Dynamic modeling of bundled tillage-crop choices: impact of soil erodibility on the interactions between continuous conservation tillage and crop rotations in Iowa

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Abstract

Recent agronomic and soil science research draws attention to the importance of continuous conservation tillage (CCT), as many environmental benefits of this conservation tillage are realized only when it is used continuously over a period of years. However, little is known about the dynamics of farmers' tillage choices. To address the need for quantitative estimates of time patterns of tillage practices and the factors that affect the use of CCT, the paper to be presented develops and estimates a dynamic model of bundled tillage-crop choices for the state of Iowa. We develop a first-order, four-state Markov chain model of tillage-crop dynamics for corn and soybean production systems. We assume that matrixes of transition from one tillage-crop state to another could vary by county but remain stationary from 1992 to 1997, and use quadratic programming to estimate the transition matrix for each of the 99 counties in the state using county-average, year–and crop–specific tillage data from Conservation Technology Information Center for 1992-1997. Analysis of Variance of the estimated county-specific transition matrixes shows that CCT occurs more often on Highly Erodible Land (HEL) when compared to other cropland. Also, the county-average probabilities of rotational conservation tillage (RCT), i.e., the farming systems in which CT is rotated with conventional tillage systems, are higher in the counties that have higher proportion of HEL. In addition, we identified a significant effect of crop rotations on tillage dynamics: the cropland under corn monoculture is less likely to be in RCT when compared to land in corn-soybean rotation. The results of the study indicate that both natural conditions (soil erodibility) and other economic choices (crop rotations) affect farmers' choices of CCT and RCT in Iowa.

1. Introduction

Conservation tillage (CT), defined as any tillage system that leaves at least 30% of the soil covered with crop residue after planting (CTIC, 2015), has been a subject of considerable research. 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., tillage systems other than CT, practiced continuously over the same number of years (Kahlon et al., 2013; Lal, 2004, 2011; Rittenburg et al., 2015; Sainju et al., 2008; West and Post, 2002). Intermittent use of CT, i.e., the use of CT that is alternated with other tillage practices 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 conventional tillage even for a single year (Conant et al., 2007; Grace et al., 2011; Ratta and Lal, 1998).

Because of the associated environmental benefits, CCT use has been promoted by multiple U.S. agricultural conservation programs (Claassen et al., 2014; Duriancik et al., 2008; USDA, 2014). Although the planning, monitoring, and evaluation of such conservation programs requires historical data on land use and CT (Claassen et al., 2014; Gallant et al., 2011; Jackson-Smith et al., 2010; Osmond et al., 2012; Tomer et al., 2014), the spatial patterns of CCT, CVT, and other tillage sequences remain poorly understood. Identification of tillage data through remote sensing remain challenging (Zheng et al., 2013), and the known tillage dynamics estimates come from field-level surveys.

The surveys, conducted almost exclusively in the U.S. Corn Belt, reveal complex time patterns of tillage practices. Hill (1998) and Hill (2001) focused on no-till, the version of CT that results in the least soil disturbance (CTIC, 2015), on the fields that were in corn-soybean rotation. Hill (1998) estimated that 16% of land were in no-till for both 1994 and 1995 based on a survey of 14,748 fields in Illinois and Indiana. Hill (2001) study's tracking of 17,550 fields in Illinois, Indiana, and Minnesota from 1994 to 1999 showed that although 58%, 77%, and 29% of the fields no-tilled at least once over the study period, only 13% and 9% of all observed fields were in no-till all six years in Illinois and Indiana, and no fields have been in no-till for six years in a row in Minnesota. Napier and Tucker (2001) surveyed 1,011 farm operators in three Midwest watersheds in 1998-1999 about the use of tillage practices in the preceding five years. Crops grown by the surveyed farmers were not reported in the paper. The study found that some 22%, 6%, and 54% of the farmers used deep moldboard plowing, a form of conventional tillage, every year, and the additional 8%, 5%, and 9% percent used moldboard plowing every other year in Ohio, Iowa, and Minnesota, respectively.

More recently, Reimer et al. (2012) describes a diverse, rotational tillage regimes for corn and soybean systems for two watersheds in Indiana observed over 2007 and 2008. Andrews et al. (2013) conducted a national survey of famers growing corn, soybeans and wheat in the U.S. in 2009 and 2010. The study found that out of 622 farmers surveyed in the Corn Belt, which includes Illinois, Indiana, Iowa, Missouri, and Ohio, some 55% were using CT on all crops in both years, 14% used conventional tillage on all crops in both years, with the remaining part of the sample varying the tillage systems between the crops and/or years. The difficulty of extrapolating of the results of the survey-based studies of the time patterns of alternative tillage systems is that they are limited to few specific regions and cropping patterns, and no explanation of the spatial variation in observed rates of CCT or CVT has been attempted.

