Adoption of diverse crop rotation: Drivers and implications

Deepthi E. Kolady
Assistant Professor, Department of Economics
South Dakota State University
Deepthi.kolady@sdstate.edu

Tong Wang
Assistant Professor, Department of Economics
South Dakota State University

Jessica Ulrich-Schad
Assistant Professor, Department of Sociology
South Dakota State University

Weiwei Zhang
Assistant Professor, Department of Sociology
South Dakota State University

Selected Paper prepared for presentation at the Southern Agricultural Economics Association (SAEA) Annual Meeting, Birmingham, Alabama, February 2-5, 2019

Adoption of diverse crop rotation: Drivers and implications

Abstract

Recent changes in agricultural technologies, commodity prices, and policies have contributed to the upward trend in the continuous cultivation of corn and soybeans, particularly in the Midwestern U.S.A. While continuous cultivation may be economically beneficial for producers in the short-term, there are concerns about its long term impact on the overall ecosystem health and competitiveness of U.S. agriculture. Due to these concerns there is a renewed interest in incentivizing adoption and diffusion of diverse crop rotation (DCR), which is growing three or more crops in a rotation, particularly among row crop producers. Most of the previous studies on adoption of conservation practices focus on no-till and there is an emerging literature on cover crops. However, our understanding on the factors influencing or hindering adoption of DCR by producers is limited. This study uses survey data collected from South Dakota producers to identify the factors influencing producers' adoption decisions, particularly the role of spatial effects in adoption. Our findings demonstrate that the likelihood of adoption of DCR increases with increase in the neighborhood adoption rates for the peer group defined within 30 square mile radius. Our results suggest that the peer groups and their influence might be at bigger geographical areas than we would expect, particularly in sparsely populated areas and care must be taken in defining the peer group and leveraging it to scale up the adoption of DCR.

Introduction

Crop rotation systems are characterized by a defined sequence of crops grown on a given cultivated land and the associated management practices. Diverse crop rotation, or DCR, refers to growing three or more crops in a rotation, particularly among row crop producers. Careful selection of a crop rotation system offers the possibility of reducing the trade-off between farm profitability and environmental impact by internal nutrient recycling, maintaining the long-term productivity of the land, and by breaking weed and disease cycles (Gebermedhin and Schwab 1998). Economic and environmental importance of crop rotations including pest control of weeds, diseases, insects, and nematodes; reducing soil erosion; maintaining soil fertility and enhancing productivity, promoting ecosystem services and ecosystem health, and reducing production and price risk have been recognized for a long period of time even prior to the development of modern farming (Ikerd 1991, Davis et al. 2012, Altieri 1999, Temple et al. 1994, Crookston et al. 1991, Lieman and Dyck 1993, Wu and Babcock 1998). Farmers may also choose to rotate crops in order to reduce their production risk through diversification or to manage scarce resources, such as labor, during planting and harvesting timing.

There is more recent evidence from agricultural experiment station research on the economic net return of crop rotations in the Midwestern United States by increasing soil productivity, reducing external inputs, and by increasing yields. Results from stochastic dominance analysis showed that crop rotations containing alfalfa have the potential to provide substantial economic net returns to farmers while mitigating the risk of herbicide-resistant giant rag weed infestations (Golpen et al. 2018). Results from a five year rotation study for 2006-2011, using agricultural experimental station data from Iowa State University showed that total energy use in three (corn-soybean-oats) and four year rotations (corn- soybeans-oats-alfalfa) are substantially lower (1.41

BTU and 1.50 BTU, respectively) than the typical two year rotation of corn and soybeans (3.53 BTU). The study also showed that return to land, labor, and management for three year rotation ($404.67) was higher than two year rotation ($393.70) (Johanns, Chase, and Liebman 2012). Although not conclusive, there is also some evidence on the yield enhancing effect of crop rotations (Berzsenyi, Gyorffy, and Lap 2000, Mulik 2015, 2017). To the best of our knowledge, there is no study that uses farm survey data to inquire into the determinants of adoption of DCR.

Despite these economic and environmental benefits, a combination of technological innovations in agriculture such as the introduction of genetically modified crops, federal agricultural policies such as commodity support programs focusing mainly on five crops (corn, soybean, wheat, rice, and cotton) and crop insurance and market assistance programs focusing on limited commodities, biofuel policies supporting the production of a limited number of crops, and high market prices for select commodities have contributed to a steep decline in the prevalence of diverse crop production systems particularly during the last two decades (Fausti 2015, Fausti et al. 2012, Benbrook 2012, Brookes and Barfoot 2013, EPA 2018, Lazarus and Swanson 1983). As a result, across the 12 states of the Corn Belt, corn and soybeans account for 70% of the planted acreage (Mulik 2015).

The economic impacts of the reduction in DCR systems include structural changes in the agricultural sector where farms are getting bigger and number of farms are declining; rising costs of production due to increased reliance on external inputs; disease, pest, and weed resistance development; oversupply of select commodities; and overall decline in farm incomes (Wright and Wimberly 2013, Lazarus and Swanson 1983, Meehan and Gratton 2016, Benbrook 2012, Dill, Jacob, and Padgette 2008, Fausti 2015). The increased reliance on one or two crops raises concerns about the long-term sustainability of the agricultural production system where soils are loaded with increasing levels of chemical inputs that create environmental risk in terms of water and air quality including conditions such as eutrophication/dead zone in Gulf of Mexico (Daturesearch 2014, Mulik 2015, Fausti 2015, Fausti et al. 2012, Meehan et al. 2011).

