Quantifying the dynamics of agricultural conservation practices in the Mississippi Delta region

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Abstract: The working lands conservation programs in the US are explicitly designed to assist farmers with conservation practice initiation with the expectation that the farmers would continue implementation even after the contract ends, thus promoting soil and water conservation efforts. However, little is known about the implementation levels once contracts expire. This study uses the Markov chain framework on state-level conservation practices acreage data to provide quantitative estimates of changing patterns of conservation practices adoption. The results show that there is a higher probability that the acreage in conservation tillage continues in those practices, and a higher probability that acres in cover crops and crop rotation tend to move out but add nutrient management as preferred conservation activity. However, there is very less chance that any of the acres in a conservation practice tend to move to no conservation activity at all. The transition probability estimates could serve as a useful reference for assessing future conservation practices adoption levels and aid funding agencies in prioritizing conservation practices to stimulate sustainable and efficient conservation efforts.

Keywords: adoption, agriculture, conservation, Markov chain

JEL Code: Q18, Q28, Q53

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Introduction

Agricultural nonpoint pollution is one of the major sources of water quality impairment in the United States (EPA, 2009). To reduce nonpoint source pollution from agricultural production, different conservation programs provide farmers with financial and technical incentives to adopt a variety of conservation practices on their working lands. Federal, state, or local level conservation programs have spent billions of dollars on working lands to promote soil health, water quality, and wildlife habitat through cost-share programs in recent decades. For example, the Environment Quality Incentives Program (EQIP) is authorized at $9.18 billion from 2019 to 2023 under the 2018 Farm Bill. Eligible farmers enter into contracts to receive payment for implementing agricultural best management practices (BMPs), to simultaneously sustain agricultural productivity and promote environmental quality. Most of the literature on agriculture conservation is focused on understanding farmer's decision for adopting a conservation practice (Adusumilli and Wang, 2018, Baumgart-Getz et al., 2012, Buckley et al., 2015, Daxini et al., 2018, Dewald et al., 2019, Hyland et al., 2018, Mishra et al., 2018), and impact of conservation programs on conservation practice adoption (Claassen et al. 2018, Mezzatesta et al., 2013, Pathak et al. 2021, Wang et al., 2019). These studies showed the association of adoption behavior with several variables (e.g., attitudes, costs, natural resources and ownership, program participation, land type, farm size, and farmer's socio-economic characteristics) but have not considered the spatial extent of conservation practice adoption. Kolady et al. (2021), Banerjee et al. (2021), Kurkalova and Tran (2017), and Banerjee et al. (2017) have considered the spatial aspect of agricultural conservation practices. However, to our knowledge, little is known about the dynamics of conservation practice adoption once the contracts expire, leaving a knowledge gap in understanding the impact of conservation practices on addressing the primary resource concerns in the long term.

The cost-share programs are explicitly designed to assist conservation practice(s) initiation through voluntary enrollment in contracts ranging from 3 to 10 years with a competitive renewal option. The expectation is that the farmers will continue conservation practice(s) once the contract ends, contributing to soil and water conservation efforts. According to Iacono et al. (2015), incorporating probabilistic elements makes land-use decisions more realistic while also representing associated uncertainty. This study proposes modeling year-to-year BMP choices and subsequent adoption change using the Markov chain framework, which has not yet been widely exploited in conservation literature.