To address the need for quantitative estimates of time patterns of tillage practices and the factors that affect the use of CCT, the paper develops and estimates a dynamic model of bundled tillage-crop choices for the state of Iowa. The results of estimation are then used to assess how both natural conditions (soil erodibility) and other economic choices (crop rotations) interact with the farmers' choices of CCT, CVT, and RCT, , i.e., the farming systems in which CT is rotated with conventional tillage systems.

The remainder of the paper is organized as follows. We first present the methodology. In this section, we describe the Quadratic Programming (QP) approach to estimate transition matrix (TM) in a Markov chain model and the data used for the model. We then summarize our results and discuss implications of the study as well as the power of the prediction of the model. Summary and conclusions are discussed in the last section.

2. Materials and Methods

The study involves two major steps. At step one, we develop a first-order, four-state Markov chain model of tillage-crop dynamics for corn and soybean production systems. We use quadratic programming (Lee et al., 1965) to estimate the transition matrix for each of the 99 counties in the state using county-average, year–and crop–specific tillage data from CTIC for 1992-1997 (CTIC, 2015). The estimated transition matrixes are then used to calculate the county-specific probabilities of CCT and RCT. At step two, we study how CCT and CT probabilities vary with crop rotations and soil erodibility as measured by the county proportion of Highly Erodible Land (HEL).

Corn and soybeans are the only two crops considered in this study since they occupy the overwhelming majority of Iowa cropland: according to the Census of Agriculture, the combined share of corn and soybeans in Iowa harvested cropland was 91%, 92%, 93%, and 94% in 1992, 1997, 2002, and 2007, respectively (http://www.agcensus.usda.gov/, accessed 05/2016). Typically, farmers in Iowa alternate corn and soybeans crops in consecutive years (Stern et al., 2008, 2012).

2.1. Data

The National Crop Residue Management (CRM) survey by CTIC is the only nation-wide survey that documents different tillage practices, by county and by crop. For the purposes of the study, we refer to no-till, ridge till, mulch till as CT, and the rest of the tillage systems, as conventional tillage (CV). The CRM survey data are available annually from 1989 to 1998, biannually from 1998 to 2004, and for selected counties from 2005 to present (CTIC, 2015). 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. Quantitative measures of the precision of CRM survey data are not available, but in general, the data have been assessed to be complete and deemed reasonably accurate (Baker, 2011; Gassman et al., 2006). The four tillage-crop shares including CT corn, CV corn, CT soybeans and CV soybeans, corresponding to the four states of Markov chain TM are considered in this study.

Estimation of transition matrix with time-ordered aggregate data requires the number of time periods (N) be greater than the number of Markov model states, which is equal four in our model. Based on the nature of state-aggregate CT dynamics, we choose to estimate our model using the 1992 to 1997 data, i.e., N = 6. While a longer time series could improve the precision of estimation, the six years of data are the longest time span we can have that fits the task. There is little variation in the tillage shares of CT corn and soybeans, whereas CV corn is monotone decreasing over 1989-1991 and thus tillage shares over the period might not pose the Markov properties. Beginning with 1998 the data are available biannually only (figure 1).

Vulnerable cropland is determined based soil erodibility index, which is measured by the Highly Erodible Land (HEL) code. 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). ISPAID assigns each map unit to one of four categories: 1 for HEL, 2 for a potentially HEL, 3 for a not HEL, and 0 if no data are available. Figure 3 shows the HEL acres over total acres planted for 99 counties in Iowa.

2.2. Statistical model

The choice of tillage-crop can be described as stochastic process because farmers may consider the choice as a way to reduce the loss of soil productivity, to break weed and disease cycles, and to stabilize the profits (Hill, 1998; Howitt & Reynaud, 2003). The model we propose starts with the assumption that farming choices in any given year can be classified into four distinct, non-overlapping tillage-crop states: CT corn, CV corn, CT soybeans, and CV soybeans.
It is further assumed that the TM possesses first-order stationary Markov property.