It is clear that the private and public benefits of DCR are substantial and that the lack of diverse rotations have substantial societal and individual level costs. Due to these economic and environmental concerns, there is a renewed interest in incentivizing adoption and diffusion of DCR It is clear from a recent meta-analysis study on the adoption of conservation practices in the United States that most of the previous studies focus on no-till and there is an emerging literature on cover crops (Baumgart-Getz, Prokopy, and Floress 2012b).. Empirical evidence using survey data on the rate of adoption of DCR and factors influencing or hindering adoption of this practice by producers in the Corn Belt are limited or none. Additionally, although social interactions have been shown to be important in technology adoption and diffusion in a variety of contexts(Conley and Udry 2010b, Foster and Rosenzweig 1995b, Genius et al. 2014), empirical analysis on the role of peer effects in individual decision making on adoption of conservation agriculture practices including DCR is limited (Baumgart-Getz, Prokopy, and Floress 2012a). Policy makers may be able to leverage peer effects to scale up adoption of DCR where DCR is perceived to be more profitable and environmentally more feasible. Using survey data collected from South Dakota producers, this study addresses the existing gap in the literature.

The objectives of the study are three-fold: (i) estimate the adoption rate of DCR in Eastern South Dakota; (ii) identify the factors hindering adoption of DCR, and (iii) examine the role of peer effects in producers' adoption of DCR.

Data

The data used in this study was collected from a farm level survey conducted in South Dakota during spring 2018. We used the survey to collect information on perception of benefits and challenges of farm management practices particularly conservation tillage, cover crops, DCR and integrated crop and livestock management systems; years of adoption of these practices; farmer demographics; and farm characteristics. The list of eligible survey participants in the state was obtained from the Farm Service Agency (FSA). Using FSA as the source for participants list is reasonable as most of the farm operations in South Dakota work with FSA programs. We employed proportionate stratified-random sampling to select a representative sample of 3,000 farm operators in the Eastern part of the state where most of the corn and soybean production occurs. We used four rounds to contact survey participants in two week intervals: (i) an invitation letter that describes the survey with a link to answer the survey online was sent to all operations selected (including a $2 bill incentive in half of the letters to test for the effects on response rates), (ii) a hard copy of the survey with return envelopes were sent to those who did not respond to the survey online; (iii) a reminder post card was sent to those who did not respond in round 2; and (iv) a hard copy of the survey with return envelopes were sent to remaining non-responders. We received 708 completed survey responses. Excluding operations that stopped farming or rented out all of their land, we had a 30% response rate. However, 190 of the returned survey responses had P.O. boxes as the postal address making it impossible to geocode them for categorizing them into peer groups. Figure 1 demonstrates the presence of spatial pattern in the adoption pattern in our sample which justifies our focus on peer effects in this study. Table 1 presents the adoption rate of DCR and other conservation practices. It is clear from Table 1 that adoption rate of DCR is low (24%) compared to the other conservation practices inquired about, such as conservation tillage (77%), cover crops (47%), and integrated crop and livestock management (58%). While adopters of DCR are more likely to adopt other conservation practices than non-adopters of DCR, the low adoption rate for DCR suggest that the factors influencing producers' adoption decisions on DCR might be different from those of conservation tillage, cover crops, and integrated crop and livestock management systems.

Summary statistics of key demographic variables associated with participants are presented in Table 2. It is evident from Table 2 that there are no statistically significant differences in demographic characteristics such as age, education, and years of farm operation decision making, between adopters and non-adopters. As per Table 2, adopters' total farm land under operation, and acres under pasture are statistically significantly higher than those of non-adopters. Overall the data in Tables 1 and 2, and Figure 1 suggest the importance of factors independent of typical demographic and farm characteristics and that focusing on spatial effects in DCR adoption may be important.

Conceptual framework

Spatial effects may potentially affect the likelihood of technology adoption independent of other social, economic, and institutional factors (Foster and Rosenzweig 1995a, Genius et al. 2014, Conley and Udry 2010a, Sampson and Perry 2019). Spatial effects can be conceptualized as two types of impacts that influence farmer's adoption decision through different processes. The first type of spatial effects is related to geographic factors such as soil, climate, and topography. The observed distributional pattern of farmers' adoption decision can be explained partially by the variations in these factors. We define these exogenous/contextual characteristics commonly shared by individuals within a group as spatial heterogeneity effects (Sampson and Perry 2019).

The other type of spatial effects refers to the impact of neighbors' adoption decisions on the focal farmer's adoption decision. Farmers may observe and learn from their neighbors about technologies and practices through social interactions that are strongly conditioned by the spatial distance between individuals (Festinger, Schachter, and Back 1950, Haynes 1974, Gonzalez, Hidalgo, and Barabasi 2008, Sampson and Perry 2019). Therefore, the diffusion of information, ideas, and technology may occur within a certain spatial distance. We define these interactions in which the behavior of an individual is impacted by the behavior of other individuals in the group as spatial dependence effects also known as endogenous effects.

Neighboring farmers may not be the only individuals that affect adoption of new farming practices through diffusion. Friends and relatives in the farmer's social network may also expose and exchange their knowledge and information with the farmer and thus increase the farmer's awareness of new practices and technologies (Lionberger 1960). The current study aims to assess the spatial dependence effects (endogenous/peer effects) that are independent of such social networks. The diffusion of new practices through social networks increases the farmer's awareness and interest. However, such an impact may be less comparable to the influence from a "locality group", defined by spatial distance instead of social distance (Lionberger 1960). To control for any potential bias from contextual factors, we use crop district dummies.