Markov chain estimates the transition probabilities across various BMPs using time-ordered spatially aggregated data and provides quantitative estimates of time patterns of BMPs adoption. These estimates will allow policymakers to evaluate what is happening with on-farm conservation practice after cost-share contracts end. Markov transition probabilities from spatially aggregated data have been successfully used, albeit limitedly, for studying land-use dynamics, including crop sequences (Aurbacher and Dabbert, 2011; Castellazzi et al., 2010; Salmon-Monviola et al., 2012) and certain conservation practices (Kurkalova and Tran, 2017). Aurbacher and Dabbert (2011) proposed a method to calibrate transition matrices of a Markov chain to predict land use sequences by using minimum cross-entropy. The land-use sequences constructed using this method have smaller deviations from the crop shares than those obtained using the unconditional probabilities in the stochastic process. Salmon-Monviola et al. (2012) estimated crop sequences based on spatial dynamics of cropping systems from limited data available using the first-order Markov chain approach. They demonstrated that the model conforms to the main constraints for cropping system modeling to construct alternative cropping systems corresponding to agricultural practices. Castellazzi et al. (2010) showed that the Markov chain approach could estimate crop sequences and allocate the management operations with a crop for every field for each year at the landscape scale from a case study without requiring mechanistic modeling. The authors pointed out that this approach provides a general method for generating landscape-scale crop arrangement scenarios spatially and temporally. In contrast, Kurkalova and Tran (2017) improved modeling the time patterns using the Markov chain framework to assess the transition probabilities from one tillage-crop conservation practice to another tillage-crop practice based on time-ordered spatially aggregated data in Iowa. They suggested that the four-state Markov chain model of conservation practice dynamics in crop production systems could be applied to a significant portion of cropland statewide.

The Markov chain method provides a systematic pathway to model sequences of land use (Aurbacher and Dabbert, 2011) while overcoming the shortcomings of stochastic simulation, linear programming, and optimization models. This approach can simulate crop practice succession dynamics at a local and regional scale with limited aggregated or missing data and does not require describing the complex relationships between biophysical and social-economic factors (Salmon-Monviola et al., 2012). Our study relies on the four-state Markov chain approach proposed by Kurkalova and Tran (2017) to estimate the transition probabilities and infer the dynamics of conservation practice scenarios from available data. The quantification of BMPs time patterns complements the historical BMPs adoption in working lands for assessing the effects of present and future conservation programs adopting the cost-share model (Gallant et al., 2011). We show how conservation practice adoption may be represented mathematically as a transition matrix when a conservation contract expires and how this allows estimating the long-term adoption of each practice. The transition matrices for BMPs sequences could be potentially used in program targeting by weighing alternative scenarios that could bolster future adoption of BMPs and foster environmental conservation by addressing nonpoint source pollution associated with agricultural production at the regional scale.

Data and methods

Data

This study relies on conservation program data from the Natural Resources Conservation Service of the United States Department of Agriculture (USDA-NRCS, 2020). We obtained state-level annual data on acres under conservation practices from 2007 to 2019 in the three states of the Mississippi Delta region–Arkansas, Louisiana, and Mississippi. We focused on two major row crops–corn and soybeans–

to calculate the share of (non)conservation acres in the Mississippi Delta region.[1] Under government cost-share programs, farmers voluntarily enroll in a specific conservation program through contracts up to a maximum term of ten years in length. Environmental Quality Incentives Program (EQIP) and Conservation Stewardship Program (CSP) are two major cost-share programs for cropland soil management practices.

Conservation tillage (CT), conservation crop rotation (CCR), cover crop (CC), nutrient management and other conservation practices (NMOT)[2], and less conservation practice (LESS)[3] are the five states considered in this study. These conservation practices are all used to reduce nutrient pollution and soil erosion. Figure 1 shows the trend of the conservation acres over time in the Mississippi Delta region. In general, conservation acres are increasing in the Mississippi Delta region.

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[1] We did not consider other major crops of the Mississippi Delta region such as sugarcane and rice in this study because the conservation practices evaluated in this study are minimally implemented in these crops.

[2] The list of other conservation practices can be accessed through the link (https://www.nrcs.usda.gov/Internet/NRCS_RCA/reports/cp_la.html) under the table entitled 'Land Unit Acres Receiving Conservation by Practice (including practice count) and Fiscal Year – Cropland Soil Quality Practices.' All practices excluding conservation tillage, cover crop, conservation crop rotation, and nutrient management practices constitute other conservation practices in our study.

[3] LESS includes both corn and soybeans planted acres that did not implement any conservation practice or did not receive any payment from federal conservation programs even after adopting conservation practice(s). The data on corn and soybeans planted acres (2007-2019) are obtained from https://www.fsa.usda.gov/news-room/efoia/electronic-reading-room/frequently-requested-information/crop-acreage-data/index.