Each element of the transition matrix, p_{ij}, represents the probability of tillage-crop state j in the current year given tillage-crop choice i in the year before. Here $i, j = 1$ (CT corn), 2 (CV corn), 3 (CT soybeans), 4 (CV soybeans):

$$0 \le p_{ij} \le 1, \quad i, j = 1, \dots, 4; \quad \sum_{j=1}^{4} p_{ij} = 1, \quad i = 1, \dots, 4. \tag{1}$$

Due to the problems with soybean cyst nematode (CAST, 2009), as well as the significant yield decline associated with consecutive years of soybeans (Hennessy, 2006;), following soybeans with soybeans is a highly unlikely choice for Iowa farmers (Sahajpal et al., 2014; Secchi et al., 2011; Stern et al., 2008). Therefore, all the probabilities of transitioning from soybeans to soybeans are restricted to zero in the model:

$$p_{ij} = 0, \quad i, j = 3, 4. \tag{2}$$

The Markov model is specified as follows:

$$\mathbf{s^n} = P'\mathbf{s^{n-1}} + \boldsymbol{\varepsilon}^\mathbf{n} \ , \tag{3}$$

where $n = 2, \dots, N$, N is the number of years for which tillage-crop shares are observed, s^n is the four-by-one vector of proportions s_j^n of the four tillage-crop areas of the region in year *n* such that $0 \le s_j^n \le 1, \quad j = 1, \dots, 4, \quad \sum_{j=1}^{4} s_j^n = 1$, P' is the transpose of the transition matrix, and ε^n is the four-by-one vector of year *n* random errors $\varepsilon_j^n, \quad j = 1, \dots, 4$.

2.3. Model estimation and fit

We use the QP approach to estimate the transition matrix *P* (Lee at al., 1965, 1970), which is regarded as preferred method for estimating the Markov model with time-ordered spatially aggregate data (MacRae 1977; Kelton 1981, 1994). Under QP, the estimates of transition matrix probabilities are found by minimizing the sum of squared errors in model (1) – (3), i.e., by minimizing the quadratic form $\sum_{n=2}^{N}\sum_{j=1}^{4}\left(\varepsilon_j^n\right)^2$ subject to constraints (1) and (2). We used MATLAB R2014a routine lsqlinsolver to perform QP.

We evaluate measure of accuracy of the estimates, Mean Absolute Error (MAE), which is defined by

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

We used the shares in 1992 as a starting point to calculate MAE to avoid ambiguity.

Let $\hat{P}$ be the estimated transition matrix. $\hat{s}^n$ in equation (4) is estimated as (5)

$$\hat{s}^n = \left(\hat{P}'\right)^{n-1} s^1, \quad n = 2,\ldots,6\cdot \tag{5}$$

We also calculate correlation coefficient (r) to evaluate how well the approach performs. Correlation coefficient shows the ability of the approach to simulate not only the shares but also the trend of these shares.

2.4. Dynamics of CT in relation to HEL and crop rotation.

Statistical analyses of variance for the data were conducted using the SAS version 9.2 statistical package (SAS, 2013). Effect of the HEL on the probabilities of CCT, ACT and CCV were evaluated using the Proc GLM. We used the Proc ANOVA to analyze the influence of crop rotation on the probabilities. In this study, we evaluated the effects of HEL and crop rotation for the CCT, ACT and CCV for two and three-year tillage-crop sequences. Probabilities for longer tillage-crop sequences can be computed in the same fashion.

3. Result and discussions

3.1. Model estimation and fit

Figure 2 presents the measures of in-sample MAE prediction error, calculated as the difference between observed shares and estimated ones for each county. MAE is relatively small: MEA are less than 10% for all counties and majority of counties have less than 5% in MEA. Figure 6 shows the graphical results of the comparison of simulated and observed shares for CT corn, CV corn, CT soybeans and CV soybeans in 1993. The simulated shares clearly agree well with observed shares: all correlation coefficients are greater than 0.75 (0.82, 0.87, 0.80 and 0.77, respectively) and the p-values (at 5% least significant difference) are smaller than 0.0001. The points on the graphs are very close to y=x line of perfect correspondence.

For the years 1994, 1995, 1996 and 1997, p-value and r are showed in table 1. High *r*-values indicate that the percentage QP tillage-crop shares estimations are quite close to the observed shares: all the *r*-values are in between 0.69-0.86. Kalbfleisch and Lawless (1984) and McLeish (1984), who studied the least squares approach to estimate Markov Models from aggregate data, noted that aggregate data often do not contain much information about a Markov chain. However, in this case, the Markov model shows the ability to infer the parameters of interest with very limited data. Moreover, since all the predicted tillage-crop shares in the MAE reported are computed from the 1992 observed tillage-crop shares and the *r*-values are all positive, the model captures the time-path of the shares as well.

Table 1 shows the estimation of CCT, ACT and CCV probabilities for both two and three-year tillage-crop sequences. Overall, the findings imply that when farmers use CT, they more often than not rotate it with CV. The ACT probability increases after one year. The increase indicates that farmers will alternate CT with CV tillage practices at one point in the future after CT has been adopted. CT has a smaller chance of being followed by CT than being followed by CV: for two-year tillage-crop sequences, probability of being ACT is almost equal to the sum of the probability of CCV and CCT whereas there is 70% acres in ACT for three-year tillage-crop sequences, an increase by 21% after one year.