Defining a peer group is a major challenge in studies focusing on spatial effects (Sampson and Perry 2019). In sparsely populated rural areas, we expect that the "peer effects" may not emerge at the same level of geography as it would be in an urban or more populated setting. In this study we use two different peer group definitions: (i) neighbors in a 15 square mile radius; and (ii) neighbors in a 30 square mile radius. The 15 square mile radius more or less corresponds to the average school district boundary in South Dakota. Given the large farm sizes in South

Dakota, inclusion of a larger geographic boundary (30 square miles) will enable us to test the sensitivity of peer effects to specification of peer group definition, particularly the effect of distance on peers. We have also used two separate measures to capture the peer effects: (i) number of peer adopters in the peer group, and (ii) peer adoption rate. Building on the conceptual framework described above, we test the following hypothesis that the likelihood of adopting DCR by a producer increases with an increase in the neighborhood adoption rates (peer effects).

Empirical model

Suppose there are N producers in the region and consider that farmer i will adopt diverse crop rotation if the utility after adoption which includes stochastic monetary profit exceeds or at least equal the utility before adoption. The stochastic monetary profit depends on costs of production, change in yield, market prices, government subsidies, weather effects, and farm and farmer characteristics etc.

Let $d_i=1$ denote the decision of producer i to adopt diverse crop rotation (DCR) and let $d_i=0$ denote the decision to not adopt DCR. Let the perceived profit associated with adoption decision be denoted by π_i^{di}. The relative net profit from adopting DCR is defined as $\pi_i = \pi_i^1 - \pi_i^0$.

Let U_i^{di} denotes the utility for producer i from decision di. Adoption of DCR ($d_i=1$) occurs when $U_i^1 \geq U_i^0$ that is

$$U(1, \pi_i^1 - C, X) \geq U(0, \pi_i^0, X) \quad (1)$$

where 1 indicates producer i’s decision to adopt DCR and 0 indicates non-adoption. C is the cost associated with adopting DCR and X is a vector of observable covariates including peer effects.

The producer's utility function $U(d_i, \pi_i^{di}; X)$ is unknown to us, and the deterministic part of the utility function is $V(d_i, \pi_i^{di}; X)$. So the inequality in (1) can be written as

$$V(1, \pi_i^1\text{-}C, X)+Ʋ_1 \geq VU(0, \pi_i^0, X)+ Ʋ_0 \tag{2}$$

Where $Ʋ_1$ and $Ʋ_0$ are independently and identically distributed random disturbances with zero means and unit variances.

The model can be represented as the following latent equation;

$$D^*_i=\beta`X+\varepsilon i \tag{3}$$

Where Di* is the latent variable such that we observe only the binary outcome

$$D_i=\beta`Xi+\varepsilon i \quad \text{(Whether the producer i adopted DCR or not).} \tag{4}$$

Where β is the vector of parameters to be estimated, and εi is the error term. We estimate equation (4) using a probit model.

Results and Discussion

Participants in the study were asked to report whether they agree or disagree with each of the listed potential benefits and challenges associated with DCR where 1 indicates strong disagreement and 4 indicates strong agreement with the statement. Table 3 summarizes producers' perceptions of the benefits of DCR. As reported previously in the literature, adopters and non-adopters both perceive the environmental benefits such as breaking pest and disease cycle, promoting ecological diversity, and increasing soil fertility and productivity as the most important benefits (Mulik 2015). Additionally, both adopters and non-adopters perceive the potential role of DCR in reducing commodity price volatility as less important benefits of adoption. However, it is evident from Table 3 that adopters' perception of direct and indirect economic benefits such as reduced herbicide usage and fertilizer application and increased crop yields are much more positive at statistically significant levels than that of non-adopters. Results in Table 3 suggest that adopters of DCR are those who have higher positive perceptions on both economic and environmental benefits.

It is evident from Table 4 that the non-adopters' perceptions of challenges associated with DCR are more negative than that of adopters at statistically significant levels. The challenges for which we collected producers response include previously reported factors such as lack of profitable $3^{rd}/4^{th}$ crop, lack of access to specialized equipment, and crop insurance constraints. The finding that many producers consider crop insurance policy as an important factor challenging or hindering the adoption of DCR suggests that initiatives such as whole farm revenue protection plan introduced in the 2014 Farm Bill are not having the desired effect to date (Mulik 2015). Table 4 shows that adopters and non-adopters of DCR are less likely to perceive negative neighborhood opinions as important challenge in the adoption decision of DCR. Results in Table 5 show that majority of the current adopters are likely to continue their adoption of DCR and more than a quarter of current non-adopters, and some of the dis-adopters are likely to adopt DCR in future.

We use the variables reported in Table 3 (producers' perceptions of benefits of DCR) to create two indices for producers, profit perception index and environmental perception index to examine the role of these perceptions on adoption decision.. The profit perception index is generated by developing a weighted average of the rankings for reduces herbicide usage, reduces fertilizer requirement, increases crop yields, and protects against commodity price volatility. The environmental perception index is created by developing a weighted average of rankings for breaks pest and disease cycle, increases soil fertility and productivity, and promotes ecological diversity. Summary statistics for the key variables (not already reported in Table 2) are presented in Table 6. It is evident from Table 6 that adopters' profit and environmental indices are statistically significantly higher than those of non-adopters. Among the variables related to peer effects, percentage of adopters in 15 square miles, number of adopters in 30 square mile radius, and percentage of adopters in 30 square mile radius are statistically different between adopters and non-adopters. To compute the two measurements of spatial effects, we first create a radius of a given distance (15 and 30 miles respectively) for each farmer. Within the radius for each farmer, we then count the total number of adopters. If the focal farmer is not an adopter, then the number of adopters is the number of neighboring adopters. If the focal farmer is an adopter, the number of neighboring adopters is calculated by subtracting 1 from the number of adopters. To calculate the neighborhood adoption rate for each farmer, we first count the total number of neighboring farmers within the radius by subtracting 1 from the number of farmers to remove the focal farmer. The rate is then calculated by dividing the number of neighboring adopters by the number of neighboring farmers.

