{1k}^t + p_{13k}p_{21k}s_{2k}^t \\ & + p_{23k}p_{12k}s_{1k}^t + p_{23k}p_{22k}s_{2k}^t + p_{14k}p_{11k}s_{1k}^t \\ & + p_{14k}p_{21k}s_{2k}^t + p_{24k}p_{12k}s_{1k}^t + p_{24k}p_{22k}s_{2k}^t.\end{aligned} \tag{A.2}$$

$P_{k,CCT|SCS} = \frac{1}{4}\sum_{t=1992}^{1995}\left(\frac{p_{13k}p_{31k}s_{3k}^t}{P(SCS_k^t)}\right)$, where

$$P\left(SCS_k^t\right) = p_{13k}p_{31k}s_{3k}^t + p_{13k}p_{41k}s_{4k}^t + p_{23k}p_{32k}s_{3k}^t + p_{23k}p_{42k}s_{4k}^t + p_{14k}p_{31k}s_{3k}^t + p_{14k}p_{41k}s_{4k}^t + p_{24k}p_{32k}s_{3k}^t + p_{24k}p_{42k}s_{4k}^t. \tag{A.3}$$

The average probabilities of three-year ACT conditional on alternative crop rotations:

$P_{k,ACT|CCC} = \frac{1}{4}\sum_{t=1992}^{1995}\left(\frac{P(ACT_k^t \cap CCC_k^t)}{P(CCC_k^t)}\right)$, where $P(CCC_k^t)$is given in (A.1), and

$$\begin{aligned}P\left(ACT_k^t \cap CCC_k^t\right) = {} & p_{11k}p_{21k}s_{2k}^t + p_{21k}p_{12k}s_{1k}^t + p_{21k}p_{22k}s_{2k}^t \\ & + p_{12k}p_{11k}s_{1k}^t + p_{12k}p_{21k}s_{2k}^t + p_{22k}p_{12k}s_{1k}^t.\end{aligned}$$

$P_{k,ACT|CCS} = \frac{1}{4}\sum_{t=1992}^{1995}\left(\frac{P(ACT_k^t \cap CCS_k^t)}{P(CCS_k^t)}\right)$, where $P(CCS_k^t)$is given in

[2] We thank an anonymous reviewer for making this point.

(A.2), and

$$P\left(ACT_k^t \cap CCS_k^t\right) = p_{11k}p_{41k}s_{4k}^t + p_{21k}p_{32k}s_{3k}^t + p_{21k}p_{42k}s_{4k}^t + p_{31k}p_{23k}s_{2k}^t$$
$$+p_{41k}p_{14k}s_{1k}^t + p_{41k}p_{24k}s_{2k}^t + p_{12k}p_{31k}s_{3k}^t + p_{12k}p_{41k}s_{4k}^t + p_{22k}p_{32k}s_{3k}^t$$
$$+p_{32k}p_{13k}s_{1k}^t + p_{32k}p_{23k}s_{2k}^t + p_{42k}p_{14k}s_{1k}^t + p_{13k}p_{21k}s_{2k}^t + p_{23k}p_{12k}s_{1k}^t$$
$$+p_{23k}p_{22k}s_{2k}^t + p_{14k}p_{11k}s_{1k}^t + p_{14k}p_{21k}s_{2k}^t + p_{24k}p_{12k}s_{1k}^t.$$

$P_{k,ACT|SCS} = \frac{1}{4}\sum_{t=1992}^{1995}\left(\frac{P(ACT_k^t \cap SCS_k^t)}{P(SCS_k^t)}\right)$, where $P(SCS_k^t)$is given in (A.3), and

$$P\left(ACT_k^t \cap SCS_k^t\right) = p_{13k}p_{41k}s_{4k}^t + p_{23k}p_{32k}s_{3k}^t + p_{23k}p_{42k}s_{4k}^t + p_{14k}p_{31k}s_{3k}^t$$
$$+p_{14k}p_{41k}s_{4k}^t + p_{24k}p_{32k}s_{3k}^t.$$

References

Adusumilli, N., & Wang, H. (2018). Analysis of soil management and water conservation practices adoption among crop and pasture farmers in humid-south of the United States. *International Soil and Water Conservation Research, 6*(2), 79–86. https://doi.org/10.1016/j.iswcr.2017.12.005.