3.2. Dynamics of CT in relation to HEL

The 1993 probability of (or share of cropland in) two-year CCT can be estimated as the probability that tillage is CT in both years 1992 and 1993, i.e., as the sum of three shares of land: that in CT corn after CT corn, $\hat{p}_{11}s_1^1$, CT corn after CT soybeans, $\hat{p}_{31}s_3^1$, and CT soybeans after CT corn: $\hat{p}_{13}s_1^1$. The 1993 probability of (or share of cropland in) two-year CCV is estimated as the probability that tillage is CV in both years 1992 and 1993, i.e., as the sum of three shares of land: that in CV corn after CV corn, $\hat{p}_{22}s_2^1$, CV corn after CV soybeans, $\hat{p}_{42}s_4^1$, and CV soybeans after CV corn: $\hat{p}_{24}s_2^1$. The 1994 probabilities of three-year CCT and CCV are calculated in a similar fashion, as $\hat{p}_{11}\hat{p}_{11}s_1^1 + \hat{p}_{11}\hat{p}_{13}s_1^1 + \hat{p}_{13}\hat{p}_{31}s_1^1 + \hat{p}_{31}\hat{p}_{13}s_3^1 + \hat{p}_{31}\hat{p}_{11}s_3^1$ and $\hat{p}_{22}\hat{p}_{22}s_2^1 + \hat{p}_{22}\hat{p}_{24}s_2^1 + \hat{p}_{24}\hat{p}_{42}s_2^1 + \hat{p}_{42}\hat{p}_{22}s_4^1 + \hat{p}_{42}\hat{p}_{24}s_4^1$, respectively. The probabilities of CCT and CCV for the other years under consideration could be calculated by replacing s^1 with the corresponding $\hat{s}^n$ for the appropriate years n = 2,…,N. Similarly, we can be computed probabilities of ACT for any year n. It is noted that the sum of CCT, CCV and ACT in any year n is equal to one.

Statistical comparison between adoption level of CCT for two-year tillage-crop sequences and HEL gives a slope of 0.19 with the p-value of 0.006, indicating significant relationship between CCT adoption for two-year tillage-crop sequences and HEL. Similarly, HEL is found significant effect the CCT adoption for three-year tillage-crop sequences, with the slope of 0.13 and the p-value of 0.036. The results show that there are no significant differences in probabilities of CCV and ACT between HEL and non-HEL for both two and three-year-year tillage-crop sequences. Figure 4 and 5 represent the spatial distribution of the probability of CCT for two-year tillage-crop sequences. In general, it can be seen that if counties have more cropland in HEL, the average probability of CCT are higher than those have less HEL.

3.3. Dynamics of CT in relation to crop rotation

Table 3 shows the effect of crop rotation on CCT for two-year tillage-crop sequences. It is not surprising that there are no significant differences in CCT probability between the two standard corn-soybeans rotations, alternating corn and soybeans crops in consecutive years for a single field (called corn-soybeans rotations). Comparison of CCT probability among corn after corn, and corn-soybeans rotations show that the CCT probability is significantly lower under corn after corn than corn-soybeans rotations: averagely, just 0.10 under corn after corn rotation compared to 0.44 and 0.51 under corn after soybeans and soybeans after corn, respectively. Likewise, corn-soybeans rotations have higher likelihood of being ACT than corn after corn rotations whereas there is no significant difference between ACT probability of the two corn after corn rotations (table 4).

Table 5 represents the comparison of ACT and CCT probabilities between more corn and less corn rotations in three-year tillage-crop sequences. If farmer only planted one year of corn in three-year tillage-crop sequences, both the probability of CCT and ACT are significant higher than who adopt more corn rotations (i.e., corn monoculture, soybeans after corn after corn and corn after corn after soybeans rotations). For CCT, less corn rotation increases the average probability of CCT by 0.1, from 0.03 to 0.13. In comparison with more corn rotations, the average probability of ACT is significantly higher compare with less corn rotation: average probability of ACT for more corn and less corn rotation are 0.17 to 0.53, respectively.

4. Summary and conclusions

Despite the importance of yearly tillage dynamics, the spatial patterns of CCT, CVT, and other tillage sequences remain poorly understood. To fill the gap in the understanding of tillage dynamics, we considered CT adoption in a dynamic framework using Markov chain. We apply QP approach to model the dynamics of CT adoption, and quantify the effect of HEL and crop rotation on the probability of CCT, RCT and CCV.