Table 7 presents the regression results from three different probit models varying based on the type of peer group variable included, for the 15 square mile radius peer group. As per models in Table 7, producers with larger farm areas under operation, more acres under pasture, and higher environmental index are more likely to adopt DCR. The positive effects of larger farms on the likelihood of DCR adoption may be because DCR can support spatial diversity, larger farm operations are more conducive for it. It has been reported previously in the literature that DCR are specifically beneficial for farms that integrate crop and livestock operations and the findings from our study that shows positive effect of pasture acre support it (Mulik 2015). Our results also show that producers with higher acceptance of the environmental benefits of DCR are more likely to adopt DCR. However, none of the peer effects variables, distance to the nearest adopter, number of adopters of DCR in q 15 square mile radius, or percentage of adopters of DCR in a 15 square mile radius are significant predictors of adoption. This may be because our definition of peer group as peers in the 15 square mile radius may not be relevant in the context of South Dakota as it may not be enough to generate the threshold level of peer adopters to motivate adoption.

Table 8 presents the regression results from two different probit models, varying based on the type of peer group variable included, for the 30 square mile radius peer group. All the variables significant for DCR adoption in Table 7 for peer group defined within the 15 square mile radius are also significant for peer group defined within the 30 square mile radius. Unlike in the case of the 15 square mile radius peer group, both peer group related variables; the number of adopters of DCR and percentage of adopters of DCR, are significant for the 30 square mile radius peer group and support our hypothesis that the likelihood of adopting diverse crop rotation by a producer increases with the neighborhood adoption rates (spatial dependence/peer effects).

Figure 2 shows the marginal peer effects evaluated at different number of peer adopters and percentage of peer adopters for the 30 square mile radius peer group in our study. Figure 2 further supports our hypothesis that the likelihood of adoption increases with an increase in the extent of peer effects captured by the number or percentage of adopters in the peer group.

The non-significance of the peer effect variables in the 15 square mile radius peer group regression and the significance of the peer effect variables in the 30 square mile radius peer group regression may suggest that due to the low population density and large operation size in agriculture dominated states like South Dakota, defining peer group using the typical school district boundary (15 square miles) may not provide the threshold level for peer adopters to emerge in rural areas. The results re-emphasize the importance and challenges of defining a peer group, especially if policy makers want to leverage peer effects/social interactions to scale up the adoption of technologies or practices (Sampson and Perry 2019).

Conclusion

In this study we analyzed the role of peer effects in adoption decisions. We also estimated the adoption status of DCR in eastern South Dakota, the future likelihood of adopting diversified crop rotation by current adopters and non-adopters, and producers' perceptions about the benefits and challenges of adoption of DCR.

We found that adoption rate of DCR is low relative to the adoption of other conservation practices such as conservation tillage, cover crops, and integrated crop and livestock systems. Findings from the study demonstrated that while adopters and non-adopters value the environmental benefits of adoption of DCR, adopters' perceptions of economic benefits are higher relative to non-adopters. This suggest that perceptions of economic benefits are important in producers' adoption decisions.

The study showed that lack of profitable third or fourth crop, lack of specialized equipment, and crop insurance constraints are the top three challenges of adopting DCR. This suggests that more outreach efforts are required to increase producers' awareness about new crop insurance policy initiatives such as whole farm revenue protection plan which is intended to promote adoption of practices such as DCR. Our results also showed that the majority of the current adopters are likely to continue their adoption of DCR and more than a quarter of current non-adopters, and some of the dis-adopters are likely to adopt DCR in future.

Findings from the regression analyses demonstrate that the likelihood of adoption of DCR increases with increase in the neighborhood adoption rates (spatial dependence/peer effects) for the peer group defined within 30 square mile radius while no such effect is present for the peer group defined within 15 square mile radius. Our results demonstrated that peer groups and their influence in sparsely populated rural areas might be at bigger geographical areas than we would normally expect. This suggest that using the geographic distance or unit at which the spatial effects start to emerge in urban areas/more populated areas may not be an optimal choice for studying spatial effects in rural areas. Since population and business density are often much lower in rural areas, the diffusion via people and key business locations over the space is more difficult and subtler to capture in rural areas.

Our results suggest that peer effects play an important role in adoption of DCR and care must be taken in defining the peer group. Fruitfulness of efforts to leverage peer effects to scale up the adoption of DCR will depend heavily on accurately identifying peer groups.

References

Altieri, M.A. 1999. "The ecological role of biodiversity in agroecosystems." *Agriculture Ecosystems & Environment* 74:19-31.

Baumgart-Getz, A., L.S. Prokopy, and K. Floress. 2012a. "Why farmers adopt best management practice in the United States: A meta-analysis of the adoption literature." *Journal Enviornmental Management* 96:17-25.

Baumgart-Getz, A., L.S. Prokopy, and K. Floress. 2012b. "Why farmers adopt best management price in the United States: A meta-analysis of the adoption literature." *Journal of Enviornmental Management*:17-25.

Benbrook, C. . 2012. " Impacts of genetically engineered crops on pesticide use in the U.S. – The first sixteen years." *Environmental Sciences Europe* 24 (24). doi: https://doi.org/10.1186/2190-4715-24-24.

Berzsenyi, Z., B. Gyorffy, and D. Lap. 2000. "Effect of crop rotation and fertilisation on maize and wheat yields and yield stability in a long-term experiment." *European Journal of Agronomy* 13:225-244.

Brookes, G. , and P. Barfoot. 2013. "Key environmental impacts of global genetically modified (GM) crop use 1996–2011." *GM Crops & Food* 4 (2):109-119. doi: DOI: 10.4161/ gmcr.24459.