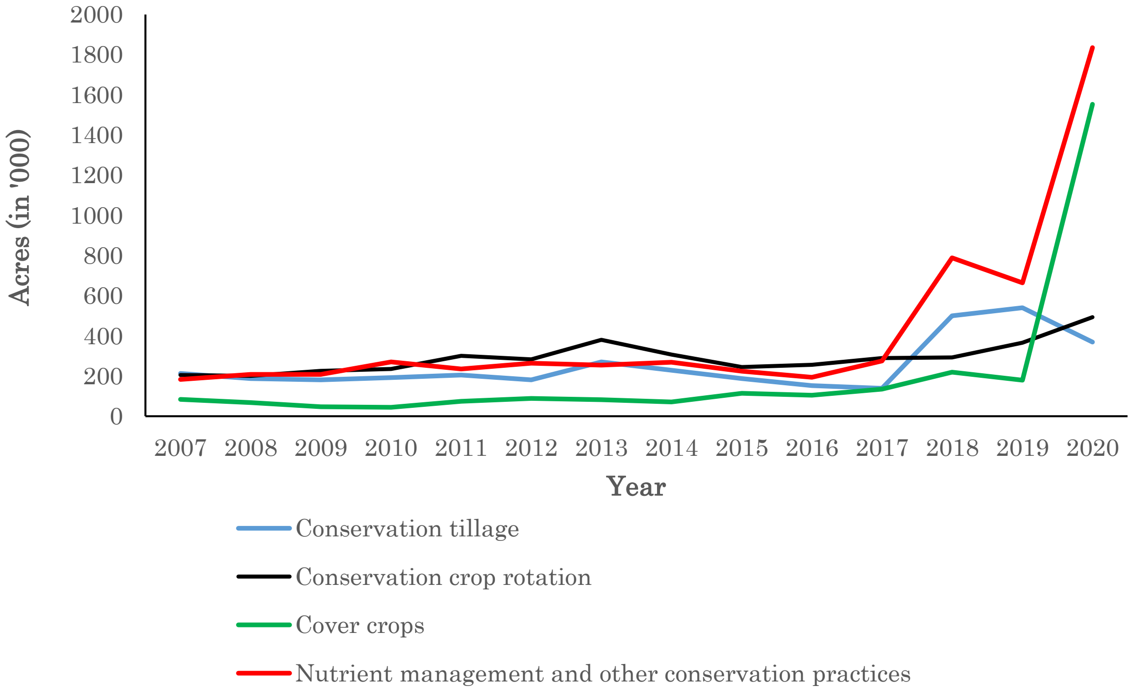


Fig 1. Acres receiving conservation in the Mississippi Delta region

Markov chain model

Markov chain is a mathematical process model that describes a shift from one state to another according to a transition probability matrix (Gagniuc, 2017). By definition, a sequence of random variables $\{X_t\}$ $(t = 0, 1, \dots)$ is called Markov chain if the random variables are characterized by the Markov property–that is, the distribution of the anticipated state is independent of the past state and depends only upon the current state and can be expressed as:

$$Pr[X_{t+1} = S_{t+1}|X_t = S_t, \cdots, X_0 = S_0] = Pr[X_{t+1} = S_{t+1}|X_t = S_t] \quad (1)$$

The probability ($P_{ij} = Pr\left[X_{t+1} = S_j|X_t = S_i\right]$ to move from state i to state j at time t and t+1 in one step is named transition probability and expressed as:

$$[P_{ij}] = \begin{bmatrix} P_{00} & P_{01} & P_{02} & \cdots \\ P_{10} & P_{11} & P_{12} & \cdots \\ \vdots & \vdots & \vdots & \vdots \\ P_{i0} & P_{i1} & P_{i2} & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix} \quad i,j = 0,1,2,\cdots \tag{2}$$

where $0 \leq P_{ij} \leq 1$ and $\sum_{j=0}^{\infty} P_{ij} = 1$.