A number of interesting and pertinent findings have emerged. The findings show that HEL and crop rotation are found to have significant effects of the CCT adoption, and the overwhelmingly large share of CT is in RCT, both for corn and soybeans. Analysis of Variance shows that CCT occurs more often on HEL when compared to other cropland. Also, the county-average probabilities of RCT are higher in the counties that have higher proportion of HEL. In addition, we identified a significant effect of crop rotations on tillage dynamics: the cropland under corn monoculture is less likely to be in RCT when compared to land in corn-soybean rotation. The results of the study indicate that both natural conditions (soil erodibility) and other economic choices (crop rotations) affect farmers' choices of CCT and RCT in Iowa.

There is an urgent need for understanding the farmer's tillage choices over time and the factors driving the choices. While micro (e.g., farm-level) data for modeling bundled tillage-crop dynamics are often incomplete and/or unavailable, this study provides an alternative approach to leverage and increase the use of available data. The probabilities estimated would benefit simulation modeling for assessment of the economic and environmental effects of the policies that encourage CT adoption. From the methodological perspective, the modeling approach introduced in the study is applicable to corn-soybean production systems in other regions and is generalizable to other cropping systems.

5. References

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Table 1. Average probability for two and three-year tillage-crop sequences

Tillage-crop	Two-year tillage-crop sequences	Three-year tillage-crop sequences
CCT	0.27	0.16
ACT	0.49	0.70
CCV	0.24	0.14

Source: Authors' calculations based on estimated transition probabilities and shares in 1992

Table 2. Correlation coefficient of alternative two-year tillage-crop sequences

	Tillage-crop share			
Year	CT Corn	CV Corn	CT Soybeans	CV Soybeans
1993	0.82	0.87	0.80	0.77
1994	0.78	0.80	0.78	0.65
1995	0.83	0.81	0.81	0.85
1996	0.84	0.81	0.82	0.86
1997	0.84	0.74	0.69	0.73

Source: Authors' calculations based on CTIC (2015a) and estimated shares in 1992

Notes: p-values are smaller than 0.0001 for all correlation coefficients

Table 3. Estimated mean CCT probabilities of alternative two-year tillage-crop sequences

Current tillage-crop, year t	Previous tillage-crop, year t-1	probability*
CT corn	CT corn	0.10[a]
CT corn	CT soybeans	0.44[b]
CT soybeans	CT corn	0.51[b]
LSD (0.05)		0.07

*Within-column simulated means followed by the same letter are not significantly different using Fisher's LSD at P≤0.05.

Source: Authors' calculations based on estimated transition probabilities and shares in 1992

Table 4. Crop rotation effect on ACT probabilities of alternative two-year tillage-crop sequences

Current tillage-crop, year t	Previous tillage-crop, year t-1	probability*
CT corn	CV corn	0.12[a]
CV corn	CT corn	0.13[a]
CT corn	CV soybeans	0.40[b]
CV corn	CT soybeans	0.56[c]
CT soybeans	CV corn	0.48[d]
CV soybeans	CT corn	0.27[e]
LSD (0.05)		0.07

*Within-column simulated means followed by the same letter are not significantly different using Fisher's LSD at P≤0.05.

Source: Authors' calculations based on estimated transition probabilities and shares in 1992

Table 5 Crop rotation effect on CCT and ACT probabilities of alternative three-year tillage-crop sequences

Rotation	CCT*	ACT*
Less corn rotations	0.13[a]	0.53[a]
More corn rotations	0.03[b]	0.17[b]
P(T<=t)	<0.001	<0.001

*Within-column simulated means followed by the same letter are not significantly different using Fisher's LSD at P≤0.05.

Source: Authors' calculations based on estimated transition probabilities and shares in 1992

Notes: more corn rotations include; less corn rotations has only one year of corn in three-year tillage-crop sequences

Figure 1. Shares of alternative tillage-crop areas in the combined corn and soybeans total area, Iowa, based on CTIC (2015a) data