Andrews, A. C., Clawson, R. A., Gramig, B. M., & Raymond, L. (2013). Why do farmers adopt conservation tillage? An experimental investigation of framing effects. *Journal of Soil and Water Conservation, 68*(6), 501–511.

Baker, N. T. (2011). *Tillage practices in the conterminous United States*, 1989-2004-Datasets Aggregated by Watershed (2327-638X) https://pubs.usgs.gov/ds/ds573/. (Accessed 6 December 2016).

Baumgart-Getz, A., Prokopy, L. S., & Floress, K. (2012). Why farmers adopt best management practice in the United States: A meta-analysis of the adoption literature. *Journal of Environmental Management, 96*(1), 17–25.

Bégué, A., Arvor, D., Bellon, B., Betbeder, J., Abelleyra, D, d., Ferraz, R.,P. D., et al. (2018). Remote sensing and cropping practices: A review. *Remote Sensing, 10*(99), 1–32. https://doi.org/10.3390/rs10010099.

Bowman, M., Wallander, S., & Lynch, L. (2016). *An economic perspective on soil health*. Amber Waves, 1_9A.

Busari, M. A., Kukal, S. S., Kaur, A., Bhatt, R., & Dulazi, A. A. (2015). Conservation tillage impacts on soil, crop and the environment. *International Soil and Water Conservation Research, 3*(2), 119–129. https://doi.org/10.1016/j.iswcr.2015.05.002.

Carlisle, L. (2016). Factors influencing farmer adoption of soil health practices in the United States: A narrative review. *Agroecology and Sustainable Food Systems, 40*(6), 583–613. https://doi.org/10.1080/21683565.2016.1156596.

Casella, G., & Berger, R. L. (2002). *Statistical inference* (2nd ed.). California: Thomson Learning.

Choi, S. W., & Sohngen, B. (2010). The optimal choice of residue management, crop rotations, and cost of carbon sequestration: Empirical results in the midwest US. *Climatic Change, 99*(1), 279–294.

Claassen, R., Bowman, M., Breneman, V., Wade, T., Williams, R., Fooks, J., … Loesch, C. (2017). *Conservation compliance: How farmer incentives are changing in the crop insurance era*. Retrieved from https://www.ers.usda.gov/publications/pub-details/?pubid=84456.

Claassen, R., Cattaneo, A., & Johansson, R. (2008). Cost-effective design of agri-environmental payment programs: U.S. Experience in theory and practice. *Ecological Economics, 65*(4), 737–752.

Claassen, R., & Ribaudo, M. (2016). Cost-effective conservation programs for sustaining environmental quality. *Choices, 31*(3), 1–12.

Conant, R. T., Easter, M., Paustian, K., Swan, A., & Williams, S. (2007). Impacts of periodic tillage on soil C stocks: A synthesis. *Soil and Tillage Research, 95*(1), 1–10.

Conservation Tillage Information Center (CTIC). (2018). *Tillage survey*. http://www.ctic.purdue.edu/CRM/. (Accessed 10 January 2018).

Cooper, J. (1997). Combining actual and contingent behavior data to model farmer adoption of water quality protection practices. *Agricultural and Resource Economics, 22*(1), 30–43.

Dayer, A. A., Lutter, S. H., Sesser, K. A., Hickey, C. M., & Gardali, T. (2017). Private landowner conservation behavior following participation in voluntary incentive programs: Recommendations to facilitate behavioral persistence. *Conservation Letters, 11*(2), 1–11. https://doi.org/10.1111/conl.12394.