Conley, T.G., and C.R. Udry. 2010a. "Learning about a new technology: Pineapple in Ghana." *American Economic Review* 100 (1):35-69.

Conley, Timothy G., and Christopher R. Udry. 2010b. "Learning about a New Technology: Pineapple in Ghana." *The American Economic Review* 100 (1):35-69.

Crookston, R.K., J.E. Kurle, P.J. Copeland, H.H. Ford, and W.E. Lueschen. 1991. "Rotational cropping sequence affects yield of corn and soybean." *Agronomy Journal* 83:108-113.

Daturesearch. 2014. Adoption of conservation agriculture: Economic incentives in the Iowa. Datu Research.

Davis, Adam S., Jason D. Hill, Craig A. Chase, Ann M. Johanns, and Matt Liebman. 2012. "Increasing Cropping System Diversity Balances Productivity, Profitability and Environmental Health." *PLOS ONE* 7 (10):e47149. doi: 10.1371/journal.pone.0047149.

Dill, G.M., C.A. Jacob, and S.R. Padgette. 2008. "Glyphosate-resistant crops: Adoption, use and future considerations." *Pesticide Management Science* 64:326-331.

EPA, U.S. 2018. Biofuels and the Environment: The Second Triennial Report to Congress.

Fausti, S. W. 2015. "The causes and unintended consequences of a paradigm shift in corn production practices." *Environmental Science & Policy* 52:41-50.

Fausti, S. W., M. M. Tia, J. G. Lundgren, J. Li, A. R. Keating, and M. Catangui. 2012. "Insecticide use and crop selection in regions with high GM adoption rates." *Renewable Agriculture and Food Systems* 27 (4):295-304.

Festinger, L., S. Schachter, and K. Back. 1950. *Social pressures in informal groups; a study of human factors in housing*. West Atrium: John Wiley & Sons, Limited.

Foster, A.D., and M.R. Rosenzweig. 1995a. "Learnign by doing and learning from others: Human capital and technical change in agriculture." *Journal of Political Economy* 103 (6):1176-1209.

Foster, Andrew D., and Mark R. Rosenzweig. 1995b. "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture." *Journal of Political Economy* 103 (6):1176-1209.

Gebermedhin, Berhanu, and Gerald Schwab. 1998. The economic importance of crop rotation systems: Evidence from the literature. Department of Agricultural Economics, Michigan State University.
Genius, Margarita, Phoebe Koundouri, Céline Nauges, and Vangelis Tzouvelekas. 2014. "Information Transmission in Irrigation Technology Adoption and Diffusion: Social Learning, Extension Services, and Spatial Effects." *American Journal of Agricultural Economics* 96 (1):328-344. doi: 10.1093/ajae/aat054.
Golpen, J.J., J.A. Coulter, C.C. Sheaffer, R.L. Becker, F.R. Breitenbach, L.M. Behnken, and J.L. Gunsolus. 2018. "Economic performance of crop rotations in the presence of herbicide-resistant giant ragweed." *Agronomy Journal* 110:260-268.
Gonzalez, M. C., C. A. Hidalgo, and A. L. Barabasi. 2008. "Understanding individual human mobility patterns." *Nature* 453 (7196):779.
Haynes, R. M. . 1974. "Application of exponential distance decay to human and animal activities." *Human Geography* 56 (2):90-104.
Ikerd, John. 1991. "A decision support system for sustainable farming." *Northeastern Journal of Agricultural Economics* 20 (1):109-113.
Johanns, Ann, Craig Chase, and Matt Liebman. 2012. Energy and economic return by crop rotation. Iowa State University.
Lazarus, W.F. , and E. R. Swanson. 1983. "Insecticide use and crop rotation under risk: Rootworm control in corn." *American Journal of Agricultural Economics* 65:738–747.
Lieman, M., and E. Dyck. 1993. "Crop rotation and intercropping strategies for weed management." *Ecol Appl.* 3 (1):92-122.
Lionberger, H. F. . 1960. Adoption of new ideas and practices: a summary of the research dealing with the acceptance of technological change in agriculture, with implications for action in facilitating such change.
Meehan, T. D., and C. Gratton. 2016. "A Landscape View of Agricultural Insecticide Use across the Conterminous US from 1997 through 2012." *PLoS One* 11 (11):e0166724. doi: 10.1371/journal.pone.0166724.
Meehan, T. D., B. P. Werling, D. A. Landis, and C. Gratton. 2011. "Agricultural landscape simplification and insecticide use in the Midwestern United States." *Proc Natl Acad Sci U S A* 108 (28):11500-5. doi: 10.1073/pnas.1100751108.
Mulik, K. 2015. "Economic impacts of diversified cropping systems." Agricultural and Applied Economics 2015 Annual Meeting, San Francisco, CA.
Mulik, K. 2017. Rotating crops, turning profits: how diversified farming systems can help farmers while protecting soil and preventing pollution. Union of Concerned Scientists.
Sampson, G., and E.D. Perry. 2019. "The role of peer effects in natural resource appropriation-The case of groundwater." *American Journal of Agricultural Economics* 101 (1):154-171.
Temple, S., D. Friedman, O. Samson, H. Ferris, K. Scow, and K. Klonsky. 1994. "An interdisciplinary experiment station based participatory comparision of alternative crop management systems for California's Sacramento Valley." *American Journal of Alternative Agriculture* 91 (1&2):64-71.
Wright, C.K., and M.C. Wimberly. 2013. "Recent land use change in the western Corn Belt threaten grasslands and wetlands." *PNAS* 110 (10):4134-4139.