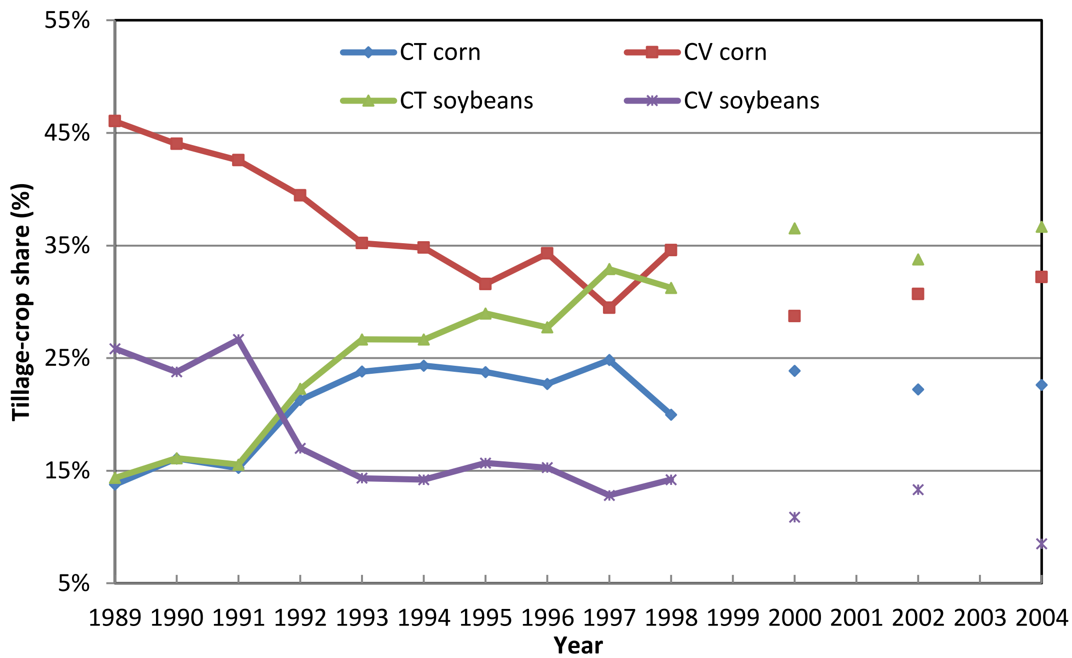
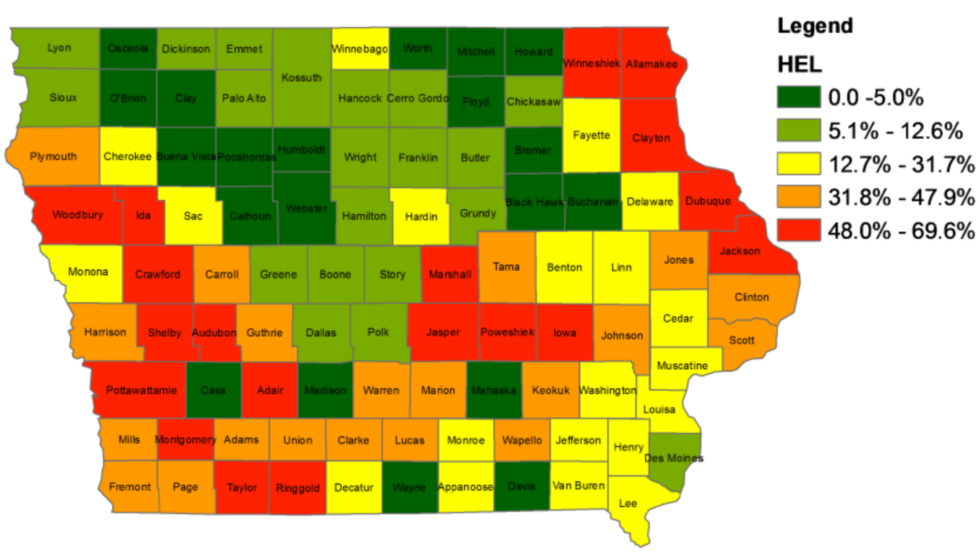
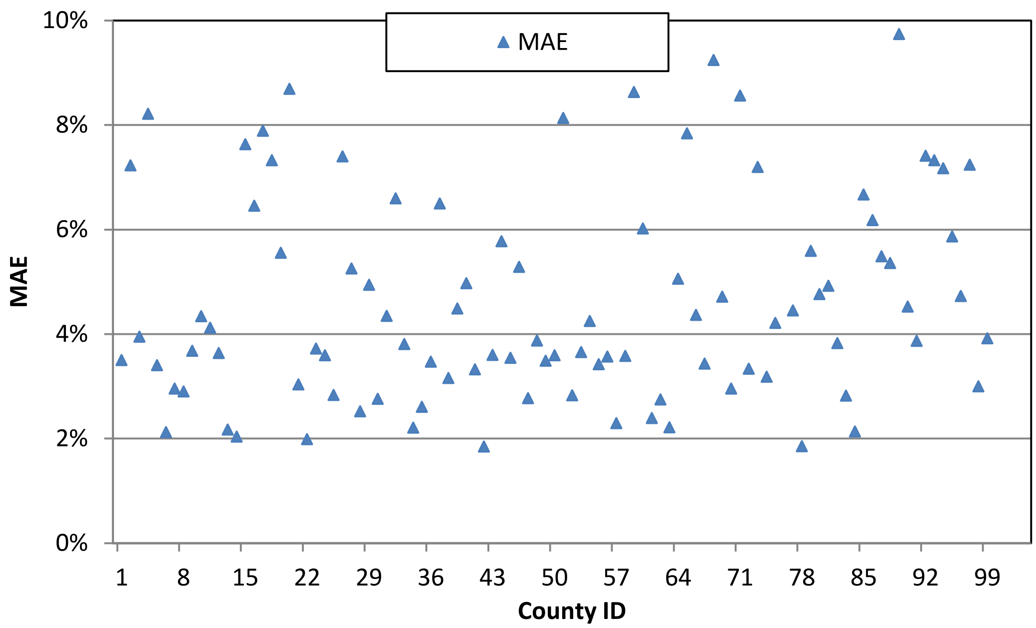