Ding, Y., Schoengold, K., & Tadesse, T. (2009). The impact of weather extremes on agricultural production methods: Does drought increase adoption of conservation tillage practices? *Journal of Agricultural and Resource Economics, 34*(3), 395–411.

Duriancik, L. F., Bucks, D., Dobrowolski, J. P., Drewes, T., Eckles, S. D., Jolley, L., et al. (2008). The first five years of the conservation effects assessment Project. *Journal of Soil and Water Conservation, 63*(6), 185A–197A.

Fuglie, K. O. (1999). Conservation tillage and pesticide use in the Corn Belt. *Journal of Agricultural & Applied Economics, 31*(01), 133–148.

Gallant, A. L., Sadinski, W., Roth, M. F., & Rewa, C. A. (2011). Changes in historical Iowa land cover as context for assessing the environmental benefits of current and future conservation efforts on agricultural lands. *Journal of Soil and Water Conservation, 66*(3), 67A–77A.

Gassman, P. W., Secchi, S., Jha, M., & Kurkalova, L. A. (2006). Upper Mississippi river basin modeling system part 1: SWAT input data requirements and issues. In Y. P. Singh, & Y. Jun Xu (Eds.), *Coastal hydrology and processes* (pp. 03–115). Colorado: Water Resources Publications, LLC.

Grace, P. R., Robertson, P., Millar, N., Colunga-Garcia, M., Basso, B., Gage, S. H., et al. (2011). The contribution of maize cropping in the midwest USA to global warming: A regional estimate. *Agricultural Systems, 104*(3), 292–296. https://doi.org/10.1016/j.agsy.2010.09.001.

Grandy, A. S., Robertson, G. P., & Thelen, K. D. (2006). Do productivity and environmental trade-offs justify periodically cultivating no-till cropping systems? *Agronomy Journal, 98*(6), 1377–1383. https://doi.org/10.2134/agronj2006.0137.

Hill, P. R. (1998). Use of rotational tillage for corn and soybean production in the eastern corn belt. *Journal of Production Agriculture, 11*(1), 125–128.

Hill, P. R. (2001). Use of continuous no-till and rotational tillage systems in the central and northern Corn Belt. *Journal of Soil and Water Conservation, 56*(4), 286–290.

Horowitz, J., Ebel, R., & Ueda, K. (2010). *No-till farming is a growing practice*. Economic Information Bulletin Number 70. Washington: USDA https://www.ers.usda.gov/publications/pub-details/?pubid=44515. (Accessed 7 December 2017).

Howard, R. A. (1971). *Dynamic probabilistic systems*. New York: Wiley.

Iowa State University (ISU). (2004). *Soil survey & digital soil data: ISPAID version 7.1*. http://www.extension.iastate.edu/soils/ispaid.

Jackson-Smith, D. B., Halling, M., de la Hoz, E., McEvoy, J. P., & Horsburgh, J. S. (2010). Measuring conservation program best management practice implementation and maintenance at the watershed scale. *Journal of Soil and Water Conservation, 65*(6), 413–423. https://doi.org/10.2489/jswc.65.6.413.

Knowler, D., & Bradshaw, B. (2007). Farmers' adoption of conservation agriculture: A review and synthesis of recent research. *Food Policy, 32*(1), 25–48.

Knowler, D., Bradshaw, B., & Holmes, E. (2014). Conservation agriculture: Farmer adoption and policy issues. In P. B. Thompson, & D. M. Kaplan (Eds.), *Encyclopedia of Food and agricultural ethics* (pp. 1–10). Netherlands: Springer.

Kurkalova, L. A., & Tran, D. Q. (2017). Is the use of no-till continuous or rotational? Quantifying tillage dynamics from time-ordered spatially aggregated data. *Journal of Soil and Water Conservation, 72*(2), 131–138. https://doi.org/10.2489/jswc.72.2.131.