Wu, J., and B.A. Babcock. 1998. "The Choice of Tillage, Rotation, and Soil Testing Practices: Economic and Environmental Implications." *American Journal of Agricultural Economics* 80 (3):495-511.

Table 1: Percent of producers using diverse crop rotation and other conservation practices

	N	Diverse crop rotation	Conservation tillage	Cover crops	Integrated crop and livestock management
Adopters	141	2%	84%	63%	69%
Non-adopters	404	69%	74%	42%	53%
Discontinued	45	8%	77%	20%	39%
Total	590	100	77%	47%	58%

Table 2: Key characteristics of survey participants

Variable	N	Non-adopters Mean (SD)	Adopters Mean (SD)	Whole sample Mean (SD)
Age	536	56.42 (14.11)	56.50 (13.29)	56.44 (13.90)
Education	551	3.09 (0.93)	3.19 (0.98)	3.12 (0.94)
Gender	552	1.03 (0.17)	1.01 (0.12)	1.03 (0.16)
Years primary decision maker	541	27.07 (16.12)	25.93 (15.22)	26.78 (15.89)
Total land in operation	532	1007.55 (1129.10)	1734.06** (3439.08)	1182.35 (1973.05)
% of owned acres	496	0.75 (1.49)	0.76 (1.15)	0.75 (1.42)
Acres under pasture	590	144.31 (344.90)	410.09** (1202.13)	207.83 (668.46)

*Note: We have used Student t-test to compare the mean values of adopters and non-adopters. ** indicates mean values of adopters are statistically significant from non-adopters at 5% level.*

Table 3: Producers' perceptions of benefits of DCR

Benefits	Non-adopters	Adopters	Total
Breaks pest and disease cycle	3.15	3.35***	3.20
	(0.60)	(0.66)	(0.62)
Reduces herbicide usage	2.87	3.01**	2.91
	(0.64)	(0.74)	(0.67)
Reduces fertilizer requirement	2.72	2.86**	2.76
	(0.67)	(0.69)	(0.67)
Increases soil fertility and productivity	3.02	3.20***	3.07
	(0.57)	(0.59)	(0.58)
Increases crop yields	2.94	3.14***	2.99
	(0.60)	(0.65)	(0.62)
Promotes ecological diversity	3.00	3.25***	3.07
	(0.57)	(0.60)	(0.59)
Protects against commodity price volatility	2.46	2.64**	2.50
	(0.76)	(0.79)	(0.77)

*Figure in parentheses indicate standard deviation. **, and *** indicate mean values of adopters and non-adopters are statistically different at 5% and 1% levels, respectively.*

Table 4: Producers' perception of challenges of DCR

Challenges	Non-adopters	Adopters	Total
Lack of profitable 3rd/4th crop	2.95***	2.60	2.86
	(1.00)	(1.04)	(1.02)
Lack access to the specified planting equipment	2.63***	2.03	2.48
	(1.04)	(1.00)	(1.06)
Crop insurance constraints	2.55***	2.04	2.42
	(1.02)	(1.05)	(1.05)
Lack of marketing information	2.45***	1.90	2.31
	(0.96)	(0.95)	(0.99)
Negative neighborhood opinions	1.45	1.37	1.43
	(0.77)	(0.71)	(0.75)

*Figure in parentheses indicate standard deviation. *** indicate mean values of adopters and non-adopters are statistically different at 1% level.*

Table 5: Likelihood of future adoption of DCR

Future Usage	Non-adopters (%)	Adopters (%)	Dis-adopters (%)
Not at all likely	29.4	10.0	31.1
Somewhat likely	29.1	5.7	44.4
Moderately likely	15.7	9.3	13.3
Very likely	17.0	34.3	4.4
Extremely likely	8.8	40.7	6.8
Number of observations	*388*	*140*	*45*

Table 6: Summary statistics of variables used in the regression

Variable	N	Non-adopters	Adopters	Whole sample
		Mean (SD)	**Mean (SD)**	**Mean (SD)**
Profit index	532	0.69 (0.13)	0.73*** (0.15)	0.70 (0.14)
Environmental index	540	0.76 (0.12)	0.82*** (0.14)	0.78 (0.13)
Distance to nearest adopter	504	0.14 (0.09)	0.13 (0.09)	0.13 (0.09)
Number of adopters in 15 sq.miles	504	3.20 (2.04)	3.13 (2.10)	3.18 (2.05)
% of adopters in 15 sq.miles	504	22.79 (16.60)	26.63** (16.05)	23.77 (16.53)
Number of adopters in 30 sq.miles	504	11.32 (5.17)	13.22*** (5.83)	11.80 (5.40)
% of adopters in 30 sq.miles	504	22.84 (12.66)	29.76*** (10.48)	24.60 (12.50)

*Figures in parentheses are standard deviations. **, and *** indicate mean values of adopters and non-adopters are statistically different at 5% and 1% levels, respectively.*

Note: Some of the variables used in regression are already listed in Table 2.