Figure 2. Percentage of cropland in HEL for counties in Iowa



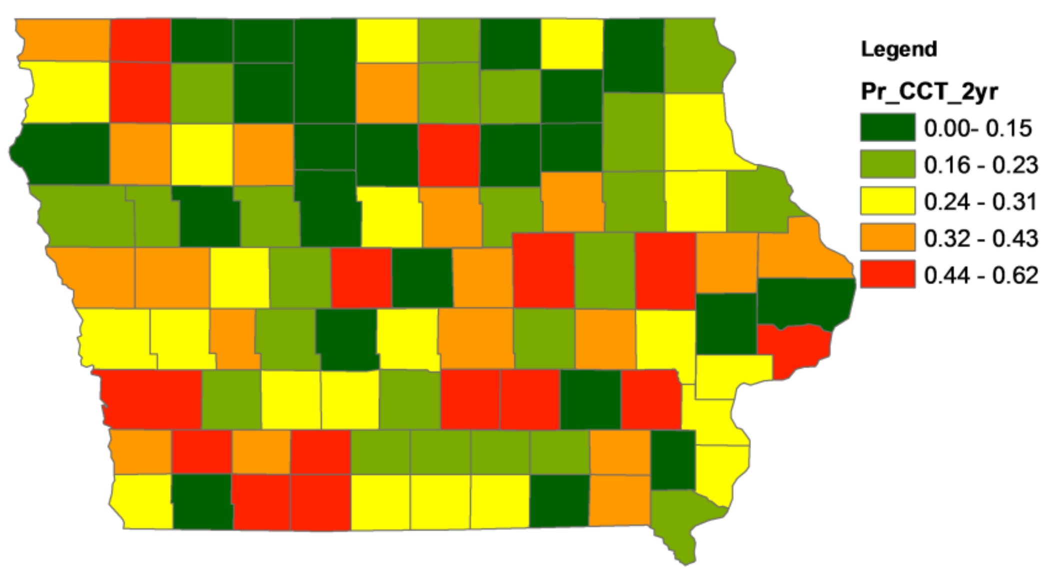
Source: Authors' calculations based on Iowa Soil Properties and Interpretations Database (ISPIAD). Note: Percentage cropland in HEL was computed by dividing total cropland acres in HEL (code 1) by total cropland acres.

Figure 3. Mean absolute error (MAE)



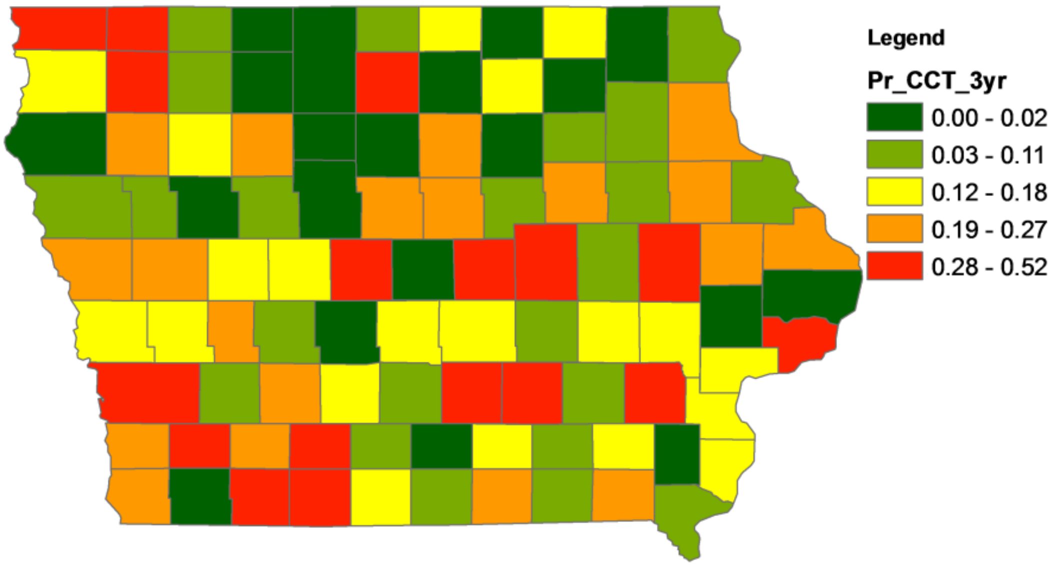
Source: Authors' calculations based on CTIC (2015a) data and simulated shares. Note: Counties are sorted in alphabetical order.