Lal, R. (2004). Soil carbon sequestration impacts on global climate change and food security. *Science, 304*(5677), 1623–1627.

Lal, R. (2014). Soil conservation and ecosystem services. *International Soil and Water Conservation Research, 2*(3), 36–47. https://doi.org/10.1016/S2095-6339(15)30021-6.

Lambert, D. M., Sullivan, P., Claassen, R., & Foreman, L. (2007). Profiles of US farm households adopting conservation-compatible practices. *Land Use Policy, 24*(1), 72–88.

Lee, T. C., Judge, G. G., & Takayama, T. (1965). On estimating the transition probabilities of a Markov process. *Journal of Farm Economics, 47*(3), 742–762.

Lewandrowski, J., Peters, M., Jones, C., House, R., Sperow, M., Eve, M., et al. (2004). *Economics of sequestering carbon in the US agricultural sector*. Technical Bulletin Number 1090, USDA ERS http://extension.agron.iastate.edu/soilmgmt/Publications/EconSeqCarbon.pdf.

Lobb, D. A., Huffman, E., & Reicosky, D. C. (2007). Importance of information on tillage practices in the modelling of environmental processes and in the use of environmental indicators. *Journal of Environmental Management, 82*(3),

377–387. https://doi.org/10.1016/j.jenvman.2006.04.019.
Mangalassery, S., Sjögersten, S., Sparkes, D. L., Sturrock, C. J., Craigon, J., & Mooney, S. J. (2014). To what extent can zero tillage lead to a reduction in greenhouse gas emissions from temperate soils? *Scientific Reports, 4*, 4586. https://doi.org/10.1038/srep04586.
Mueller, D., Robertson, A., Sisson, A., & Tylka, G. (2010). *Soybean diseases*. Iowa State University Extension, publication CSI-0004.
Napier, T.,L., & Tucker, M. (2001). Use of soil and water protection practices among farmers in three midwest watersheds. *Environmental Management, 27*(2), 269–279.
Ogle, S. M., Breidt, F.,J., Easter, M., Williams, S., Killian, K., & Paustian, K. (2010). Scale and uncertainty in modeled soil organic carbon stock changes for US croplands using a process-based model. *Global Change Biology, 16*(2), 810–822. https://doi.org/10.1111/j.1365-2486.2009.01951.x.
Osmond, D., Meals, D., Hoag, D., Arabi, M., Luloff, A., Jennings, G., et al. (2012). Improving conservation practices programming to protect water quality in agricultural watersheds: Lessons learned from the national Institute of food and agriculture–conservation effects assessment Project. *Journal of Soil and Water Conservation, 67*(5), 122A–127A. https://doi.org/10.2489/jswc.67.5.122A.
Panagopoulos, Y., Gassman, P. W., Jha, M. K., Kling, C. L., Campbell, T., Srinivasan, R., et al. (2015). A refined regional modeling approach for the Corn Belt – experiences and recommendations for large-scale integrated modeling. *Journal of Hydrology, 524*, 348–366. https://doi.org/10.1016/j.jhydrol.2015.02.039.
Panagopoulos, Y., Gassman, P. W., Kling, C. L., Cibin, R., & Chaubey, I. (2017). Water quality assessment of large-scale bioenergy cropping scenarios for the upper Mississippi and Ohio-Tennesee river basins. *JAWRA Journal of the American Water Resources Association, 53*(6), 1355–1367. https://doi.org/10.1111/1752-1688.12594.
Perry, E. D., Moschini, G., & Hennessy, D. A. (2016). Testing for complementarity: Glyphosate tolerant soybeans and conservation tillage. *American Journal of Agricultural Economics, 98*(3), 765–784. https://doi.org/10.1093/ajae/aaw001.
Plourde, J. D., Pijanowski, B. C., & Pekin, B. K. (2013). Evidence for increased monoculture cropping in the Central United States. *Agriculture, Ecosystems & Environment, 165*, 50–59. https://doi.org/10.1016/j.agee.2012.11.011.