Table 7: Regression results for peer group defined as 15 square mile radius

Variable	Model 1 Coefficient (SE)	Model 2 Coefficient (SE)	Model 3 Coefficient (SE)
Age	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)
Education			
HS diploma/GED	0.45	0.43	0.46
	(0.60)	(0.60)	(0.59)
Some college/tech.	0.62	0.60	0.63
	(0.60)	(0.60)	(0.59)
College grad	0.41	0.38	0.42
	(0.61)	(0.61)	(0.60)
Post-grad degree	1.00	0.97	1.02
	(0.64)	(0.64)	(0.63)
Total farmland operated	0.00**	0.00**	0.00**
	(0.00)	(0.00)	(0.00)
Proportion of owned acres	0.07	0.07	0.07
	(0.11)	(0.11)	(0.11)
Yrs in decision making	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)
Pasture acres	0.00*	0.00*	0.00*
	(0.00)	(0.00)	(0.00)
Gross sales			
$50k-99,999	-0.63**	-0.63**	-0.65**
	(0.32)	(0.32)	(0.32)
$100k-249,999	-0.27	-0.26	-0.28
	(0.29)	(0.29)	(0.29)
$250k-499,999	-0.50*	-0.50*	-0.51*
	(0.29)	(0.29)	(0.30)
$500k-999,999	-0.47	-0.46	-0.48
	(0.32)	(0.33)	(0.33)
$1million or more	-0.60	-0.59	-0.60
	(0.38)	(0.38)	(0.38)
Profitindex	0.19	0.20	0.17
	(0.77)	(0.77)	(0.77)
Envionindex	1.79**	1.80**	1.81**
	(0.88)	(0.89)	(0.88)
District			
30	0.27	0.31	0.26
	(0.25)	(0.27)	(0.26)

50	0.15	0.15	0.14
	(0.32)	(0.32)	(0.31)
60	-0.37	-0.35	-0.35
	(0.25)	(0.26)	(0.26)
90	-0.29	-0.28	-0.27
	(0.25)	(0.25)	(0.26)
Near_dist)adopter	-0.57	-0.79	-0.41
	(0.84)	(0.95)	(0.88)
n_adopter_15miles		-0.02	
		(0.04)	
pct_adopter_15miles			0.00
			(0.01)
_const	-2.39**	-2.30**	-2.48**
	(1.00)	(0.10)	(0.10)
Number of observations	383	383	383
Prob>Chi^2	0.0001	0.0001	0.0001
Log pseudolikelihood	-193.70	-193.60	-193.60
Pseudo R^2	0.1313	0.1318	0.1317

Note:(***), (**), (*) denote significance at the 1%, 5% and 10% levels, respectively.

Table 8: Regression results for peer group defined as 30- square mile

Variable	Model 1 Coefficient (SE)	Model 2 Coefficient (SE)
Age	0.00	0.00
	(0.01)	(0.01)
Education		
HS diploma/GED	0.41	0.42
	(0.58)	(0.59)
Some college/tech.	0.63	0.60
	(0.58)	(0.58)
College grad	0.42	0.43
	(0.58)	(0.59)
Post-grad degree	1.07*	1.01
	(0.62)	(0.62)
Total farmland operated	0.00**	0.00*
	(0.00)	(0.00)
Proportion of owned acres	0.07	0.07
	(0.11)	(0.11)
Yrs in decision making	0.00	0.00
	(0.01)	(0.01)
Pasture acres	0.00**	0.00
	(0.00)	(0.00)
Gross sales		
$50k-99,999	-0.67**	-0.73**
	(0.31)	(0.31)
$100k-249,999	-0.26	-0.30
	(0.29)	(0.29)
$250k-499,999	-0.48	-0.53*
	(0.30)	(0.30)
$500k-999,999	-0.44	-0.50
	(0.32)	(0.32)
$1million or more	-0.55	-0.54
	(0.37)	(0.38)
Profitindex	0.38	0.29
	(0.78)	(0.77)
Envionindex	1.50*	1.69*
	(0.89)	(0.88)
Crop District		
30	0.04	0.13
	(0.28)	(0.26)
50	0.14	0.07
	(0.32)	(0.32)

60	-0.47*	-0.12
	(0.25)	(0.28)
90	-0.30	-0.06
	(0.25)	(0.27)
Near_dist_adopter	0.34	0.28
	(0.95)	(0.90)
n_adopter_30miles	0.04**	
	(0.02)	
pct_adopter_30miles		0.02***
		(0.01)
_const	-2.83***	-3.12***
	(1.00)	(1.02)
Number of observations	383	383
Prob>Chi^2	0.0000	0.0000
Log pseudolikelihood	-191.65	-190.67
Pseudo R^2	0.1405	0.1449

Note:(***), (**), (*) denote significance at the 1%, 5% and 10% levels, respectively.