Figure 4. Probability of CCT for two-year tillage-crop sequences



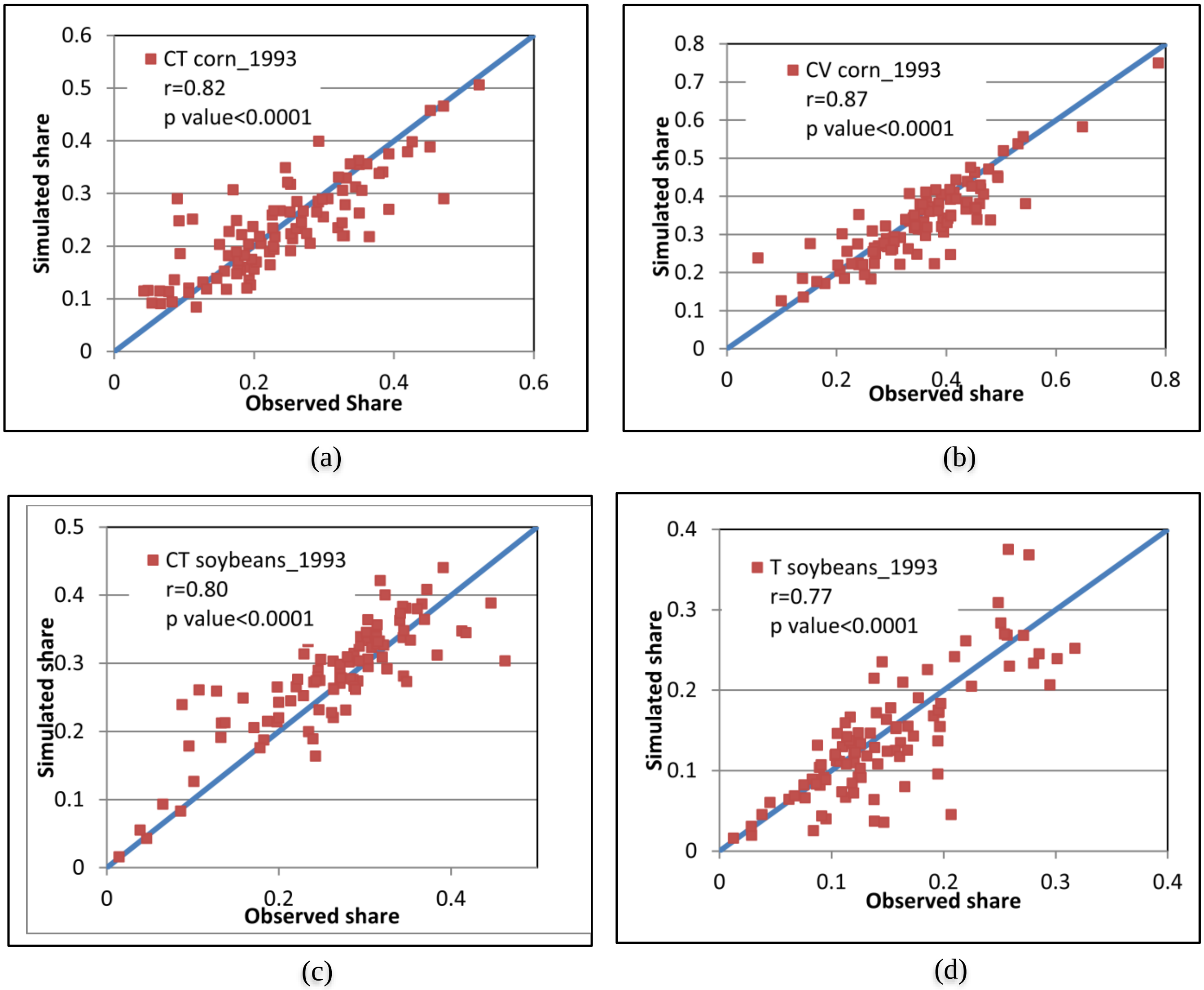
Source: Authors' calculations based on estimated transition probabilities and shares in 1992.

Figure 5. Probability of CCT for three-year tillage-crop sequences



Source: Authors' calculations based on estimated transition probabilities and shares in 1992

Figure 6. Correlation of simulated and observed shares: (a) for CT corn, (b) for CV corn, (c) for CT soybeans and (d) for CV soybeans in 1993



Source: Authors' calculations based on CTIC (2015a) data and simulated shares