Powlson, D. S., Stirling, C. M., Jat, M. L., Gerard, B. G., Palm, C. A., Sanchez, P. A., et al. (2014). Limited potential of no-till agriculture for climate change mitigation. *Nature Climate Change, 4*(8), 678–683. https://doi.org/10.1038/nclimate2292.
Prokopy, L. S., Floress, K., Klotthor-Weinkauf, D., & Baumgart-Getz, A. (2008). Determinants of agricultural best management practice adoption: Evidence from the literature. *Journal of Soil and Water Conservation, 63*(5), 300–311.
Robertson, P. G., Gross, K. L., Hamilton, S. K., Landis, D. A., Schmidt, T. M., Snapp, S. S., et al. (2014). Farming for ecosystem services: An ecological approach to production agriculture. *BioScience, 64*(5), 404–415. https://doi.org/10.1093/biosci/biu037.
Sahajpal, R., Zhang, X., Izaurralde, R. C., Gelfand, I., & Hurtt, G. C. (2014). Identifying representative crop rotation patterns and grassland loss in the US Western Corn Belt. *Computers and Electronics in Agriculture, 108*, 173–182. https://doi.org/10.1016/j.compag.2014.08.005.
Sainju, U. M., Senwo, Z. N., Nyakatawa, E. Z., Tazisong, I. A., & Reddy, K. C. (2008). Soil carbon and nitrogen sequestration as affected by long-term tillage, cropping systems, and nitrogen fertilizer sources. *Agriculture, Ecosystems & Environment, 127*(3–4), 234–240. https://doi.org/10.1016/j.agee.2008.04.006.
Schlotzhauer, S. D., & Littell, R. C. (1997). *SAS system for elementary statistical analysis* (2nd ed.). Cary (NC): SAS Institute, Inc.
Secchi, S., Gassman, P. W., Jha, M., Kurkalova, L. A., Feng, H., Campbell, T., et al. (2007). The cost of clean water: Assessing agricultural pollution reduction at the watershed scale. *Journal of Soil and Water Conservation, 62*(1), 10–21.
Secchi, S., Gassman, P. W., Williams, J. R., & Babcock, B. A. (2009). Corn-based ethanol production and environmental quality: A case of Iowa and the conservation reserve program. *Environmental Management, 44*(4), 732–744. https://doi.org/10.1007/s00267-009-9365-x.
Secchi, S., Kurkalova, L., Gassman, P. W., & Hart, C. (2011). Land use change in a biofuels hotspot: The case of Iowa. *Biomass and Bioenergy, 35*(6), 2391–2400. https://doi.org/10.1016/j.biombioe.2010.08.047. USA.
Sharma, V., Irmak, S., Kilic, A., Sharma, V., Gilley, J. E., Meyer, G. E., et al. (2016). Quantification and mapping of surface residue cover and tillage practices for maize and soybean fields in south central Nebraska-USA using Landsat imagery. *T ASABE, 59*(3), 925–939. https://doi.org/10.13031/trans.59.11489.
Six, J., Ogle, S. M., Jay, B. F., Conant, R. T., Mosier, A. R., & Paustian, K. (2004). The potential to mitigate global warming with no-tillage management is only realized when practised in the long term. *Global Change Biology, 10*(2), 155–160. https://doi.org/10.1111/j.1529-8817.2003.00730.x.
Stern, A. J., Doraiswamy, P. C., & Raymond, H. J. E. (2012). Changes of crop rotation in Iowa determined from the United States Department of Agriculture, National Agricultural Statistics Service cropland data layer product. *Journal of Applied Remote Sensing, 6*(1), 063590. https://doi.org/10.1117/1.jrs.6.063590, 063590.
Tomer, M. D., Moorman, T. B., James, D. E., Hadish, G., & Rossi, C. G. (2008). Assessment of the Iowa river's south fork watershed: Part 2. Conservation practices. *Journal of Soil and Water Conservation, 63*(6), 371–379. https://doi.org/10.2489/jswc.63.6.371.