The modeling procedure follows Kurkalova and Tran (2017) in this study. We assume that given the history of BMP choices in the Mississippi Delta region, the current year BMP choice depends only on the state in the year before. Thus, a choice of conservation practice may be regarded as a Markov chain, represented by a stochastic matrix. The transition probability matrix can be written as:

$$\begin{bmatrix} P_{CT\to CT} & P_{CT\to CCR} & P_{CT\to CC} & P_{CT\to NMOT} & P_{CT\to LESS} \\ P_{CCR\to CT} & P_{CCR\to CCR} & P_{CCR\to CC} & P_{CCR\to NMOT} & P_{CCR\to LESS} \\ P_{CC\to CT} & P_{CC\to CCR} & P_{CC\to CC} & P_{CT\to NMOT} & P_{CC\to LESS} \\ P_{NMOT\to CT} & P_{NMOT\to CCR} & P_{NMOT\to CC} & P_{NMOT\to NMOT} & P_{NMOT\to LESS} \\ P_{LESS\to CT} & P_{LESS\to CCR} & P_{LESS\to CC} & P_{LESS\to NMOT} & P_{LESS\to LESS} \end{bmatrix} \tag{3}$$

where, each element of position (i,j) indicates the transition probability $P_{i\to j}$. For instance, the probability of transition from CT state to CC state is denoted as $P_{CT\to CC}$ and P_{ii} denotes the probability of remaining in the same state. The region-level five practice shares, corresponding to the five states that we model in the Markov process, are shown in equation (2). The smallest share of conservation acres, approximately 10%, is attributed to cover crop practice. Even with a small share, the cover crop acres have been increasing over time, in general. Between 2012 and 2017, cover crop planting increased by five million acres in the US (USDA-NASS, 2019).

The transition matrix P is estimated using the restricted least square (RLS) approach (Lee et al., 1970, Lee et al., 1965). RLS is a preferred choice for evaluating the Markov model with time-ordered spatially aggregated data. Since the conservation contract can extend up to 10 years, we estimate the transition probabilities based on a three-year average of conservation acres. In this case, the number of periods (n = 13) is greater than the number of states in the Markov model (i = 5), which meets the Markov chain model requirement to estimate the transition matrix. The shares of conservation practices show a monotonic trend from 2007 to 2019 (Figure 2). This trend implies that the data are likely to appear from a regular Markov chain (Lee et al., 1970).