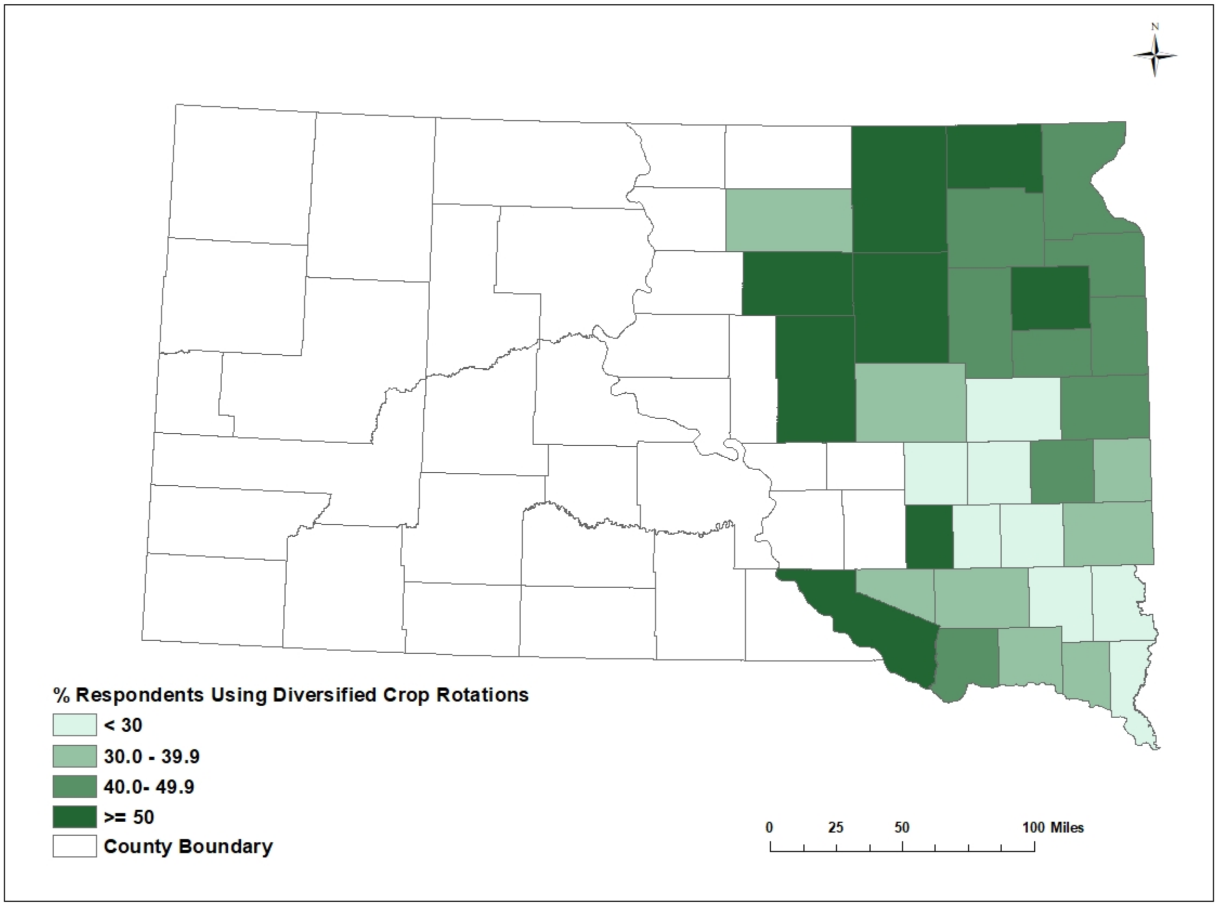

Figure 1: County-wise percentage of respondents using DCR

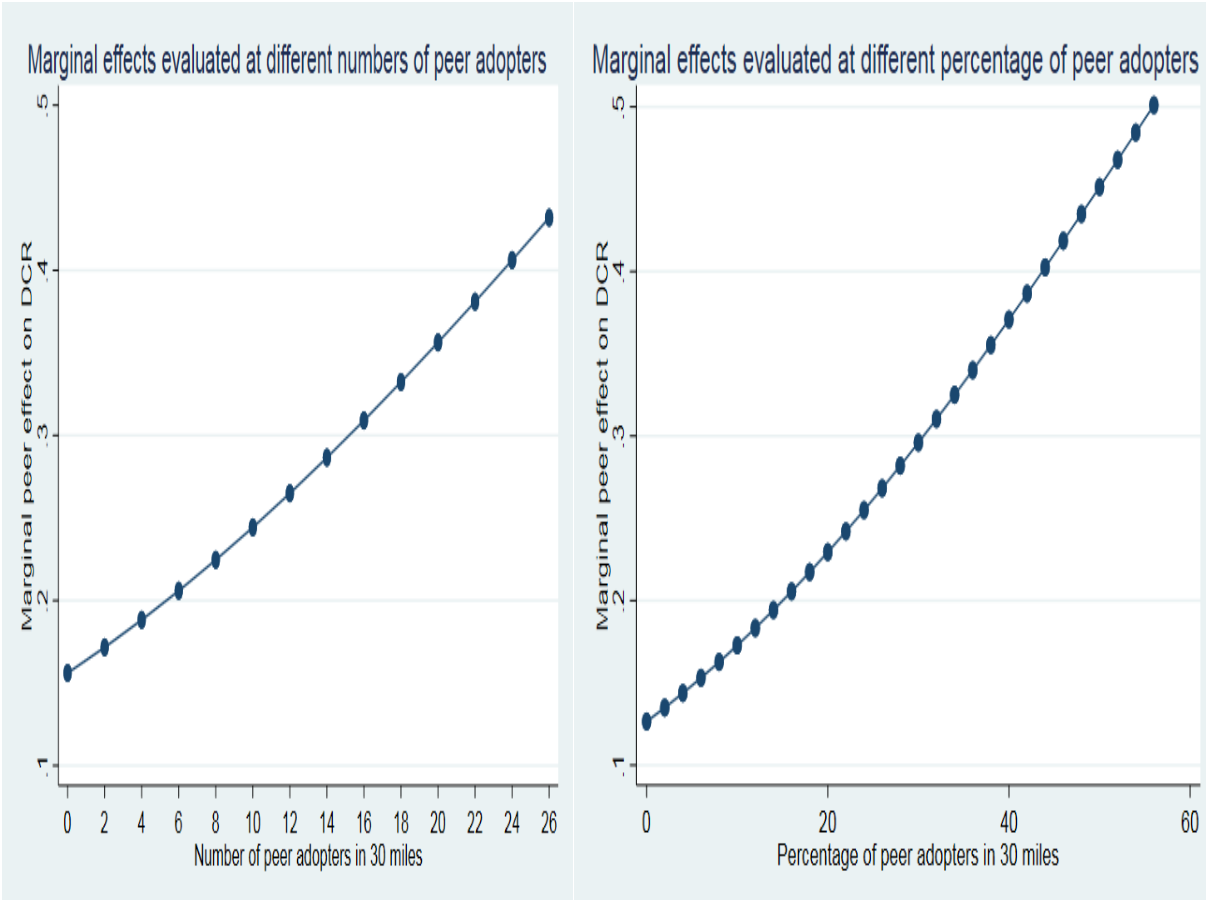

Figure 2: Marginal peer effects on adoption of DCR in 30 square mile radius peer group