Tomer, M. D., Sadler, E. J., Lizotte, R. E., Bryant, R. B., Potter, T. L., Moore, M. T., et al. (2014). A decade of conservation effects assessment research by the USDA Agricultural Research Service: Progress overview and future outlook. *Journal of Soil and Water Conservation, 69*(5), 365–373. https://doi.org/10.2489/jswc.69.5.365.
Torre Ugarte, D. G. D. L., Hellwinckel, C. M., & Larson, J. A. (2004). Enhancing agriculture's potential to sequester carbon: A framework to estimate incentive levels for reduced tillage. *Environmental Management, 33*(1), S229–S237. https://doi.org/10.1007/s00267-003-9133-2.
UNEP. (2013). *The Emissions Gap Report 2013 A UNEP Synthesis Report*.
Uri, N. D. (2001). The potential impact of conservation practices in US agriculture on global climate change. *Agroecology and Sustainable Food Systems, 18*(1), 109–131. https://doi.org/10.1300/J064v18n01_09.
U.S. Department of Agriculture, Natural Resources Conservation Service (USDA-NRCS). (2002). *Farm Bill 2002 highly erodible land & wetland conservation compliance*. https://prod.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs143_007707.pdf. (Accessed 12 May 2017).
U.S. Department of Agriculture, Natural Resources Conservation Service (USDA-NRCS). (2012). *Assessment of the effects of conservation practices on cultivated cropland in the Upper Mississippi River Basin*. Washington, DC https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb1042093.pdf.
U.S. Department of Agriculture, Natural Resources Conservation Service (USDA-NRCS). (2015). *Soil health literature summary – effects of conservation practices on soil properties in areas of cropland*. https://www.nrcs.usda.gov/wps/portal/nrcs/detailfull/soils/health/?cid=stelprdb1257753. (Accessed 5 January 2018).
U.S. Department of Agriculture- National AgricultuStatistical Service (USDA-NASS). (2019). *Census of agriculture*. February 2019 https://www.nass.usda.gov/Quick_Stats/.
U.S. Department of Agriculture–Economic Research Service (USDA-ERS). (2018). *Tailored reports: Crop production practices*. https://data.ers.usda.gov/reports.aspx?ID=17883#Pe3788618d83047a98245ed80997d743b_8_65iT0R0T0R0x0. (Accessed 5 January 2018).
VandenBygaart, A. J. (2016). The myth that no-till can mitigate global climate change. *Agriculture, Ecosystems & Environment, 216*, 98–99. https://doi.org/10.1016/j.agee.2015.09.013.
Wade, T., & Claassen, R. (2017). Modeling no-till adoption by corn and soybean producers: Insights into sustained adoption. *Journal of Agricultural & Applied Economics, 49*(2), 186–210. https://doi.org/10.1017/aae.2016.48.
Wallander, S., Bowman, M., Beeson, P., & Claassen, R. (2018). *Farmers and habits: The challenge of identifying the sources of persistence in tillage decisions*. Invited paper presented at the 2018. Philadelphia, PA: ASSA Annual Meeting. January 05-07.
Wu, J., & Babcock, B. A. (1998). The choice of tillage, rotation, and soil testing practices: Economic and environmental implications. *American Journal of Agricultural Economics, 80*(3), 494–511. https://doi.org/10.2307/1244552.
Zheng, B., Campbell, J., Serbin, G., & Galbraith, J. (2014). Remote sensing of crop residue and tillage practices: Present capabilities and future prospects. *Soil and Tillage Research, 138*(0), 26–34.
Zimmermann, A., & Heckelei, T. (2012). Structural change of european dairy farms – a cross-regional analysis. *Journal of Agricultural Economics, 63*(3), 576–603. https://doi.org/10.1111/j.1477-9552.2012.00355.x.