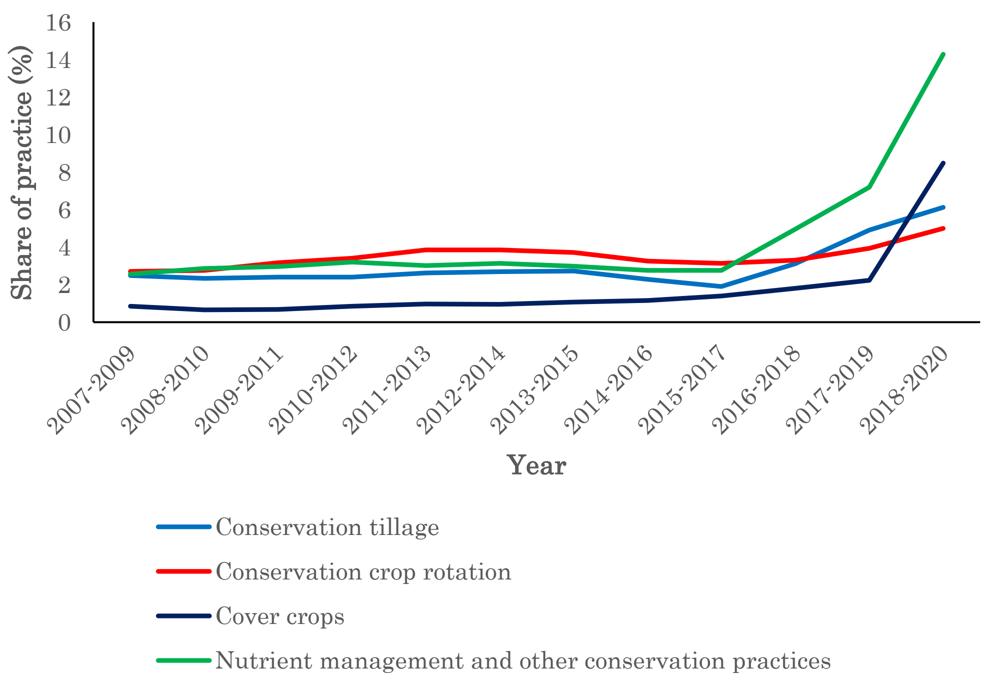
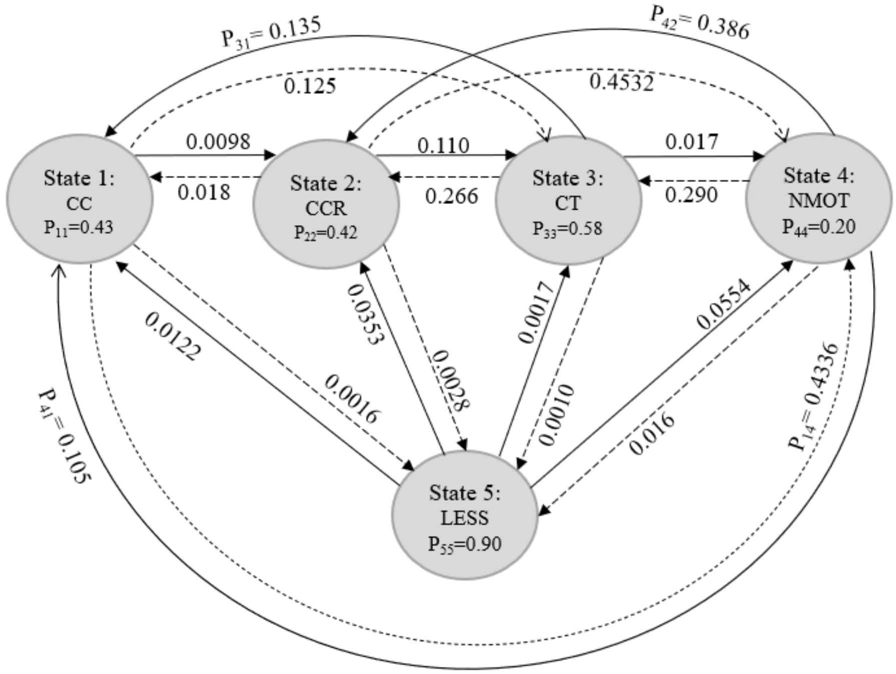


Fig 2. Shares of conservation practice acres in the Mississippi Delta region

The first-order, four-state Markov chain model has been developed and validated as a model for tillage-crop combinations in corn and soybean production systems by Kurkalova and Tran (2017). The Markov analysis was performed using the MATLAB R2018a.

Results and discussions

Figure 3 shows the transition probabilities matrix derived from Markov chain analysis for the Mississippi Delta region. The transition matrix revealed that CT acreage has an approximately 58% chance of remaining in conservation tillage practice, and the CCR acreage has an around 42% chance of remaining in conservation crop rotation practice. Similarly, CC acreage has an approximately 43% chance of remaining in cover crop practice, and NMOT acreage has an approximately 20% chance of remaining in nutrient management and other conservation practices category in the Mississippi Delta region.



State 1- CC: Cover crop
State 2- CCR: Conservation crop rotation
State 3- CT: Conservation tillage
State 4- NMOT: Nutrient management and other conservation practices
State 5- LESS: Less conservation practice

Fig 3. Estimated conservation practice transition probabilities in Mississippi Delta region, 2007 to 2019

The estimated probability suggested that there is an almost 27% chance that all CT acres transition to CCR practice and only ~14% chance of being followed by cover crop acres after the initial contract period of three years. In contrast, CC acres are less likely to be followed by CT acres. The estimated probabilities also indicated that acres under CCR have ~45% chance of being transitioned to NMOT. Conversely, NMOT has a 39% chance of being followed by CCR acreage. CT acres have ~27% chance of being converted to CCR practice but less likely to be converted to NMOT acres. NMOT has a 29% chance of being followed by CT, while there is 43% chance that the acres under CC will be followed by NMOT. In addition, it is less likely that CC acres convert to CCR and vice versa.

Conservation tillage methods include no-till planting, strip-till, and direct seeding leave more of the field surface covered with crop residue that reduces soil erosion. The highest probability of acreage remaining consistent in conservation tillage (58% probability that the number of acres in CT remains consistent after a three-year period) in the study area may imply that farmers directly benefit from reducing operation costs by using less tractor, equipment, and labor. Farmers have generally realized the short and long-run benefits from conservation tillage practice. For example, conservation tillage can reduce operating costs, enhance soil organic matter in the short run and improve water availability and quality, reduce soil erosion and nutrient runoff, increase wildlife habitat, and promote environmental quality in the long run. In addition, changes in tillage practice often require changes to farm equipment. Such changes to the equipment are relatively expensive and usually permanent. Therefore, it is not surprising that the acres tend to continue in conservation tillage practices after the contract period. The higher probability also reflects the general trend of conservation tillage acreage, which increased from 212,707 to 540,045 acres in the Mississippi Delta region during 2007-2019 (http://www.nrcs.usda.gov/programs/).

Conservation crop rotation involves growing different crops on the same agricultural land annually in a planned, recurring sequence. This practice can be used between a high residue-producing crop, such as corn, to a low residue-producing crop like soybeans to improve nutrient recycling, reduce soil erosion, and increase yield. It is more likely that the number of acres is retained in conservation crop rotation practice at the end of a three-year period, indicating that farmers either gained more economic return by applying fewer inputs with higher yield through conservation crop rotation practice or farmers have realized the economic benefit of conservation crop rotation practice and added acres under the practice. Many studies have shown the positive economic and ecological effects of crop rotation (Al-Kaisi et al., 2015, Bowles et al., 2020, Gentry et al., 2013, Karlen et al., 2013, Zhao et al., 2020).

There is a 43% probability that the total acres in cover crops tend to remain constant after a three-year contract period in the Mississippi Delta region, the second-highest probability among conservation practices evaluated in this study. This result may be attributed to several beneficial aspects of cover crops, such as water quality improvement, reduce soil erosion, enhance nutrient management, improve yields, and reduce the need for herbicides and pesticides. The results are consistent with the general trend of cover crop acreage. Cover crop acreage increased over time from 35,489 acres in 2005 to 179,473 acres in 2019 in the study area. The 40% probability of acres moving out of cover crops to nutrient management and other conservation practice could be influenced by challenges associated with the availability of cover crop seed, labor for timely termination activities, and limited program funds to support additional acres of cover crops.

In addition, the cost-share funding may not always cover the protentional additional costs (Roesch-McNally et al., 2018).

Although we observed only a 20% chance for total acres in nutrient management remain constant at the end of the cost-share contract in the Delta Region, we find that these acres shift to other conservation practices such as conservation tillage and crop rotation to optimize economic returns.

The probability estimates from this study have implications for conservation programs; however, this study is not without limitations. The state-level aggregate data may overlook the farm-level changes in implementation, or lack thereof, of conservation practices over time. Moreover, we only provide an aggregate estimate of the transition probabilities without considering the actual shift in acres from one practice to another practice.

Conclusion

This study attempts to probabilistically determine whether farmers would stay in the same or switch to alternative conservation practices after the cost-share program contract ends. Using data on acreage under different conservation practices, we applied the first-order Markov chain model to estimate the transition probabilities among alternatives and study the dynamics of conservation practices adoption. We consider major conservation practices and provide a regional assessment that helps assess the potential shift in future BMPs adoption scenarios, and consequently the resulting environmental benefits from conservation activities.

The transition probabilities imply that acreage in conservation practices mostly shift among other conservation activities but less likely to revert to no conservation. The change in conservation practice(s), or lack thereof, is driven by both economic and environmental factors. The results presented provide useful information to policymakers to investigate current and potential policies to encourage the initiation and adoption of certain BMPs on the agricultural production system in an intensive farming context to meet local conservation priorities and achieve regional natural resource goals.

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